Is Business Strategy a Priced Fundamental-broad Information Risk Factor?

A dissertation submitted in partial fulfilment of the requirement for the degree of Doctor of Philosophy

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DECLARATION

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ABSTRACT

While Francis et al. (2005) claim that accruals quality as a proxy for information risk is priced by investors, Core et al. (2008) find no pricing evidence for accruals quality and suggest future studies use a broader or more fundamental proxy for information risk to investigate the pricing of information risk. Subsequently, Ogneva (2012) suggests that the lack of pricing evidence on accruals quality as documented by Core et al. (2008) is due to the offsetting effect of such risk, for instance through cash flow shocks, on asset prices. Thus, whether information risk is priced by investors remains an empirical question.

The purpose of this thesis is to investigate the pricing of information risk. The investigation is conducted as follows. First, the thesis identifies a proxy for information risk comprising various components that are likely to be priced differently by investors. Second, it shows that the lack of pricing evidence on such proxy (similar to accruals quality) could be due to the offsetting effect of the risk of such components on asset prices. As suggested by Core et al. (2008), the effect of a fundamental or broad information risk proxy is more likely to be captured in asset prices when testing the pricing of information risk. Following that suggestion, this thesis employs an *ex ante* and fundamental-broad information risk proxy, that is business strategy, to investigate the pricing of information risk. This thesis identifies a firm's business strategy through the methodology of Bentley et al. (2013), which is based on the Miles and Snow (1978) strategic typology, and focuses on the contrasting innovation-oriented prospector versus efficiency-oriented defender strategies. Bentley et al. (2013) suggest that prospectors experience higher inherent information asymmetry (i.e. poorer quality of information), whereas Bentley et al. (2014) argue that defenders exhibit a poorer external information environment (i.e. less quantity of information). According to Easley and O'Hara (2004), both quality and quantity of information are relevant to equity pricing. Thus, it is possible that investors simultaneously associate the innovation component of business strategy which signifies higher inherent information asymmetry (i.e. poorer quality of information) with a higher required rate of return, and the efficiency component of business strategy which signifies poorer external information environment (i.e. less quantity of information) with a higher required rate of return. The pricings of these two components may offset each other yielding insignificant pricing of business strategy.

With U.S. data spanning 1972-2010, the thesis conducts a battery of asset pricing tests and concludes that business strategy, in aggregate, is not priced by investors. Therefore, the results do not lend support to Core et al.'s (2008) suggestion that a fundamental-broad information risk proxy can maximize the likelihood of information risk being captured in the asset pricing models, as it neglects the potential offsetting effect of the information risk proxy on asset prices as noted by Ogneva (2012). Further analyses provide evidence supporting the offsetting pricing effect argument of business strategy components, rather than the traditional view that information risk is diversifiable and thus irrelevant to equity pricing (Fama, 1991). Specifically, investors, simultaneously price innovation and efficiency components of business strategy, leading to insignificant business strategy pricing in aggregate.

CHAPTER 1: INTRODUCTION

1.0 Introduction

The objectives of this thesis are two-fold. First, to investigate whether business strategy, as an *ex ante* and fundamental-broad information risk factor, is priced by investors. Second, if there is no evidence indicating business strategy as a priced fundamental-broad information risk factor, to investigate whether there is an offsetting pricing effect emanating from variables or components used to construct the business strategy measure.

Francis, LaFond, Olsson and Schipper (2005) claim that accruals quality, as a proxy for information risk, is a priced risk factor by showing a significant positive correlation between the accruals quality factor return and contemporaneous stock returns, after controlling for the Fama and French (1992, 1993) three factors. Nevertheless, Core, Guay and Verdi (2008) argue that the model employed in Francis et al. (2005) only examines a contemporaneous association between excess returns and factor returns rather than whether accruals quality is priced. Core et al. (2008) find no evidence of accruals quality pricing when they conduct well-specified asset pricing tests (e.g., two stage cross-sectional regression). Ogneva (2012) provides an offsetting pricing argument for Core et al.'s (2008) findings. She suggests that Core et al.'s (2008) measure of accruals quality which is based on Dechow and Dichev (2002)'s residual accrual volatility is negatively correlated with future cash flow shocks.[1] Decomposing realized returns into cash flow shocks and returns excluding cash flow shocks, Ogneva (2012) finds that low accruals quality firms are

[1] Ogneva (2012) defines cash flow shocks as the return resulting from a revision in expectation of a firm's future earnings.

subject to lower cash flow shocks, whereas high accruals quality firms are subject to higher cash flow shocks. She argues that these lower cash flow shocks offset the higher expected returns of lower accruals quality firms, and these higher cash flow shocks offset the lower expected returns of higher accruals quality firms. After excluding cash flow shocks, she documents that low accruals quality firms are associated with a higher required rate of return. The findings from these studies suggest that the pricing of information risk remains an empirical issue worthy of investigation.

In their concluding remarks, Core et al. (2008) note that "accruals quality is but one of many potential proxies for information risk" (p.21). Core et al. (2008) suggest future research uses an alternative broad information risk proxy, or an underlying factor that drives disclosure quality, financial reporting quality and even information risk, to investigate the pricing of information risk. They imply that a fundamental-broad information risk proxy may withstand the asset pricing tests. In response to Core et al.'s (2008) call, this thesis investigates pricing of business strategy as a fundamental-broad information risk proxy in the asset pricing models. Business strategy, selected in a preliminary stage of a firm’s history, remains relatively stable over time due to long-term resource commitments (Snow & Hambrick, 1980; Hambrick, 1983; Burgelman, 2002) and determines a firm's strategic direction (Miles & Snow, 1978, 2003), that fundamentally influence its inherent and external information environment (Bentley, Omer & Sharp, 2013; Bentley, Omer & Twedt, 2014). The information risk emanating from inherent and external information environment refers to the risk from quality and quantity of information, respectively, and both are relevant to equity pricing in the framework of

Easley and O'Hara (2004).[2] Business strategy can lead to inherent information risk since it shapes decisions made in the (1) entrepreneurial (i.e. product and market domain), (2) engineering (i.e. technology), and (3) administrative (i.e. organizational structure and process) dimensions in a firm’s adaptive cycle (Miles & Snow, 1978).[3] More specifically, managerial freedom, the extent of control, and the complexity of a firm's operating environment emanating from the above dimensions can potentially lead to variability in managerial discretion, opportunism and monitoring influencing a firm's information asymmetry (risk) environment (Jensen & Meckling, 1976). Existing studies including Bentley (2012) and Bentley et al. (2013) articulate that business strategy can affect a firm's ethical climate and culture for fraudulent behaviour through incentive, opportunity, and rationalization, thereby serving as an *ex ante* factor for financial statement misreporting. In support, Higgins, Omer and Phillips (2013) find that business strategy is a determinant of a firm's tax avoidance activities which can affect both tax and information risks.

Business strategy can also lead to external information risk. Bentley et al. (2014) propose that business strategy is an underlying determinant of a firm's (external) information environment since it affects the level of voluntary disclosures, analyst and media coverage. More specifically, business strategy determines investments such as research and development (R&D) and advertising that provide the media and analysts with

[2] In this thesis, inherent information environment refers to information asymmetry faced by a firm internally including agency conflicts between shareholders and managers, subsequently affecting the quality of financial reporting, corporate governance and disclosures. On the other hand, external information environment refers to the level of information covering the firm in the market and the extent of external monitoring a firm experiences, which are affected by analyst coverage, media coverage, institutional holdings and voluntary disclosures. In other words, 'inherent' and 'external' information environment signify "quality" and "quantity" of information, respectively, with both relevant to equity pricing in the framework of Easley and O'Hara (2004).

[3] The adaptive cycle refers to the process by which firms make critical strategic decisions in product and market domain, technology, structure and organizational process so as to correspond to the environment chosen, with the aim to attain an effective position in the market (Miles & Snow, 1978; Miles, Snow, Meyer & Coleman Jr, 1978).

incentives to follow a firm, and financing needs that affect the level of voluntary disclosures, thereby influencing the quantity of firm-specific information circulating in the market. Investment decisions in R&D and advertising induced by business strategy also affect the level of institutional holdings (Grullon, Kantas & Weston, 2004), and prior studies (e.g., Shleifer & Vishny, 1986; Elyasiani & Jia, 2010) suggest that institutional holders serve as an external monitoring and disciplinary mechanism that reduces a firm's information risk.

The second objective of the thesis is conditioned on the first objective. That is, if insignificant pricing of a fundamental-broad information risk proxy measured by business strategy is found, is it attributable to: (1) the diversifiable nature of information risk as a form of firm-specific risk as suggested by traditional finance (e.g., Sharpe, 1964; Lintner, 1965; Black, 1972; Fama, 1991)?; or (2) an offsetting pricing effect from variables or components used to compute business strategy? The thesis identifies a firm's business strategy based on the Miles and Snow (1978) strategic typology, following the methodology of Bentley et al. (2013) which employs variables that can be broadly classified into two components: innovation and efficiency. Potentially, these variables and components of business strategy (i.e. innovation versus efficiency) capture different forms of information risk (i.e. quality versus quantity of information), and are priced accordingly and simultaneously by investors. There may be offsetting pricing of business strategy components leading to insignificant pricing of business strategy in aggregate. This alternative explanation is in a similar vein to Ogneva (2012) who offers an offsetting pricing argument for Core et al.'s (2008) results.

Divergent perspectives with regard to whether information risk is diversifiable or whether it is a priced risk factor have increasingly attracted attention in capital market research. Traditionally, the Capital Asset Pricing Model (CAPM) suggests that stocks are efficiently priced based on their association with the market risk; and hence firm-specific risk, that can be diversified away through the construction of investment portfolios, is irrelevant to equity pricing (Fama, 1991). This model was subsequently modified to acknowledge that risk emanating from firm attributes, such as size and book-to-market, is considered by investors in their price setting process (Fama & French, 1992, 1993). There are theoretical and empirical debates around whether other firm attributes such as information risk are priced. Several analytical studies contest the traditional asset pricing argument by suggesting that information risk is not diversifiable and thus it is priced, based on: the liquidity effect (Demsetz, 1968; Copeland & Galai, 1983; Glosten & Milgrom, 1985; Amihud & Mendelson, 1986a; Diamond & Verrecchia, 1991); the incomplete but symmetric information effect (Merton, 1987; Basak & Cuoco, 1998; Shapiro, 2002); the information asymmetry effect (Grossman & Stiglitz, 1980; Admati, 1985; Wang, 1993; Easley, Hvidkjaer & O’Hara, 2002; Easley & O’Hara, 2004); and the estimation risk effect (Klein & Bawa, 1976; Barry & Brown, 1985; Coles & Loewenstein, 1988; Handa & Linn, 1993; Coles, Lowenstein & Suay, 1995; Clarkson, Guedes & Thompson, 1996; Leuz & Verrecchia, 2004).

Of particular note, Easley and O’Hara (2004) argue that the information asymmetry between informed and uninformed investors disadvantages uninformed investors, because informed investors have access to both public and private information, allowing them to hold more good-news stocks and less bad-news stocks. By contrast, uninformed investors only have access to public information, therefore in bad times their portfolios are overweight in bad-news stocks, whereas in good times their portfolios are underweight in good-news stocks. While uninformed investors do not know the proper weights of each asset to hold in a portfolio, holding a portfolio with many stocks cannot diversify away asymmetric information risk. Therefore, this results in information risk being translated into a form of non-diversifiable risk. In equilibrium, investors expect a higher rate of return as compensation for such risk. Easley and O'Hara's (2004) proposition based on a finite economy is, however, contested by studies such as Hughes, Liu and Liu (2007) and Lambert, Leuz and Verrecchia (2007), who argue that information risk is diversifiable in a large economy and is already impounded into the market risk premium. The tension caused by the above literature in relation to pricing of information risk motivates the investigation of the pricing of a fundamental-broad based information risk factor (Core et al., 2008) in this thesis.

While empirical studies have documented an association between the information risk, emanating from the level or quality of disclosures, financial reporting, and corporate governance, and implied cost of equity (e.g., Botosan, 1997; Francis, LaFond, Olsson & Schipper, 2004; Ogneva, Subramanyam & Raghunandan, 2007), these information risk proxies are not priced when they are included in the asset pricing models (e.g., Core et al., 2008; McInnis, 2010; Mashruwala & Mashruwala, 2011; Barth, Konchitchki & Landsman, 2013). The pricing of information risk, therefore, remains an important puzzle to be addressed given the critical role information plays in the capital markets. Core et al. (2008) propose that a relatively more fundamental- or broader-based proxy for information risk than accruals quality may withstand asset pricing tests. The quality of financial reporting, disclosures and corporate governance used by prior studies only represent *ex post* information risk proxies that are uni-dimensional, and not the fundamental cause of information risk.

Responding to the call by Core et al. (2008), this thesis uses a fundamental-broad information risk proxy, business strategy, to test whether information risk is priced by investors. Specifically, this thesis investigates the following first research question: Is business strategy a priced fundamental-broad information risk factor? Business strategy is the way a firm achieves, maintains or enhances its performance, with an enduring nature that renders it less likely to change considerably in the short term (Snow & Hambrick, 1980; Hambrick, 1983; Zajac & Shortell, 1989). Burgelman (2002) asserts that business strategy has a far-reaching impact on the firm, as it leads to resource commitments and strategic direction that are not easily reversible. Business strategy is a fundamental information risk proxy that has been shown to drive financial reporting, disclosure and corporate governance quality, the level of tax avoidance, and external information environment (e.g., Bentley et al., 2013; Higgins et al., 2013; Bentley et al., 2014). Business strategy as a fundamental-broad based proxy for information risk has not previously been investigated by prior asset pricing and implied cost of equity studies. Some studies have employed a single component measure of business strategy such as R&D (Shangguan, 2005; Hedge & Mishra, 2014), advertising (Huang & Wei, 2012), and efficiency (Nguyen & Swanson, 2009; Frijns, Dimitris & Maria, 2012) and offered pricing evidence of these components.

Business strategy leads to the alignment of decisions made in the entrepreneurial, engineering, and administrative dimensions in a firm's adaptive cycle, so as to ensure firm competitiveness in the market (Miles & Snow, 1978, 1984, 1986, 2003; Miles et al., 1978; Milgrom & Roberts, 1995; Thomas & Ramaswamy, 1996). Such an alignment requires firms with different business strategies to establish different product and market domains, technologies, structures and organizational processes, that can ultimately affect: (1) the exercise of managerial discretion at the expense of shareholders' wealth; (2) the complexity of a firm's operating environment; and (3) the level of monitoring and control, being fundamental determinants of agency conflicts and hence information risk argued by Jensen and Meckling (1976). Building on the framework in *Statement on Auditing Standards (SAS) No. 99: Consideration of fraud in a financial statement audit* (American Institute of Certified Public Accountants [AICPA], 2002), Bentley (2012) and Bentley et al. (2013) propose that business strategy serves as an *ex ante* factor for financial statement misreporting, as it affects incentive, opportunity, and rationalization for fraudulent behaviour. Further, Bentley et al. (2014) assert that business strategy is an underlying determinant of a firm's (external) information environment, as it affects the level of voluntary disclosures, analyst coverage and media coverage.

Given that firms adopt different business strategies, the level of information risk (both inherent and external) fluctuates commensurate with their strategies. This thesis measures firms' fundamental-broad information risk with Bentley et al.'s (2013) business strategy score and uses this measure to categorise firms into prospector, analyzer and defender strategic types consistent with the Miles and Snow (1978) typology. As discussed in the following subsections, existing literature finds that prospectors, typified by an innovation-orientated business strategy, exhibit greater inherent information asymmetry but a richer external information environment. In contrast, defenders characterized by an efficiency-orientated business strategy display less inherent information asymmetry but a poorer external information environment. Thus, it is unclear, whether defenders or prospectors have an overall higher level of information risk. Analyzers possessing characteristics of both prospectors and defenders are assumed to have a medium level of information risk, and therefore the focus of this thesis is on prospector and defender strategies.[4]

1.0.1 Higher (Lower) Inherent Information Asymmetry of a Prospector (Defender) Strategy

Firms with a prospector business strategy aggressively exploit new market opportunities and introduce new products to maintain the reputation of being innovative leaders (Miles & Snow, 1978). Correspondingly, prospectors adopt less formalized technologies, recruit high human capital individuals, impose less monitoring and control, and employ a decentralized organizational structure to give employees a degree of autonomy (Damanpour, 1991; Rajagopalan, 1997; Miles & Snow, 2003; Siggelkow & Rivkin, 2006). This allows high human capital individuals to perform their tasks in a timely and flexible manner, minimizes the costs of knowledge transfer, and motivates the individuals (Pfeffer, 1995; Acemoglu, Aghion, Lelarge, van Reenen & Zilibotti, 2007; Lawler III, 2009).

Consequently, prospectors can be associated with greater inherent information asymmetry, due to the following reasons. First, high human capital individuals are more

[4] Reactor, the fourth type of business strategy mentioned in Miles and Snow (1978), is not a focus of this thesis. This strategy is not considered viable because it fails to achieve strategic fit (i.e. alignment among decisions made in the entrepreneurial, engineering and administrative dimensions, and consistency in strategic position across time). Further, this thesis operationalizes business strategy based on Bentley et al. (2013) who have not incorporated a measure capturing a reactor strategy.

likely to abuse the discretion afforded to pursue self-interests, knowing that prospectors have greater tolerance towards their opportunism, as they are difficult to replace (Williamson, 1979; Brüderl, Preisendörfer & Ziegler, 1992; Rajagopalan & Finkelstein, 1992; Monteverde, 1995; Rajagopalan, 1997; Colf, 2002; Naiker, Navissi & Sridharan, 2008). Second, a decentralised administrative structure intensifies control complexity and divergent interests between top and lower level managers (Bruns & Waterhouse, 1975; Eisenhardt, 1989; Acemoglu et al., 2007). Insufficient monitoring also gives managers and employees opportunities to shirk and pursue self-interests that exaggerate information risk (Alchian & Demsetz, 1972; Fama, 1980; Klein, 1989; Abernethy, Bowens & van Lent, 2004; Raes, Heijltjes, Glunk & Roe, 2011). Third, as a consequence of pursuing innovation, prospectors operate in an environment characterized with fierce competition and unpredictable change in consumers' choices. This heightens firm performance and managerial remuneration uncertainties that complicate managerial assumptions in financial reporting and imposes greater barriers to managers in making more accurate estimations about firm future prospects (Bentley et al., 2013). It also incentivizes managers to undertake sub-optimal investment decisions (Jensen & Meckling, 1976; Smith & Watts, 1992) or engage in opportunistic financial reporting (Watts & Zimmerman, 1990; Skinner & Sloan, 2002), leading to greater information risk.

In contrast, firms with a defender business strategy aspire to offer high quality and cost-efficient products to regular customers in market niches, with no or little focus on research and development, thereby reducing uncertainty (Miles & Snow, 1978; Thomas & Ramaswamy, 1996; Naiker et al., 2008). To achieve this, they constantly enhance the efficiency of technologies and adopt a centralized organizational structure to facilitate stringent monitoring and control (Ittner & Larcker, 1997; Miles & Snow, 2003; Bentley et al., 2013). Consequently, managers and employees in defenders are afforded less discretion, and are more subject to task programmability and strict monitoring and control that can curb employee opportunism and information asymmetry (Ittner, Larcker & Rajan, 1997; Naiker et al., 2008).

Similarly, Bentley (2012) and Bentley et al. (2013) suggest that prospectors exhibit higher inherent information asymmetry since they are more exposed to three factors for financial reporting irregularities under the framework of *SAS No. 99*. First, prospectors are characterized with rapid and sporadic growth through market exploitation (Miles & Snow, 1978), stock-option-based compensation that encourages risk taking (Rajagopalan & Finkelstein, 1992; Rajagopalan, 1997; Singh & Agarwal, 2002), greater need for external financing (Miles & Snow, 2003), and a higher likelihood to poor performance and financial distress (Hambrick, 1983; Ittner et al., 1997). They have greater incentives for financial misreporting (AICPA, 2002; Efendi, Srivastava & Swanson, 2007; Hogan, Rezaee, Riley & Velury, 2008), relative to defenders. Second, the administrative structure of prospectors characterized by a lack of monitoring, greater complexity, and less organizational stability, as a consequence of decentralization policy and high senior management turnover (Miles & Snow, 1978; Simons, 1987; Loebbecke, Eining & Willingham, 1989), provides greater opportunities for them to engage in financial misreporting (AICPA, 2002), compared to defenders. Third, prospectors tend to develop an individualistic and egoism based ethical climate and culture that can rationalize the pursuit of self-interested behaviour and increase the risk to misreport, as opposed to defenders with a more principle based ethical climate and culture (Victor & Cullen, 1988; AICPA, 2002; Miles & Snow, 2003).

Consistent with the discussions above, a strand of literature associates some attributes of a prospector strategy with higher information asymmetry. For example, studies such as Aboody and Lev (2000) and Barth, Kasznik and McNichols (2001) associate R&D, a significant attribute of prospectors, with higher levels of information asymmetry. This is because investors find it difficult to derive asset pricing information absent an active market for intangible assets, and greater uncertainty about firm value inherent in R&D firms can lead to mispricing. Lev and Zarowin (1999) suggest lower earnings informativeness for firms with substantial intangible investments. Aboody and Lev (2000) document excess returns by insiders in R&D-intensive firms who have superior knowledge about the future payoffs of a firm's R&D investments. Boone and Raman (2001) and Barron, Byard, Kile and Riedl (2002) find that firms in R&D-intensive industries have greater bid-ask spreads, and analyst forecast dispersion (which are proxies for information asymmetry), respectively. Penman and Zhang (2002) notice excess returns as a consequence of investors being misled by conservative accounting treatment of R&D. Shangguan (2005) and Hedge and Mishra (2014) find a positive association between a firm's cost of equity capital and R&D expenditures which signify uncertainty and asymmetric information about the commercial success of innovative activities. Bentley et al. (2013) report that prospectors exhibit higher financial reporting irregularity and require more audit effort. Higgins et al. (2013) document that prospectors are more aggressive in their tax position relative to defenders, and several studies (Hutchens & Rego, 2013; Goh, Lee, Lim & Shevlin, 2013) provide evidence that aggressive tax avoidance is associated with a higher implied cost of equity through tax and information risks. Nguyen and Swanson (2009) and Frijns et al. (2012) observe higher required returns from inefficient firms (presumably associated with greater default and distress risks), however their studies motivate the pricing of efficiency through the angle of business rather than information risks.

1.0.2 Richer (Poorer) External Information Environment of a Prospector (Defender) Strategy

Another strand of literature, however, associates firms with prospector characteristics with lower information asymmetry, due to their intensive R&D, advertising activities and growth opportunities that can enhance firm visibility (Grullon et al., 2004; Chordia, Huh & Subrahmanyam, 2007) and thereby affect equity pricing. Under an incomplete information framework, Merton (1987) argues that firm value is a positive function of investor recognition (i.e. the number of investors who know about a particular stock), holding fundamentals constant. Investors only know about a subset of securities, and this knowledge differs across investors. Investors require higher expected returns to compensate them for holding securities that they are less familiar with (Lehavy & Sloan, 1998). Consistently, Huang and Wei (2012) find that advertising intensity is related to a lower implied cost of equity capital. R&D, advertising activities, and growth opportunities are also possible channels to attract analysts' coverage, institutional holders and media coverage. This further enhances firm visibility and investor recognition, as well as increasing liquidity and reducing firm information asymmetry, thereby reducing a firm's cost of capital (Amihud & Mendelson, 1986b; Bhushan, 1989; Falkenstein, 1996; Barth et al., 2001; Huberman, 2001; Grullon et al., 2004; Piotriski & Roulstone, 2004; Miller, 2006; Dyck, Volchkova & Zingales, 2008; Fang & Peress, 2009; Bushee, Core, Huay & Hamm, 2010; Patton & Verardo, 2012). Parallel to this argument, Bentley et al. (2014) show that prospectors have smaller bid-ask spreads, lower analyst forecast dispersion, and higher analyst forecast accuracy, relative to defenders, as they are associated with greater analyst coverage and media coverage which can mitigate the inherent level of information asymmetry. Besides, prospectors tend to experience lower profitability rendering them not having sufficient internal funds to facilitate extensive innovative activities, thus they need to heavily rely on external financing (Hambrick, 1983; Ittner et al., 1997). As a result, Bentley et al. (2014) find that prospectors have greater incentives to lower information asymmetry through voluntary disclosures as a tactic to reduce the cost of capital, relative to defenders.

In summary, the existing literature does not yield a consensus as to whether information risk is priced, and whether prospectors or defenders are associated with an overall higher level of fundamental-broad information risk after simultaneously contemplating the impact of business strategy on a firm’s inherent and external information environment. Since Easley and O'Hara (2004) conclude that investors simultaneously price quality and quantity of information, it leads to two competing expectations: (1) in aggregate, defenders are associated with a higher required rate of return if they exhibit an overall higher level of fundamental-broad information risk relative to prospectors; or (2) in aggregate, prospectors are associated with a higher required rate of return if they exhibit an overall higher level of fundamental-broad information risk relative to defenders.

Nevertheless, Core et al.'s (2008) expectation that a fundamental-broad information risk proxy maximizing the likelihood of obtaining pricing evidence for information risk may not be supported, as Ogneva (2012) highlights that there can be an offsetting effect of such information risk on asset prices, for instance through cash flow shocks. Since business strategy in this thesis is operationalized using various variables based on Bentley et al. (2013), it is possible that these components of business strategy capture different forms of information risk and are priced by investors in different ways leading to an offsetting pricing argument. If the investigation of the first research question concludes that business strategy does not constitute a priced fundamental-broad information risk factor, the thesis poses the second research questions: Is there an offsetting pricing effect from variables or components of business strategy? Potentially, the pricing of inherent information risk (i.e. poorer quality of information) associated with innovation component of business strategy may offset the pricing of external information risk (i.e. less quantity of information) associated with efficiency component of business strategy, thereby leading to insignificant pricing of business strategy, representative of a fundamental-broad information risk proxy, in aggregate. Such investigation is critical before one simply attributes insignificant pricing of fundamental-broad information risk proxied by business strategy to the traditional asset pricing view that firm-specific risk is diversifiable and irrelevant to equity pricing (e.g., Sharpe, 1964; Lintner, 1965; Black, 1972; Fama, 1991).

The subsequent discussion of this chapter is as follows. Section 1.1 discusses the motivation for this thesis. Section 1.2 summarizes the findings of this study. Section 1.3 discusses the contributions of this thesis. Section 1.4 outlines the structure of this thesis.

1.1 Motivation

The primary motivation for this study stems from the unresolved tension in accounting and finance research with regard to the pricing of risk emanating from information. Traditional asset pricing models disregard idiosyncratic risks including information risk in equity pricing (Fama, 1991). Analytical research has challenged that information risk is relevant to equity pricing (e.g., Admati, 1985; Amihud & Mendelson, 1986a; Diamond & Verrecchia, 1991; Wang, 1993; Clarkson et al., 1996; Easley et al., 2002; Easley & O'Hara, 2004; Leuz & Verrecchia, 2004). However, other studies question the assumptions in the analytical studies, and reinforce the diversifiability, and hence non-pricing, of information risk (e.g., Hughes et al., 2007; Lambert et al., 2007). Beyer, Cohen, Lys and Walther (2010) state that the hypothesis of whether financial reporting and disclosures influence asset prices depends on whether information risk is diversifiable, and therefore the pricing of information risk remains an open question subjecting to proxies for information risk. Clarkson et al. (1996) advocate that the question of diversifiability for information risk can only be empirically addressed. This motivation is reinforced by Ghoul, Guedhami, Ni, Pittman and Saadi (2013) who recognize that the absence of a widely accepted proxy for information risk impedes the reliable testing for the impact of information risk on equity pricing. Core et al. (2008) suggest future studies consider a fundamental or broad information risk proxy. In response to Core et al.'s (2008) call, this thesis uses business strategy, as a fundamental-broad information risk variable, to test the impact of information risk in the asset pricing models. Thus, the first research question in this thesis is addressed using a theoretically underlying and broader measure of information risk, consistent with the suggestion by Core et al. (2008), and empirically tests this measure in the existing asset pricing models.

Furthermore, Naiker et al. (2008), examining whether the regulation-related effect of stock equity varies with business strategies,[5] suggest that prior research has largely

[5] In 2000, the New Zealand government introduced a new unionization legislation that increased the bargaining power of labour unions. This legislation had a more adverse impact on firm value for prospectors relative to defenders. This is because when strikes take place, prospectors have greater difficulty in replacing

overlooked a firm's strategic position as a factor affecting stock prices. Although they do not directly test the role of business strategy in asset pricing, their study provides a motivation for this thesis to expand and provide empirical evidence on this line of reasoning, by investigating whether business strategy, as a fundamental-broad information risk factor, is priced by investors.

The second motivation is driven by the tension in the literature as to whether firms with a prospector or defender strategy are associated with an overall higher level of information risk. While Bentley et al. (2013) and Higgins et al. (2013) associate prospectors with more financial reporting irregularities, audit effort and aggressive tax positions relative to defenders, Bentley et al. (2014) find a richer information environment (e.g., more analyst coverage, media coverage and frequent voluntary disclosures) for prospectors *vis-à-vis* defenders. It is therefore essential to examine the pricing of information risk proxied by business strategy to explore how investors perceive and react to the overall level of information risk between prospectors and defenders. Further, if the results show insignificant pricing of information risk proxied by business strategy, the second research question in this thesis aims to explore the underlying reason, as to whether the diversifiablity argument based on a traditional finance view or the offsetting pricing argument concurs. The second research question is motivated by Ogneva (2012) who proposes that there can be offsetting effect of information risk on equity pricing that explains the insignificant pricing of such information risk proxy. Possibly, different forms of information risk emanating from innovation and efficiency components of business

highly skilled employees, and hence disrupted operations increases firms' economic burden. On the other hand, defenders can reduce the economic burden triggered by strikes through more easily replacing less skilled workers to continue their operations.

strategy are simultaneously priced by investors that can mechanically, in aggregate, lead to insignificant pricing of information risk proxied by business strategy, thereby counteracting Core et al.'s (2008) proposition that the employment of a fundamental-broad information risk proxy maximizes the likelihood of information risk pricing in the asset pricing models.

1.2 Summary of Findings

This thesis utilizes 87,866 non-financial non-utility U.S. firm-year observations from 1972 to 2010 with available Bentley et al.'s (2013) business strategy scores to perform various asset pricing tests,[6] including (1) cross-sectional regression of monthly excess returns on the Fama-French three factors and business strategy related measures (aggregate, individual measure or component); (2) time-series business strategy related measure portfolio regressions of monthly excess returns on the Fama-French three factors; and (3) two-stage cross-sectional regression. The initial results from the above tests show that business strategy constructed based on Bentley et al. (2013), as an *ex ante* and fundamental-broad measure of information risk as suggested by Core et al. (2008), is not priced by investors. Analyses are replicated in sub-periods with 1990 chosen as the cut-off

[6] Bentley et al.'s (2013) business strategy measure is a composite score ranging from 6 to 30, computed as the sum of SIC 2-digit industry-year quintile ranks of six measures. These measures are: (1) research intensity measured as the ratio of research and development expenditures to sales computed over a rolling prior five-year average (*RDS5*); (2) marketing and advertising efforts measured as the ratio of selling, general and administrative expenses to sales computed over a rolling prior five-year average (*SGA5*); (3) historical growth or investment opportunities measured as one-year percentage change in total sales computed over a rolling prior five-year average (*REV5*); (4) operational efficiency measured as the ratio of the number of employees to sales computed over a rolling prior five-year average (*EMPS5*); (5) capital intensity or technological efficiency measured as the ratio of net property, plant, and equipment to total assets computed over a rolling prior five-year average (*CAP5*), and (6) organizational stability measured as the standard deviation of the total number of employees computed over a rolling prior five-year period (*TEMP5*). Within each SIC 2-digit industry and year, *RDS5*, *EMPS5*, *REV5*, *SGA5*, and *TEMP5* are ranked in an ascending manner, whereas *CAP5* is ranked in a descending manner. Thus a higher (lower) rank of these variables captures prospector (defender) characteristics. These quintile ranks are summed every year to construct business strategy score (*BS*). According to Bentley et al. (2013), the range of scores for each business strategy type is determined as follows: defender (6-12); analyzer (13-23); prospector (24-30).

point due to the technology boom to mitigate the concern of a structural break in the data given that it spans around 40 years. Results continue to observe insignificant pricing of business strategy as a fundamental-broad measure of information risk. Given that the individual measure indicative of a firm's historical growth or investment opportunities (*REV5*) captures the similar dimension of the Fama and French's book-to-market and *HML*, a modified measure of Bentley et al.'s (2013) business strategy is constructed by excluding *REV5*. The analysis based on this modified business strategy measure corroborates the main results, whereby there is no evidence that business strategy is a priced fundamental-broad information risk factor.

Analyses for the second research question supports the offsetting pricing argument as the alternative explanation to the lack of pricing evidence for information risk measured by business strategy. When asset pricing tests are employed using the individual measures of Bentley et al.'s (2013) business strategy, there is evidence that the measure representative of a firm's research intensity or propensity to search for new products (*RDS5*), and the measure reflective of a firm's marketing and advertising efforts and focus on exploiting new products and services (*SGA5*), are unfavourably priced by investors (i.e. higher average returns). Conversely, the measures capturing a firm's historical growth or investment opportunities (*REV5*), and a firm's operational efficiency or ability to produce and distribute products and services efficiently (*EMPS5*, notably, a higher rank is associated with **lower** efficiency for this measure), are favourably priced by investors (i.e. lower average returns). No pricing evidence is observed for the measures reflecting a firm's capital intensity or commitment to technological efficiency (*CAP5*) and a firm's organizational stability (*TEMP5*). While four out of the six individual measures of business strategy are priced in asset pricing tests, the different directions of pricing lead to insignificant pricing of the composite business strategy measure.

Further, a principal component analysis (PCA) conducted categorizes these variables into three groups: (1) *RDS5* and *SGA5;* (2) *EMPS5* and *TEMP5*; and (3) *REV5* and *CAP5*. Using these groups, the thesis finds consistent results with the pricing of individual components with some evidence suggesting that the component representing *RDS5* and *SGA5* is unfavourably priced by investors (i.e. higher average returns), and the component representing *EMPS5* and *TEMP5* is favourably priced by investors (i.e. lower average returns). No pricing evidence is found for the component representing *REV5* and *CAP5*. The results from this analysis show that business strategy component measures are priced at different directions, which plausibly explains the insignificant pricing of business strategy, in aggregate.

Since *REV5* is significantly and favourably priced by investors (i.e. lower average returns), and it may be highly correlated with the book-to-market or *HML* as one of the Fama-French three factors, it is excluded for the replication of PCA and component pricing analyses. The PCA re-groups the five remaining variables used to compute the modified business strategy measure (i.e. *BS2*) into two components: (1) *RDS5* and *SGA5* reflective of an innovation factor; and (2) *EMPS5*, *CAP5* and *TEMP5* reflective of an efficiency factor.[7]

[7] The grouping of *RDS5* and *SGA5* into an innovation factor is consistent with existing studies that associate R&D and marketing and advertising with innovativeness (e.g., Gupta & Wilemon, 1990; Naiker et al., 2008; Song & Song, 2010). While *EMPS5* representing operational efficiency and *CAP5* representing capital intensity or technological efficiency are clear indicators of efficiency (Thomas & Ramaswamy, 1996; Ittner et al., 2007; Bentley et al., 2013), prior studies also relate *TEMP5* representing organizational stability to efficiency. Specifically, employee turnover (measuring organizational stability) creates the need for knowledge transfer that leads to inefficiency, because firms incur costs, time and effort to train new employees to get familiar with job duties of departed employees (Grant, 1996; Shaw, Gupta & Delery, 2005; Kacmar, Andrews, Van Rooy, Steilberg & Cerrone, 2006; Morrow & McElroy, 2007). Therefore, *EMPS5*, *CAP5* and *TEMP5* are grouped into an efficiency factor.

Asset pricing tests based on these two components yield similar evidence that supports the alternative offsetting pricing argument. The two components representing innovative and efficiency factors are priced by investors. Specifically, investors of firms with greater innovation and investors of firms with greater efficiency are both compensated with higher average returns. This is less likely a demonstration of business risk pricing in equity as one should otherwise observe the contrasting component to be priced in an opposite way.[8] This result is more likely a manifestation of different information risk pricing in equity whereby investors price the inherent information asymmetry of prospectors and the poorer external information environment of defenders accordingly. As Easley and O'Hara (2004) claim that both quality and quantity of information are simultaneously priced by investors, the pricing of the two components of business strategy which mainly capture quality and quantity of information offset each other. In aggregate, it leads to insignificant pricing of business strategy which serves as the fundamental-broad information risk proxy. Collectively, the thesis does not lend support to Core et al. (2008) that a fundamental-broad information risk proxy can maximize chances of information risk pricing in the asset pricing tests, but supports Ogneva (2012) that the information risk proxy employed may trigger offsetting effect on asset prices that leads to insignificant pricing of the information risk proxy itself.

1.3 Contributions

This study offers several contributions. It provides critical insights into the debate over the pricing of information risk. There is no pricing evidence of information risk when

[8] If this is evidence of business risk pricing, one should expect that when innovative firms are associated with higher average returns, efficient firms are associated with lower average returns, and *vice versa*. Nevertheless, asset pricing tests conducted in this thesis suggest that both innovative and efficient firms are associated with higher average returns.

using an *ex ante* and fundamental-broad information risk proxy (i.e. business strategy) as suggested by Core et al. (2008). It calls for cautious interpretation for prior empirical evidence on the pricing of information risk (through the implied cost of equity setting) because those results may be subject to a correlated omitted variable issue (i.e. failing to control for business strategy) or the employment of an isolated and a less rigorous *ex post* information risk measure such as financial reporting quality, disclosure quality, R&D expenditure and marketing and advertising expenditure. However, this thesis also shows that insignificant pricing of information risk proxied by business strategy can be explained by the offsetting pricings of distinctive business strategy components, which encompass different forms of information risk. Therefore, in the spirit of Ogneva (2012), it offers a new insight to the literature that investors possibly react to different forms of information risk emanating from business strategy and simultaneously incorporate these into equity pricing.

This study also contributes to the management literature by providing evidence that firms embracing a particular business strategy (e.g., defender, analyzer, or prospector) are not advantaged in asset pricing over firms with alternative business strategies. The findings can be applied in cross-discipline social science research such as management, economics, management accounting, financial accounting and finance to more fundamentally and comprehensively explain business strategy related phenomena or outcomes.

From a practical viewpoint, results from this thesis are of interest to portfolio managers. The lack of pricing evidence for business strategy suggests that portfolio managers are unable to maximize clients' wealth by forming a portfolio based on business strategy due to the cancelling pricing effect of individual measures and components of business strategy. This is critical as pricing evidence offered by prior studies that associate a single characteristic of firms such as R&D, advertising, and efficiency with required rate of returns (e.g., Shangguan, 2005; Nguyen & Swanson, 2009; Huang & Ng, 2012; Frijns et al., 2012; Hedge & Mishra, 2014) are subject to correlated omitted variable bias. As firms are more likely to pursue a particular business strategy, portfolio constructions based on an isolated strategy-related characteristic with the aim to generate abnormal returns may not materialize in reality subjecting to the counterbalancing pricing from other business strategy-related characteristics. For instance, the higher required returns for a prospector firm with higher R&D intensity subjecting to greater inherent information asymmetry (i.e. poorer quality of information) are neutralized by lower required returns for richer external information environment (i.e. greater quantity of information). The reverse is true for a defender firm. In other words, abnormal returns observed in prior studies that employ an isolated strategy-related characteristic may not exist in reality, as the results are, at least, an artefact of a less rigorous business strategy measure.

Moreover, this study provides prefatory evidence that external monitors and information intermediaries, such as institutional holders, financial analysts and the media, balance out the inherent information environment of a firm determined by business strategy. Therefore, firm managers may use the evidence offered by this thesis as a yardstick to revise their mechanisms to lower required rate of returns. For example, defenders can buy analyst coverage, raise their media exposure and increase voluntary disclosures to further mitigate their poorer external information environment. Whereas, prospectors can revise their corporate governance and impose relevant mechanisms to reduce inherent information asymmetry (provided that the level of flexibility is not compromised to spark creativity). The findings are also insightful for regulators and policy makers. Dey (2008) claims that governance requirements vary with the level of agency conflicts. In lieu of enforcing the one-size-fit-all best practice principles of corporate governance, regulators and policy makers may allow the levels of corporate governance to efficiently vary with business strategy, as neither under-compliance nor over-compliance is ideal. Regulators may also impose different levels of disclosure requirements based on business strategy, since firms exhibit different information environment as a consequence of their business strategy and investors react differently and simultaneously.

1.4 Structure of the Thesis

The remainder of the thesis is structured as follows. Chapter 2 reviews the literature on asset pricing and information risk. Chapter 3 discusses business strategy as a fundamental-broad information risk factor and how firms pursuing a prospector as opposed to a defender strategy differ in their inherent and external information environment. Chapter 4 poses the research questions and formulates the hypotheses to be tested. Chapter 5 discusses the research design and the operationalization of business strategy. Chapter 6 presents sample selection, descriptive statistics, and result analysis on the first research question (i.e. whether business strategy constitutes a priced fundamental-broad information risk factor). Chapter 7 reports sensitivity analysis results for the first research question. Chapter 8 presents result analysis for the second research question (i.e. whether there is an offsetting pricing effect from variables or components of business strategy). Chapter 9 concludes, pinpoints the limitation of the study, and recommends avenues for future research.

CHAPTER 2: ASSET PRICING AND INFORMATION RISK

2.0 Introduction

The previous chapter introduces the objectives and motivations for the thesis. As a motivation stems from the debate surrounding pricing of information risk, this chapter presents the literature review on asset pricing and information risk, and discusses the tension in more detail. Section 2.1 reviews traditional asset pricing theories and models. Sections 2.2 to 2.4 review analytical research arguing for the pricing of information risk, based on liquidity, incomplete but symmetric information, asymmetric information, and estimation risk models, respectively. Section 2.5 highlights the inconclusive results from prior research.

2.1 Asset Pricing and Information Risk

Over the past two decades, contrary perspectives with respect to the role of information risk in asset pricing have increasingly invited attention in capital market research. Traditional asset pricing models such as the Capital Asset Pricing Model (CAPM), Arbitrage Pricing Theory (APT) and the consumption CAPM view that, in equilibrium, investors are only compensated for the systematic risk (market risk premium) they assume, with no reward for holding stock with idiosyncratic risk (Sharpe, 1964; Lintner, 1965; Black, 1972; Fama, 1991). The argument supporting the non-pricing of idiosyncratic risk is that it can be diversified away in the construction of investment portfolios. Fama (1991) argues that since assets are efficiently priced, information risk plays no role in asset pricing.

Fama and French (1992, 1993) acknowledge that there might be firm-specific factors other than market risk affecting required returns, including size (market value of equity) and growth (book-to-market equity). Using U.S. data spanning 1963-1990, Fama and French (1992) examine the joint role of market beta, size, Earnings/Price ratio (E/P), leverage (Debt/Equity ratio) and growth in explaining the variation of stock returns.[9] Contradictory to the Sharpe(1964)-Lintner(1965)-Black(1972) (SLB) model,[10] they report that market beta, when used alone or in combination with other firm-specific variables, has low explanatory power on average stock returns.[11] Whereas, size,[12] E/P,[13] leverage,[14] and growth[15] show considerable explanatory power when they are used alone; in combinations, they find that size and growth capture the effects of E/P and leverage, and both suffice to explain cross-sectional expected returns.

If assets are rationally priced by investors, Fama and French (1992, 1993) suggest that size and growth represent different dimensions of stock risks. In a subsequent study,

[9] Keim (1988) claims that E/P, size, leverage and growth are different scaled versions of stock price that extract the information in prices about a firm's risk and expected returns. Fama and French (1992) conducted the study to investigate if some of them are redundant in explaining expected returns.

[10] The SLB model assumes expected stock returns as a positive linear function of market betas, and market betas suffice to explain cross-sectional expected returns.

[11] Fama and Macbeth (1973) report a strong positive association between market beta and average U.S. stock returns during the pre-1969 period. Nevertheless, consistent with Lakonishok and Shapiro (1980) and Reinganum (1981), Fama and French (1992) find no such association during the 1963-1990 period.

[12] Banz (1981) documents that small (large) stocks as indicated by low (high) market value of equity have high (low) average returns, controlling for market beta. Thus, size explains the variation in average U.S. stock returns.

[13] Ball (1978) proposes E/P as a catch-all proxy for omitted factors in expected returns. If current earnings proxy for expected future earnings, stocks with higher risks and expected returns are likely to have lower prices relative to their earnings, and hence higher E/P. However, this argument only holds for stocks with positive earnings. Basu (1983) documents that E/P, in tests that also include size and market beta, explains the variation in average U.S. stock returns.

[14] Bhandari (1988) finds that leverage explains the variation in average U.S. stock returns, controlling for size and market beta.

[15] Stattman (1980) and Rosenberg, Reid and Lanstein (1985) find a positive association between the book-to-market ratio and average U.S. stock returns. Chan, Hamao and Lakonishok (1991) further find that the book-to-market ratio explains the variation in average Japanese stock returns, controlling for market beta. Chan and Chen (1991) offer a relative-distress effect explanation for the effect of book-to-market in average returns, where it signals a firm's prospects. Firms with low (high) market value of equity have poor (strong) prospects, thus they have low (high) stock prices and high (low) book-to-market ratio.

Fama and French (1995) relate size and growth to economic fundamentals. They find that low growth firms (high book-to-market) have persistently low earnings, whereas high growth firms (low book-to-market) have persistently high earnings. Fama and French (1995) suggest this relative profitability as the source of a common risk factor that explains the positive association between the book-to-market ratio and average returns. Further, controlling for book-to-market, small firms tend to have lower earnings than large firms. This is mainly due to the 1980-1982 recession that led small firms into a pro-longed earnings depression, and they did not participate to the same extent in the economic boom of the middle and late 1980s as large firms did.[16] Fama and French (1995) suggest that small firms' vulnerability to longer earnings depression relative to large firms may be the source of a common risk factor that explains the negative association between size and average returns.[17]

Literature has also emerged challenging traditional asset pricing theories with regard to the diversifiability of information risk. This literature argues that the liquidity, incomplete but symmetric information, asymmetric information, and estimation risk effects emanating from information risk have not been fully resolved by traditional asset pricing models.[18] As presented below, this literature suggests that information risk is not diversifiable and it does affect asset pricing.

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[16] Fama and French (1995) find that until 1981, controlling for book-to-market, large firms are only slightly more profitable than small firms.

[17] Using the dividend discount model, Fama and French (2013) introduce a five factor model by expanding the existing the Fama-French three factors with the profitability and investment factors. They show that the five factor model outperforms the three factor model, yet it fails to explain low average returns on small stocks that invest a lot despite low profitability. Further the inclusion of profitability and investment factors renders the book-to-market (*HML*) factor redundant for describing average returns.This thesis, however, follows Core et al. (2008) and McInnis (2010) to expand the Fama-French three model with the test variable.

[18] There is also a line of literature suggesting how investors' reactions to information can affect stock returns. For example, behavioural finance attributes the continuation of short-term returns, an anomaly that cannot be explained by the Fama-French three factor model (Fama & French, 1996), to investors' under-reactions to

2.2 Liquidity Effect

Prior literature (e.g., Demsetz, 1968; Copeland & Galai, 1983; Glosten & Milgrom, 1985; Amihud & Mendelson, 1986a; Diamond & Verrecchia, 1991) argues that greater disclosures enhance the liquidity of stocks by lowering bid-ask spreads and/or increasing the demand for stocks that lower transaction costs and thus the cost of equity. Amihud and Mendelson (1986a) argue that voluntary disclosures of private information contribute to reducing the adverse selection component of bid-ask spreads. This consequently reduces transaction costs, illiquidity and the cost of equity of the stocks. Diamond and Verrecchia (1991) propose that potential investors, who cannot discern the true value of firms, are unwilling to hold stocks in illiquid markets due to adverse selection, and they require higher rates of return for holding these stocks. Thus, greater disclosures increase investors' willingness to hold a particular firm's stocks and hence raise the demand for such stocks. Enhanced liquidity of a firm's stocks leads to an increase in the stock price, with the firm ending up with more proceeds after giving fewer discounts upon the issuance of capital, and hence lower cost of equity.

2.3 Incomplete and Asymmetric Information

The literature on incomplete information includes Merton (1987), Basak and Cuoco (1998), and Shapiro (2002). Using an incomplete but symmetric information analytical

new information (Zhang, 2006). Examples for the continuation of short-term returns include post-earnings announcement stock price drift following analyst forecast revisions (Chan, Jegadeesh & Lakonishok, 1996) and the positive serial correlation of returns at the 3 to 12 month period (Jegadeesh & Titman, 1993). Chan et al. (1996) argue that the gradual market response to new information leads to stock price drift, as uncertainty delays the flow of information into stock prices. Daniel, Hirshleifer and Subrahmanyam (1998) illustrate that investors' overconfidence with private information introduces an under-reaction to public information (i.e. psychological biases). Further, Zhang (2006) finds that when information uncertainty (measured by firm size, firm age, analyst coverage, analyst forecast dispersion, return volatility and cash flow volatility) is greater, investors under-react more to new information, consequently greater information uncertainty produces relatively higher (lower) expected returns following good (bad) news.

framework, Merton (1987) argues that investors know about a subset of assets and there is no estimation uncertainty for this subset, however they are unaware of other assets. Since investors tend to hold assets that they are familiar with, higher returns are required to persuade them to hold less familiar assets.

The literature on asymmetric information includes Grossman and Stiglitz (1980), Admati (1985), Wang (1993), Easley et al. (2002), and Easley and O'Hara (2004). Based on a partially-revealing equilibrium model, Grossman and Stiglitz (1980) argue that information is costly and thus perfect information-based efficient markets hardly exist, making a fully-revealing equilibrium almost impossible. Using a multi-asset noisy rational expectations framework, Admati (1985) generalizes Grossman and Stiglitz's (1980) model. She illustrates that investors experience distinctive risk-return trade-offs when they have diverse information. Wang (1993), based on a two-asset multi-period model, depicts the ambiguous effect of information asymmetry on asset returns. This is because, to compensate for adverse selection problems, uninformed investors charge a premium for the risk of trading with informed investors. Nevertheless, trading by informed investors reduces the uncertainty of future cash flows by rendering prices more informative. In turn, this reduces return premiums.[19]

Easley et al. (2002) and Easley and O'Hara (2004) argue that informed investors have access to both public and private information; while uninformed investors have only access to public information. The information asymmetry between uninformed and

[19] Kim and Verrechia (1994) suggest that greater disclosures may endogenously induce more information asymmetry which increases bid-ask spreads and reduces liquidity during earnings announcements, as additional information permits certain traders to make superior judgments about a firm's future prospects than other traders.

informed investors puts uninformed investors at a disadvantage as informed investors hold more good-news stocks and less bad-news stocks, and uninformed investors hold too many bad-news stocks in bad times and too few good-news stocks in good times. While uninformed investors lack information to properly adjust weights of each asset to hold, holding a portfolio with many stocks cannot diversify asymmetric information risk. Therefore, information risk translates into a form of systematic risk that cannot be diversified away, and in equilibrium, investors require compensation for bearing such risk. Using a rational expectations model in a multi-asset-and-multi-period setting, Easley and O'Hara (2004) further illustrate that two attributes of information affect the extent of information risk priced by the market, namely the level of private information (i.e. quantity of information), and the precision of both public and private information (i.e. quality of information). To compensate for the information disadvantage where informed investors are better able to shift their portfolios to incorporate new information, uninformed investors demand a premium for firms with more private information and less precise public and private information.

2.4 Estimation Risk

The literature on estimation risk includes Klein and Bawa (1976), Barry and Brown (1985), Coles and Loewenstein (1988), Handa and Linn (1993), Coles et al. (1995), Clarkson et al. (1996), and Leuz and Verrecchia (2004). Clarkson et al. (1996) suggest that high uncertainty attributable to less information can induce non-diversifiable estimation risk that is not captured by market beta in the traditional CAPM, where investors have difficulty in anticipating parameters of an asset's return distribution. In other words, market betas are understated as a consequence of the failure to account for estimation risk. They propose that investors require a higher premium for bearing additional estimation risk, and disclosures can be a means for reducing this risk. Leuz and Verrecchia (2004) exemplify that information risk arises from the impaired coordination between firms and their investors with regard to a firm's capital investment decisions triggered by poor quality reporting. Since a portion of this risk is non-diversifiable even in a large economy, investors charge a higher premium.

2.5 Evidence on the Diversifiability and Pricing of Information Risk

Several researchers revisit and contest the studies which challenge the traditional notion that idiosyncratic risk is irrelevant to equity pricing. For instance, Hughes et al.'s (2007) analytical framework contests Easley and O'Hara's (2004) argument. They claim that the latter's pricing effect is due to under-diversification in a finite economy, and hence the cross-sectional effect of information asymmetry on the cost of capital will disappear in a large economy with diversification opportunities. In large economies, the product of betas and risk factor premiums as in an economy without private information, determine equilibrium risk premiums under asymmetric information. Idiosyncratic risk that can be eliminated via diversification affects risk premiums only as a source of noise. Holding total information constant, greater information asymmetry about systematic factors leads to greater uncertainty and hence higher factor risk premiums. They conclude that information risk is either diversifiable or already imputed into market-wide factor risk premiums, but it does not cross-sectionally impact on the cost of capital.

Using a model that allows for multiple stocks whose cash flows are correlated, Lambert et al. (2007) argue a direct and indirect impact of information quality on the cost of capital. The direct effect refers to the impact of information quality on investors' assessments of the distribution of expected cash flows. Better quality information lowers the assessed variance of a firm's cash flows, and the variance effect is diversifiable in large economies, thereby contesting the Easley and O’Hara (2004) framework. Better quality information also lowers the assessed covariance of a firm’s cash flows with other firms’ cash flows; however such a covariance effect is not diversifiable in large economies. The indirect effect refers to the impact of information quality on a firm’s cash flows, by influencing real production or investment decisions, or the amount of cash for managerial appropriation. With the indirect effect, under certain conditions, better information quality can lead to a decline in the cross-sectional cost of capital, even when opportunities for diversification exist.

Empirical research applies the aforementioned analytical arguments and tests if information risk is priced. Mixed results are obtained due to different information risk proxies and research designs. Easley et al. (2002) and Easley, Hvidkjaer and O’Hara (2010) find that the probability of informed trading (PIN) which indicates information risk based on private information in a stock, developed by Easley, Kiefer, O’Hara and Paperman (1996), is positively associated with average stock returns. Nevertheless, a few studies dispute this measure. For example, Mohanram and Rajgopal (2009) demonstrate that Easley et al. (2002)'s findings are sensitive to alternative specifications and time periods, and that there is no association between PIN and implied cost of capital derived from analysts' earnings forecasts. Duarte and Young (2009) decompose PIN into asymmetric information and illiquidity components, and find that the liquidity (asymmetric information) component is (is not) priced. In other words, the association between PIN and average stock returns is driven by liquidity effects unrelated to information asymmetry.

Based on the significant positive correlation between accruals quality factor returns and contemporaneous stock returns after controlling for the Fama-French three factors observed in their study, Francis et al. (2005) claim that accruals quality as a proxy for information risk is priced. They also observe that the pricing of accruals quality is driven by both innate (i.e. economic fundamentals) and discretionary (i.e. management choices) components, and the effect is more pronounced for the innate component. Aboody, Hughes and Liu (2005) find that the pricing of accruals quality is systematically weak, however, the pricing becomes more pronounced in the setting of insider trading. Core et al. (2008) question the appropriateness of the model employed in Francis et al. (2005) to establish accruals quality as a priced risk factor, given that the authors' regression model only examines a contemporaneous association between excess returns and factor returns. The average positive coefficient on the accruals quality factor reported does not imply that accruals quality is priced; rather it merely indicates that firms in the contemporaneous regressions have positive exposure to the accruals quality factor.

Core et al. (2008) also note that the model employed by Francis et al. (2005) is an inappropriate asset pricing test as the intercepts obtained are not jointly zero across portfolios. Performing well-specified tests that explicitly examine the hypothesis, such as a two-stage cross-sectional regression, a cross-sectional regression of firms' future excess returns on the Fama-French three factors and accruals quality, and a time-series regression of accruals quality monthly- or annually-sorted portfolio excess returns on the Fama-French three factor returns, Core et al. (2008) report no evidence that accruals quality is priced. They highlight that "accruals quality is but one of many potential proxies for information risk" (p.21) and recommend future research employs an alternative proxy that exhibits broad information risk characteristics, or an underlying factor that influences disclosure quality, financial reporting quality and even information risk.

Motivated by Yee (2006), who demonstrates that earnings quality has no impact on the cost of capital in the absence of fundamental risk, Chen, Dhaliwal and Trombley (2008) extend Francis et al. (2005) by examining whether the pricing of accruals quality increases with fundamental risk (measured by market capitalisation, firm age, return volatility and trading volume).[20] In asset pricing tests, they show no association between accruals quality and future return realizations for firms with the lowest fundamental risk; however there is a strong association between accruals quality and future return realizations for firms with the highest fundamental risk.

Ogneva (2012), however, provides an offsetting pricing argument for Core et al.'s (2008) findings. She suggests that Core et al.'s (2008) measure of accruals quality, based on Dechow and Dichev (2002)'s residual accrual volatility, is negatively correlated with future cash flow shocks. Disentangling realized returns into cash flow shocks and returns excluding cash flow shocks, Ogneva (2012) finds that low (high) accruals quality firms are exposed to lower (higher) cash flow shocks. She argues that these lower cash flow shocks offset the higher expected returns of lower accruals quality firms, and these higher cash flow shocks offset the lower expected returns of higher accruals quality firms. After excluding cash flow shocks, she documents that low accruals quality firms are associated with a higher required rate of return.

[20] Chen et al. (2008) and this thesis argue that the pricing of information risk is more prominent for firms with higher fundamental risk. Whereas, Chen et al. (2008) interact accruals quality with fundamental risk (measured by market capitalisation, firm age, return volatility, and trading volume) in the asset pricing tests, this thesis argues that accruals quality is merely an *ex-post* information risk proxy capturing a small portion of information risk. This thesis uses business strategy, a theoretically fundamental-broad information risk proxy, in the asset pricing tests.

Kim and Qi (2010) reconcile Francis et al. (2005) and Core et al. (2008). Considering that realized returns of low priced stocks can be biased due to noise trading, sentiment trading, and market-microstructure induced effects, they control for low-priced returns (i.e. a penny stock dummy variable that takes the value of one if two adjacent prices are less than $5, and zero otherwise) in a two-stage cross-sectional regression model, and report that accruals quality is priced. Further, they provide three insights. First, they examine whether the pricing effect varies with the business cycle, and find that the risk premium of accruals quality is more pronounced in expansionary periods relative to recessionary periods. This is because the accruals quality (AQ) of poorer AQ firms deteriorates when the market moves from recession to expansion, while the accruals quality of better AQ firms remains almost intact. Second, they investigate if the pricing effect also varies with macroeconomic fundamentals, and report a systematic variation of the risk premium of accruals quality with macroeconomic variables such as term spread, default premium and dividend yield. Third, they find that the aforementioned risk premium pricing of accruals quality is associated with total accruals quality and the innate component of accruals quality (i.e. economic fundamentals), but not with the discretionary component of accruals quality (i.e. managerial reporting discretion). Using Australian data, Gray, Koh and Tong (2010) conduct an out-of sample test and provide consistent results with Kim and Qi (2010), with the innate component but not the discretionary component of accruals quality being priced.[21]

[21] Gray et al. (2010) note that Australian firms are subject to continuous disclosure requirements that mitigate information risk stemming from opportunistic managerial reporting and disclosure choices, and hence the impact of the discretionary component of accruals quality on the cost of equity.

García Lara, García Osma and Penalva (2010) report that conditional conservatism as a proxy for information quality is priced,[22] after controlling for the Fama-French three factors and the Carhart's (1997) momentum factor.[23] However, when information risk is proxied by earnings smoothness,[24] McInnis (2010) finds no pricing evidence and attributes the association between earnings smoothness and the cost of equity capital found by earlier studies to analysts' opportunism in long-term earnings forecasts. Callen, Khan and Lu (2012) document a negative association between poor accounting quality (measured by accruals quality, special items, earnings surprises, and Li's (2008) FOG index)[25] and delayed stock price adjustment to information; and such higher delay firms have higher future stock returns relative to lower delay firms.

Examining the effect of seasonality, Mashruwala and Mashruwala (2011) obtain findings that are difficult to reconcile with the risk explanation for accruals quality. Specifically, they report that the positive association between accruals quality and future abnormal returns is merely evident in January; however a negative association is found for non-January months, and there is no accruals quality premium on an annual basis. Despite Barth et al. (2013) documenting a negative association between earnings transparency (measured as the extent to which earnings and change in earnings covary contemporaneously with stock returns) and subsequent returns, and thus the cost of capital;

[22] Conditional conservatism is the practice of imposing stricter verification criteria when recognising economic gains relative to losses, and hence bad news is reflected quicker than good news (Basu, 1997).

[23] Jegadeesh and Titman (1993) report that positive abnormal returns can be earned via a momentum strategy, that is buying stocks with higher past returns and selling stocks with lower past returns. Carhart (1997) extends the Fama-French three factor model with a momentum factor providing evidence that momentum explains the variation in cross-sectional expected returns. García Lara et al. (2010) control for the Carhart's (1997) momentum factor in the model because high conservatism firms tend to have negative returns.

[24] Earnings smoothness is defined as earnings volatility relative to cash flows volatility (McInnis, 2010).

[25] The FOG index measures the readability of qualitative information in annual reports (Li, 2008).

they note the failure in establishing the inference that earnings transparency is a priced risk factor under the Fama and Macbeth (1973) approach.

Based on the aforementioned analytical frameworks, other studies also document the cost of equity effects from greater disclosures or better disclosure quality (e.g., Botosan, 1997; Richardson & Welker, 2001; Botosan & Plumlee, 2002; Gietzmann & Ireland, 2005; Kothari, Li & Short, 2009), better financial reporting quality (e.g., Bhattacharya, Daouk & Welker, 2003; Francis et al., 2004; Hribar & Jenkins, 2004; Kravet & Shevlin, 2010: Barth et al., 2013) and stronger corporate governance (e.g., Bhattacharya & Daouk, 2002; Khurana & Raman, 2004; Ogneva et al., 2007; Ashbaugh-Skaife, Collins, Kinney Jr & LaFond, 2009).

Empirical studies yield mixed evidence on the effect of disclosures on the cost of equity capital.[26] Botosan (1997) observes a negative association between disclosures and the cost of equity capital only for firms with lower analyst coverage. Botosan and Plumlee (2002) document a negative (positive) association between the levels of annual (quarterly) report disclosures. Richardson and Welker (2001) show that the quality and quantity of financial disclosures are negatively related to the cost of equity capital for firms with less analyst coverage, however social disclosures are positively related to the cost of equity capital and such a positive association is attenuated with better financial performance. Gietzmann and Ireland (2005) demonstrate that voluntary disclosures are negatively associated with the cost of equity for firms with more aggressive accounting choices. Kothari et al. (2009) find systematic evidence that favourable (unfavourable) disclosures

[26] Disclosure costs, such as information production and dissemination costs, the potential costs of legal or regulatory actions, and the consequences of disclosing commercially sensitive/proprietary information to competitors (Dye, 1985; Darrough & Stoughton, 1990; Wagenhofer, 1990; Gigler, 1994; Hayes & Lundholm, 1996), can impede firms from providing more disclosures to the market (Healy & Palepu, 2001; Jones, 2007; Beyer et al., 2011).

are negatively (positively) related to the cost of equity capital, stock return volatility and analyst forecasts dispersion. Further, they explore whether the credibility and source of disclosures (i.e. whether the disclosure is from management, analysts, or the business press) affect the cost of equity capital. They report that investors strongly react to unfavourable disclosures and significantly discount positive disclosures by management and analysts who may have the intention to skew disclosures. Favourable (unfavourable) disclosures from the business press significantly decrease (increase) the cost of capital and return volatility.

The association between financial reporting quality and the cost of equity capital is also inconclusive. In a cross-country study, Bhattacharya et al. (2003) observe that the cost of equity is positively associated with earnings opacity (proxied by earnings aggressiveness, loss avoidance, and earnings smoothness). Francis et al. (2004) link better earnings quality (measured by accruals quality, earnings persistence, earnings predictability, earnings smoothness, value relevance, timeliness, and conservatism) with lower cost of equity capital. Hribar and Jenkins (2004) find that accounting restatements are associated with a higher cost of equity capital. With the Fama-French three factor model augmented with discretionary and innate information risk factors, Kravet and Shevlin (2010) document that following restatement announcements, restating firms experience a significant increase in the factor loadings on the discretionary information risk factor that translates into a higher cost of capital. Utilizing Value Line data, Core et al. (2008) find that accruals quality is associated with lower cost of equity capital, but they find no evidence that accruals quality is priced in the asset pricing models. McInnis (2010) finds no evidence that earnings smoothness is a priced risk factor, and shows that the association between earnings smoothness and the Value Line cost of equity capital found by earlier studies is driven by analysts' opportunism in long-term earnings forecasts, wherein firms with volatile earnings experience systematically excessive target prices and implied cost of capital estimates as a consequence of such opportunism. Barth et al. (2013) find that earnings transparency is negatively related to subsequent returns, and thus the cost of capital. However, they fail to establish that earnings transparency is a priced risk factor following the Fama and Macbeth (1973) approach.

Other studies examine the association between corporate governance (which affects information risk) and the cost of equity capital. For instance, Bhattacharya and Daouk (2002), in a cross-country study, show that countries with stronger enforcement of insider trading laws are associated with a reduction in the cost of equity capital. Khurana and Raman (2004) find that the negative association between Big 4 audit and the *ex ante* cost of equity capital (the proxy for financial reporting credibility) is observed in the U.S., but not in Australia, Canada, or the U.K. This implies that litigation exposure, in lieu of brand name protection, drives perceived audit quality. Ashbaugh-Skaife et al. (2009) observe higher idiosyncratic risk, systematic risk and cost of equity for firms with internal control deficiencies (presumably higher information risk). Ogneva et al. (2007) find that firms disclosing internal control weakness have a higher implied cost of equity, however such an association disappears after controlling for analyst forecast bias.

Interestingly, a recent study by Ghoul et al. (2013) posits that geographic distance from financial centres or big cities captures both information asymmetry between managers and investors and information asymmetry between local and non-local investors. They offer evidence that firms located within 100 kilometres of the city centre of the nearest of six major financial centres or in their metropolitan statistical areas exhibit lower cost of equity capital. The authors argue that firms located in remote areas are costly for investors to monitor, and are neglected by financial institutions, investment bankers and analysts located in financial centres or big cities. In addition, Hutchens and Rego (2013) and Goh et al. (2013) show that firms with more aggressive tax positions experience a higher implied cost of equity capital. They attribute their findings to the pricing of tax and information risks through the direct and indirect effects proposed by Lambert et al. (2007). Tax avoidance can translate into higher information risk that increases investors' uncertainty in evaluating a firm's future cash flows, thereby *directly* increasing its cost of equity. Further, tax avoidance can *indirectly* increase a firm's cost of equity corresponding to a reduction in future cash flows available to investors, if it exposes firms to costly litigation or is used by managers for rent extraction. Alternatively, tax avoidance can *indirectly* decrease a firm's cost of equity capital since tax savings facilitate reinvestment and improve real production/investment decisions, thereby enhancing future cash flows available to investors.

In summary, the empirical results on the association between information risk and the cost of equity are mixed, primarily because they are sensitive to the proxy for information risk and research designs (Ghoul et al., 2013). Therefore, whether the above determinants of the cost of equity capital are considered by investors when pricing stocks remains an empirical question (Beyer et al., 2010).

CHAPTER 3: BUSINESS STRATEGY AND INFORMATION RISK

3.0 Introduction

The previous chapter reviews the theoretical and empirical debates of whether information is priced. This chapter reviews the literature on business strategy and information risk, as business strategy is employed as an *ex ante* and fundamental-broad risk proxy in this thesis to contribute to the debate of information risk pricing as suggested by Core et al. (2008). Section 3.1 shows how business strategy fundamentally and broadly frames firms' exposures to information risk. It also discusses that firms embracing an innovation-orientated prospector strategy are associated with a higher level of inherent information asymmetry, but richer external information environment; whereas firms adopting an efficiency-orientated defender strategy are related to a lower level of inherent information asymmetry, but poorer external information environment. The discussions of internal and external information environment are related to the previous chapter, as they signify quality and quantity of information, respectively; both are simultaneously considered by investors in their price setting processes (Easley & O'Hara, 2004). Section 3.2 outlines risks, other than information risks, emanating from business strategy.

3.1 Business Strategy as a Fundamental-broad Information Risk Factor

A firm is viewed as a legal entity serving a nexus of contracts among various production factors, where contracts are used to mitigate agency conflicts between contracting parties (Coase, 1937; Jensen & Meckling, 1976; Fama & Jensen, 1983; Jensen, 1983). An agency relationship refers to a contract under which principals (e.g., shareholders) delegate decision making authority to agents (e.g., managers) (Jensen &

Meckling, 1976). Both principals and agents are assumed to be rational utility maximizers. Self-interested managers, who are supposed to perform stewardship functions, may not always act in the best interests of shareholders. Correspondingly, shareholders attempt to protect their wealth by reducing the divergence of interests and information asymmetry. However, this is done at a cost that gives rise to agency costs of equity.[27] Jensen and Meckling (1976) define agency costs of equity as the sum of monitoring costs by the principal,[28] bonding costs by the agent,[29] and residual loss.[30]

Jensen and Meckling (1976) identify three conditions that can give rise to agency conflicts: (1) the separation of ownership and management; (2) information asymmetry; and (3) the divergence of interests between principals and agents. Thus, information asymmetry or information risk, that exists when managers have a more complete set of information than shareholders about the characteristics of the agent (i.e. adverse selection) or the decisions and actions taken by the agent (i.e. moral hazard) (Akerlof, 1970; Zajac & Westphal, 1994), is a necessary but insufficient condition for agency problems (Beatty & Harris, 1998; Shackelford, 1999). The agent is able to misrepresent his/her ability to the principal (i.e. adverse selection) and/or shirk (i.e. moral hazard) in the presence of information asymmetry (Fong & Tosi, 2007). The magnitude of agency conflicts and

[27] There are agency costs of debt for firms with debt financing (Jensen & Meckling, 1976). However, the scope of this thesis is restricted to agency cost of equity.

[28] Monitoring costs are incurred by shareholders to monitor managerial behaviour. For instance, the costs in preparing financial statements so that shareholders are informed of, and can evaluate, the outcomes of managerial investment, audit costs to certify the true and fair view of financial statements, and costs of establishing corporate governance to oversee corporate activities.

[29] Bonding costs are costs incurred by managers whose actions are constrained by the restrictions placed by shareholders to align the principal-agent relationship, for instance through a remuneration contract that promotes goal congruence.

[30] Residual loss is the reduction of wealth suffered by shareholders due to managerial sub-optimal behaviour that cannot be eliminated by monitoring and bonding costs, as it is too costly to do so given the costs of full enforcement of contracts exceed the benefits (Fama & Jensen, 1983). For instance, significant residual control rights are assigned to managers who may misuse firms' resources for their own benefit (Shleifer & Vishny, 1997).

information asymmetry varies across firms and is determined by: (1) the exercise of managerial discretion at the expense of shareholders' wealth; (2) the complexity of a firm's operating environment; and (3) the attractiveness of perquisites (Jensen & Meckling, 1976; Dey, 2008).

Prior literature has centred on the association between a single firm specific characteristic and information asymmetry or agency costs.[31] Anderson (1988), concerned with the soundness of a construct measured using a single proxy, suggests the use of multiple combined measures. Therefore, investigating the level of information asymmetry or agency conflicts by a specific firm characteristic is more likely to capture a uni-dimensional, isolated or incomplete aspect of a firm. Even a significant coefficient in a statistical sense can be miniscule in an economic sense. In the presence of many other confounding factors, research based on an isolated firm characteristic can lead to an inability to capture the effect of such attributes in the statistical models. Conceivably, this can explain conflicting evidence on whether information risk is priced. For example, Francis et al. (2005) report that accruals quality is a priced information risk factor. Core et al. (2008) contest this finding after implementing what they deem to be more appropriate tests, and Chen et al. (2008) show that it is the higher information risk that is priced by investors. This suggests that the pricing effect of a single or narrow information risk proxy is most unlikely to be captured in the asset pricing models.

[31] Information asymmetry or agency conflicts are expected to be greater in firms with characteristics such as: larger firms (Fama & Jensen, 1983; Demsetz & Lehn, 1985; Watts & Zimmerman, 1990), excessive free cash flows (Jensen, 1986), more diffuse ownership structure (Morck, Shleifer & Vishny, 1988), greater leverage (Myers, 1977; DeFond & Jiambalvo, 1994), more diversified operations (Habib, Johnson & Naik, 1997; Givoly, Hayn & D'Souza, 1999; Gilson, Healy, Noe & Palepu, 2001; Stein, 2002), more uncertain environment (Smith & Watts, 1992; Skinner & Sloan, 2002; Dey, 2008), the degree of innovation (Francis & Smith, 1995), and they also vary with industry wide factors (Anderson, Francis & Stokes, 1993).

Further, although disclosure, financial reporting and corporate governance quality are identified by existing literature as proxies for information risk, they are not necessarily a complete and fundamental source of information risk. Drawing on theories, this thesis argues that business strategy can be considered as a complete and fundamental source of a firm's information risk. This is because business strategy simultaneously affects a firm's inherent and external information environment, and thus the quality and quantity of information; both influence asset prices in the framework of Easley and O'Hara (2004). Inherently, business strategy impacts on organizational decisions concerning: (1) the degree of managerial discretion; (2) the level of monitoring and control; and (3) the complexity of a firm’s operating environment. All of these can lead to information asymmetry that can subsequently affect disclosure, financial reporting and corporate governance quality. Further, Bentley (2012) and Bentley et al. (2013) propose that business strategy serves as an *ex ante* factor for financial statement misreporting, as it affects three elements suggested in *SAS No. 99* (AICPA, 2002), namely incentive, opportunity, and rationalization, that can lead to fraud. Bentley et al. (2014) also assert that business strategy is an underlying determinant of a firm's (external) information environment, because it affects the level of voluntary disclosures, analyst coverage and media coverage.

Business strategy, selected at a very early stage of a firm’s history, is a mechanism through which the firm achieves, maintains or enhances its performance (Snow & Hambrick, 1980; Hambrick, 1983; Zajac & Shortell, 1989). Burgelman (2002) claims that business strategy has a far-reaching impact on a firm, since it leads to resource commitments and strategic direction that are not easily reversible. Therefore, business strategy is enduring and less likely to change considerably in the short term. In their classical work, *Business Strategy, Structure, and Process*, Miles and Snow (1978) envision that firms pursuing different strategies respond differently to three dimensions in the adaptive cycle, namely entrepreneurial, engineering and administrative, to maintain competitive advantage in the market (Miles & Snow, 1978, 1984, 1986, 2003; Miles et al., 1978; Milgrom & Roberts, 1995; Thomas & Ramaswamy, 1996).[32] A consequence of aligning the decisions between entrepreneurial, engineering and administrative decisions is that firms exhibit different patterns of product and market domain, technology, and organizational structure and process that manifest into differing degrees of information risk. Specifically, in the adaptive cycle, firms first respond to the entrepreneurial dimension by defining the product and market domains, and a set of objectives related to it, according to their respective organizational strategies, such as product nature, product range, the targeted market and the path to achieve growth. Next, in response to the engineering dimension, firms choose and develop technology to serve the selected domain identified in the entrepreneurial dimension. Thus business strategy influences the nature and efficiency of technology in the engineering dimension. Following this, firms respond to the administrative dimension by selecting, rationalizing and developing organizational structure and process to coordinate and control the selected technology and reduce the uncertainty within the organizational system. To be aligned with entrepreneurial and engineering decisions, business strategy affects firms' recruiting decisions (and thus the human capital of employees),[33] firms' administrative structure, the degree of authority

[32] Consistently, other management seminal works such as Peters and Waterman (1983) claim that firms aim for a fit of seven 7s: strategy, structure, skills, systems, style, shared values, and staff. Gates (1989) also argues that strategy determines management's perceptions and behaviour.
[33] The set of knowledge and skills employees use to produce professional services, normally developed through education, training and experiences, is referred to as human capital (Becker, 1993; Pennings, Lee & van Witteloostuijn, 1998).

delegated, the degree of monitoring and control, and employees' remuneration design in the administrative dimension, all of which have profound effects on the level of a firm's information risk.

Firms that aim to be an innovative industry leader will aggressively pioneer new products. They will adopt flexible technologies, hire skilful individuals and implement a decentralization policy to accomplish the organizational goal. However, the optimal alignment of these decisions results in the firms having more complex operating environments, more managerial discretion and less effective monitoring, and a higher level of information risk. In contrast, firms that aim to be a cost-efficient leader in the industry will sell high-quality-low-cost products to regular customers and have a narrow product range. They will adopt highly formalized and continuously improved technologies, hire less skilful labour for standardized operations and implement a centralization policy to attain the organizational goal. The optimal alignment of these decisions results in the firms having less complex operating environments, less managerial discretion and more effective monitoring, and hence a lower level of information risk.

This thesis classifies firms into high and low levels of fundamental-broad information risk based on two extreme strategic types in the Miles and Snow (1978) typology, namely prospectors and defenders.[34]Among many strategic types in the

[34] Miles and Snow (1978) observed the enduring patterns exhibited by organizations from four industries in response to three main organizational dimensions in a firm's adaptive cycle. The four industries are textbook publishing, electronics, hospital, and food processing. Nevertheless, this does not limit the generalizability of the framework. Many studies have acknowledged its applicability to other industries, see for instance Snow and Hrebiniak (1980), Zahra and Pearce II (1990), James and Hatten (1995), and Thomas and Ramaswamy (1996). Based on these observations, Miles and Snow (1978) devise a comprehensive framework that typologizes organizations into four strategic types: prospectors, defenders, analyzers and reactors. Prospectors and defenders are discussed later in text. Analyzers represent an intermediate category that captures both characteristics of defenders and prospectors with differing exposures. Miles and Snow (1978) argue that the organization would be effective in its particular industry over a period of time if the management chooses a defender/prospector/analyser strategy and aligns entrepreneurial, engineering and administrative decisions

management literature,[35] the Miles and Snow (1978) typology is employed as a basis to identify a firm's business strategy related information risk for the following reasons.[36] First, it contains a comprehensive description of organizational behavior integrating product market, technology, and organizational structure and process (Segev, 1989; Ketchen Jr, 2003). This helps to explain how business strategy can be the origin of information risk. Second, it has widespread effects and has consistently gained empirical support for the typology across research disciplines (e.g., management, marketing, information technology and management accounting); firm types (e.g., small and medium enterprises, publicly held firms and public sectors); and industries and countries (e.g., Smith et al., 1989; Doty, Glick & Huber, 1993; Hambrick, 2003; Ketchen Jr & David, 2003; Fiss, 2011). Third, this typology possesses strong codification and prediction strengths as a myriad of psychometric assessments have supported its validity and reliability (Shortell & Zajac, 1990; Abernethy & Guthrie, 1994). Fourth, it can be operationalized using archival data (Ittner et al., 1997; Naiker et al., 2008; Bentley et al., 2013).

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accordingly. However, failing to do so would render the organization ineffective in its industry, and it would be classified as a reactor. Reactors may lack consistent strategy; misalign between entrepreneurial, engineering and administrative decisions; or they are unaware of the obsolete fit in the changing environment. Inkpen and Choudhury (1995) comment that a reactor strategy is akin to nil strategy, since the organization responds to external environments without its own or a consistent strategy.

[35] Other strategy typologies include Hannan and Freeman's (1977) Generalist/Specialist strategies, Brittain and Freeman's (1980) R/K strategies, Porter (1980)'s Cost Leadership/Differentiation/Focus generic strategies, and Gupta and Govindarajan's (1984) Build/Hold/Harvest model. However they are subject to conceptual limitations, and their applications are not as widespread as the Miles and Snow (1978) typology (Smith, Guthrie & Chen, 1989; Kotha & Vadlamani, 1995). Hence the Miles and Snow (1978) typology is preferred.

[36] The Miles and Snow (1978) strategic typology is, however, subject to several criticisms. For instance, several studies argue that classifying firms into mutually exclusive categories is inappropriate, as most firms are likely to adopt a hybrid strategy, but with differing exposure to prospector and defender characteristics (Ruekert & Walker, 1987; Conant, Mokwa & Varadarajan, 1990). Other studies express concern with the generalization of the framework given its original work was based on only four industries (Conant et al., 1990; DeSarbo, Di Benedetto, Song & Sinha, 2005). Further, Hambrick (1983) suggests that an environment advantages certain strategic types, and thus the framework provides incomplete insight due to its ignorance about industry and environmental peculiarities.

The following subsections juxtapose the inherent information asymmetry and external information environment of prospectors and defenders which are positioned at two extreme ends of the continuum. The thesis does not discuss analyzers, with business strategy positioned in the middle of the continuum. This is because analyzers possess both attributes of prospectors and defenders, and hence their information risk is at the intermediate level.

3.1.1 Inherent Information Asymmetry of Prospectors and Defenders

Firms with a prospector business strategy aim to offer a broad range of state-of-art products to customers over time to maintain their reputation as innovative leaders (Miles & Snow, 1978). Correspondingly, prospectors develop multiple and flexible technologies to facilitate change and innovation (Miles & Snow, 1986). They tend to recruit high human capital individuals, and their administrative dimension is characterized with decentralization, employee empowerment, low task programmability and less monitoring (Miles & Snow, 2003; Rajagopalan, 1997; Siggelkow & Rivkin, 2006). On the other hand, firms with a defender business strategy focus on selling cost efficient, well-established products to stable and narrow market niches, with no or little focus on research and development (Miles & Snow, 1978). They develop core and efficient technologies to achieve input minimization and output maximization (Miles & Snow, 1986). Their administrative dimension is correspondingly characterized with centralization, stringent organizational rules and procedures, high task programmability and extensive monitoring (Miles & Snow, 2003; Ittner et al., 1997; Rajagopalan, 1997). As such, prospectors are expected to exhibit a greater level of inherent information asymmetry, relative to defenders, due to the following reasons.

First, high human capital individuals are more likely to abuse the discretion afforded to pursue self-interests, knowing that their employers (i.e. more likely to be prospectors) have greater tolerance towards their opportunism, as they are difficult to replace (Williamson, 1979; Brüderl et al., 1992; Colf, 2002; Naiker et al., 2008). Individuals (especially at managerial and executive levels) are selected not only because they match immediate job requirements, but also they possess skills, aptitudes and behavioural styles most compatible with business strategy, policy, structure and long-term objectives (Schneider, 1983). Certain personality traits and behavioural styles are critical to the successful implementation of a firm's strategy (Olian & Rynes, 1984). High human capital contributes to productivity gains, as these professionals are better able to detect new business opportunities, more efficient in organizing and managing the production process, and even more capable to attract customers and investors if social capital is also exhibited (Brüderl et al., 1992; Coleman, 1998; Bailey & Helfat, 2003; Kor & Sundaramurthy, 2009).[37]

A firm encounters human asset specificity risk (Williamson, 1979), if it hires high human capital individuals who possess good employment opportunities in the labour market (Brüderl et al., 1992), and who are difficult to replace (Colf, 2002). Knowing that they are difficult to replace, high human capital employees can behave opportunistically, leading to behavioural uncertainty where it is hard to ascertain employees' adherence to contractual agreements (Anderson, 1985, 1988; Monteverde, 1995). Godfrey and Hill (1995) and Hope and Thomas (2008) acknowledge the difficulty in detecting agents'

[37] Social capital (also termed relational capital) is the ability an employee to access resources through relationships (Burt, 1992).

opportunism. Hill (1990) depicts the problem of undetected opportunism, where not only the reputation of exploiting actors would remain intact, but also they have further incentives to repeat such dysfunctional behaviour in subsequent transactions with impunity. Firms' tolerance towards high human capital employees' opportunism can exacerbate the divergent interests between agents and principals, resulting in information asymmetry (Rajagopalan & Finkelstein, 1992; Rajagopalan, 1997; Naiker et al., 2008). In contrast, information asymmetry emanating from such opportunism is negligible for defenders which tend to recruit managers and employees with backgrounds in throughput functions (Thomas & Ramaswamy, 1996). This is because their managers and employees are assigned to familiar and repetitive tasks, and they have less capacity to behave opportunistically given the risk of dismissal and the ease of replacement (Colf, 2002; Naiker et al., 2008).

Second, a decentralised administrative structure intensifies information risk, because it leads to control complexity, instils divergent interests between top and lower level managers, and provides managers and employees the opportunity to shirk and pursue self-interests as a consequence of insufficient monitoring (Bruns & Waterhouse, 1975; Fama, 1980; Acemoglu et al., 2007; Raes et al., 2011). Firms that focus on pioneering idiosyncratic products tend to have high research and development (R&D) intensity and hire high human capital that in turn lead to decentralization and less formalization (Damanpour, 1991; Siggelkow & Rivkin, 2006). R&D activities are difficult to control through formal mechanisms such as rules, standard procedures and budgetary targets (Langfield-Smith, 1997), as they are unique, unstructured, and experimental (Clark, 1985; Saviotti, 1998; Hill, Martin & Harris, 2000; Ecker, van Triest & Williams, 2013). Further, high human capital individuals can maximize creativity by utilizing specific knowledge and discretion if their superiors engage in supportive non-controlling behaviour (Shalley, Zhou & Oldham, 2004; Faleya, Hoitash & Hoitash, 2011). Also, to allow for high human capital individuals to perform their tasks in a timely and flexible manner, and to minimize the costs of knowledge transfer, such firms usually adopt decentralization to grant lower level managers a degree of autonomy (Acemoglu et al., 2007). Decentralization of decision making is also consistent with the motivation rationale, so that high human capital employees are able to increase productivity and attain satisfaction (Pfeffer, 1995; Lawler III, 2009).

Bruns and Waterhouse (1975), however, argue that decentralization adds to control system complexity. Loss of control exacerbates information asymmetry as lower level managers withhold specific information that is not made available to top managers (Abernethy et al., 2004), and this also gives them the opportunity to extract private interests (Klein, 1989; Acemoglu et al., 2007). Ecker et al. (2013) also note incentive problems, coordination and failure costs, and less effective use of central information as costs of decentralization. Raes et al. (2011) suggest that top and lower level managers are subject to different information bases that can lead to information asymmetry and conflict of interests. Incomplete information and divergent interests between top and lower level managers expose each party to a certain amount of risk (Eisenhardt, 1989). The information channelled from lower level managers to top managers may partially reflect lower level managers' or the business unit's interests, thus top managers face a risk in relying on such information as a basis for decision making (Guth & MacMillan, 1986). Lower level managers bear the risk of channelling information to top managers, as they are unsure if top managers will take subsequent action to their advantage or disadvantage (Sims, 2003). Conceivably, many issues pertinent to firms are resolved by lower level managers operating within their discretion and may not be channelled to top managers in the presence of managerial self-interests. Ultimately, a lack of communication by lower level managers causes top managers unable to fully understand the firm's situation, and they have insufficient information for decision making, disclosures and financial reporting, and hence, generally, information quality can be compromised (Raes et al., 2011). In contrast, defenders tend to adopt centralization where monitoring is easier, and only top managers are involved in decision making. All information is channelled to top managers, thus they fully understand problems and challenges facing the firm, allowing for better decision making, reporting and disclosures. This leads to lower information risk.

Further, the likelihood of divergence of interests between principals and agents is increased when agents are less monitored, as they have the capacity to abuse discretion afforded to pursue self-serving actions that manifest into information risk (Coase, 1937; Fama, 1980; Fama & Jensen, 1983; Watts & Zimmerman, 1986; John & Weitz, 1988; Hill, 1990; Naiker et al., 2008). For instance, a lack of monitoring provides managers with incentives to shirk, since shareholders have incomplete information and they cannot evaluate if rewarded agents have appropriately performed on the agreed job (Alchian & Demsetz, 1972; Eisenhardt, 1985). Also, less monitored opportunistic managers may have incentives to reduce their employment risk (Amihud & Lev, 1981) or increase firm size for greater compensation (Baker, Jensen & Murphy, 1988), by engaging in empire building, sub-optimal investments and opportunistic financial reporting, often at the detriment of shareholders (Myers, 1977; Stulz, 1990; Dey, 2008; Armstrong, Guay & Weber, 2010).

Conversely, rigid rules and procedures exist in defenders to constrain managerial behaviour so as to avoid any discrepancy from the organizational goal. Defender managers are likely to strictly follow these rules to secure their employment (Naiker et al., 2008). Defender managers also find there is less room to shirk or engage in sub-optimal investments and opportunistic financial reporting. Extensive monitoring and control of employees therefore reduces behavioural uncertainty, dampens opportunism and better aligns principal-agent interests that eventually mitigate information risk (Rajagopalan, 1997; Fama, 1980).

The nature and formalization of technologies in the production process also differs for prospectors and defenders and can affect information asymmetry. Prospectors that frequently change their products tend to adopt less formalized technologies and may not improve the efficiency of technologies, given that these technologies have a short life expectancy (Miles & Snow, 1978). When the production process is less formalized, less monitored employees and managers have greater capacity to engage in wasteful activities or self-serving actions at the detriment of principals since there is a lack of accountability for firm resources (Jensen, 1986; Rajagopalan, 1997), resulting in greater information risk. In contrast, defenders, serving a stable market niche with well-established products, have more formalized technologies and constantly improve the efficiency of technologies to ensure input-minimization and output-maximization. This effectively curbs agents' wasteful activities and self-serving actions, and contributes to lower information asymmetry.

The nature of technology is one of the factors affecting the availability of debt financing (Klein, Crawford & Alchian, 1978), which can serve as an external governance mechanism (Jensen & Meckling, 1976). Jensen (1986) articulates that debt can be a useful governance device in reducing the agency conflicts arising from free cash flow, by reducing the amount available to managers. With debt, managers will be more alert when they spend free cash flows, as investing in wasteful projects can reduce a firm's ability to meet contractual interest and principal repayments. In the event of default, debt holders will approach the court to bankrupt the firm and managers place their future employment at risk. Therefore when debt exists, managers are less likely to engage in wasteful actions, and more likely to utilize assets efficiently, with a positive impact on firm value. The reduction in agency conflicts reduces information risk.

Existing research has yet to explore whether defenders or prospectors have greater access to debt financing. However, arguments offered in prior studies (e.g., Klein et al., 1978; Williamson, 1979, 1988) suggest that prospectors with idiosyncratic products and technologies (i.e. assets with lower value in the secondary market) are more likely to face difficulty in obtaining debt financing and hence they face less external monitoring by debtors who can discipline the firms, as opposed to defenders with more standardized and tangible assets available as collateral. Literally, equity, as opposed to debt, financing is a more efficient way for prospectors to finance the project, and consequently internal monitoring is deemed a more efficient governance mechanism for heavily equity financed firms such as prospectors (Williamson, 1979, 1988; Fama & Jensen, 1983). Nevertheless, as discussed, prospectors are more likely to hire high human capital, rendering internal monitoring by top managers and shareholders difficult (Rajagopalan, 1997).

Third, in the pursuit of innovation, prospectors inevitably operate in an environment characterized with fierce competition and unpredictable consumers' choices. Such environmental uncertainty also leads to firm performance and managerial remuneration uncertainties, that can further trigger behavioural uncertainty and information risk. Leifer and Mills (1996) suggest that information processing requirements are a positive function of information uncertainty (i.e. there are many contingencies) and equivocality (i.e. there is ambiguity). Thus, environmental uncertainty affects the degree of certainty and clarity of information disclosed by managers to shareholders. Prospectors with higher growth options suffer from higher investment outcome uncertainty that impedes investors from accurately anticipating expected future cash flows from these investment opportunities, compared to defenders. They also suffer from greater environmental uncertainty that complicates managerial assumptions in financial reporting and imposes greater barriers to managers in making more accurate estimations about firms' future prospects, relative to defenders (Bentley et al., 2013).

Anderson (1985, 1988) argues that behavioural uncertainty arises when a firm adopts an ambiguous performance assessment that entails measurement problems, as it provides latitude for managerial opportunism that endangers principals' wealth. Thus, a firm that adopts a discretionary incentive plan without clearly pre-specified remuneration criteria may increase agents' incentives to engage in self-serving actions that exacerbate information risk. By contrast, a firm that adopts an incentive plan with clearly pre-specified remuneration criteria can lower agents' incentives for pursuing self-interests, under remuneration certainty. Rajagopalan and Finkelstein (1992) and Rajagopalan (1997) suggest that prospectors tend to be associated with discretionary incentive plans; whereas defenders tend to adopt clearly-specified incentive plans. As a result, when firm performance and managerial remuneration become uncertain in a volatile operating environment, prospector managers have greater incentives to undertake sub-optimal self-centred decisions at the expense of principals (Jensen & Meckling, 1976; Smith & Watts, 1992). They may also engage in opportunistic earnings management or poor quality disclosures to camouflage performance, achieve financial reporting goals, and affect contractual outcomes (Watts & Zimmerman, 1986, 1990; Skinner & Sloan, 2002). Conversely, defenders characterized with less aggressive competition, more certain operating environment and clearly-specified incentive plans encounter less of these issues.

Complementarily, the association between higher (lower) inherent information asymmetry and prospectors (defenders) can be viewed through three factors to financial reporting irregularities under the framework in *SAS No.99*, namely incentive, opportunity, and rationalization. Bentley et al. (2013) suggest that prospectors are more prone to incentive and opportunity to financial reporting irregularities. Bentley (2012) associates prospectors to rationalization of financial reporting irregularities through survey data.

Prospectors portray attributes compatible with greater incentives to financial irregularities relative to defenders. First, prospectors experience rapid and sporadic growth through market exploitation (Miles & Snow, 1978) that increases the propensity to misstate financial results (AICPA, 2002; Hogan et al., 2008). On the other hand, defenders experience stable and incremental growth through market penetration. Second, prospectors tend to adopt stock-option-based compensation to encourage managers taking long term perspectives and this increases risk taking (Rajagopalan & Finkelstein, 1992; Rajagopalan, 1997; Singh & Agarwal, 2002) and the incentives to misstate (AICPA, 2002; Efendi et al., 2007). Although defenders adopt fixed pay compensation, this may encourage managers to take short term focus and thus the incentives to misreport to meet stipulated accounting performance benchmarks (Rajagopalan, 1997; Ittner et al., 2007). Houqe and Monem

(2013) shed some light on this issue. They find that in high growth periods, prospectors portray less accounting conservatism while defenders engage less in earnings management. However in low growth periods, prospectors have more conservative reporting while defenders exhibit more earnings management. Third, Miles and Snow (2003) suggest that prospectors overstretch their resources and face a greater need for external (equity) financing to explore new product and market opportunities, as opposed to defenders who aim to enhance efficiency and face less need in developing new products. AICPA (2002) relates greater need for external financing to misstatement risks. Fourth, while prospectors are more likely to experience poor performance and financial distress (Hambrick, 1983; Ittner et al., 1997), they are more likely to misreport (AICPA, 2002; Hogan et al., 2008), as opposed to defenders characterized with lower business risk.

AICPA (2002) identifies several factors such as ineffective monitoring, internal control deficiencies, and organizational stability and complexity, that provide opportunities for firms to misreport. The administrative structure of prospectors is characterized with a lack of monitoring, greater complexity, and less stability, due to a decentralization policy and high turnover of senior management (Miles & Snow, 1978; Simons, 1987) leading to misreporting opportunities. This is of less concern for defenders with a centralization policy and low turnover of senior management that contributes to greater monitoring and more stable or less complex administrative structure (Loebbecke et al., 1989; Miles & Snow, 2003).[38]

[38] The dominant coalition in prospectors (defenders) is more transitory (permanent) (Miles & Snow, 1978). This is because senior managers of prospectors move across firms depending on projects, whereas those in defenders tend to be promoted internally after accumulating extensive understanding about a firm's business and production process (Thomas & Ramaswamy, 1996).

Management attitudes and rationalizations (i.e. tone at the top) influence the effectiveness of communication, implementation, support, or enforcement of a firm's values and ethical standards (AICPA, 2002). Bentley (2012) proposes that there is a greater risk for prospectors to cultivate negative ethical cultures and climates, relative to defenders. She argues that prospectors are likely to perpetuate an individualistic and egoism-based ethical climate, because innovation encourages risk taking and self-interested behaviour (Victor & Cullen, 1988). Defenders are more likely to develop a principle based ethical climate (Victor & Cullen, 1988), given detailed rules and consistent procedures strictly enforced within the firm (Miles & Snow, 1978). Using surveys, Bentley (2012) finds a relatively smaller (larger) set of prospectors generate negative (positive) ethical cultures and climates. She offers this as the explanation to findings by Bentley et al. (2013) wherein prospectors experience a higher level of financial reporting irregularities despite greater audit effort, and auditors may not be able to clearly distinguish between prospectors with different types of ethical cultures and climates (i.e. auditors generally perceive prospectors risky).

Consistent with the discussion above, Barth et al. (2001) associate R&D, a main attribute of prospectors, with higher levels of information asymmetry. This is due to investors finding it difficult to derive asset pricing information absent an active market for intangible assets which are usually unrecognized or non-disclosed estimates, and greater uncertainty about firm value inherent in R&D firms can lead to mispricing. Aboody and Lev (2000) observe that insiders in R&D-intensive firms are able to generate excess returns based on their superior knowledge about the future payoffs of a firm's R&D investments. Lev and Zarowin (1999) relate firms with substantial intangible investments to lower earnings informativeness. Boone and Raman (2001) and Barron et al. (2002) associate firms in R&D-intensive industries with greater bid-ask spreads, and analyst forecast dispersion (which are proxies for information asymmetry), respectively. Bentley et al. (2013) report that prospectors exhibit higher financial reporting irregularity and require more audit effort. Higgins et al. (2013) document that prospectors are more aggressive in their tax position, as opposed to defenders. In summary, the above discussions suggest that prospectors exhibit a greater level of inherent information risk, relative to defenders.

3.1.2 External Information Environment of Prospectors and Defenders

Bentley et al. (2014) propose that a firm's information environment is counterbalanced by the dynamic interplays of external monitoring mechanisms and information intermediaries (e.g., institutional investors, financial analysts, and media). Therefore, a firm's information environment is not only affected by the inherent information asymmetry driven by decisions made in the entrepreneurial, engineering, and administrative dimensions discussed in Subsection 3.1.1, but also by incentives for voluntary disclosures and through mechanisms such as analyst coverage, media coverage, and institutional holdings. Prospectors (defenders) portray a richer (poorer) external information environment determined by these additional factors. Generally, prospectors with greater accounting and operating uncertainty and visibility, due to a higher level of R&D intensity, marketing and advertising activities, and growth, are associated with more analyst coverage, media coverage, and institutional holdings, relative to defenders (Botosan, 1997; Barth et al., 2001; Grullon et al., 2004; Chordia et al., 2007; Bentley et al., 2014).

Bentley et al. (2014) find that prospectors have more analyst coverage compared to defenders. This is consistent with prior studies that associate firms with characteristics reflecting higher accounting and operating uncertainty (Lang, 1991; Botosan, 1997; Kirk, 2011; Lobo, Song & Stanford, 2012), including higher R&D (Barth et al., 2001; Barron et al., 2002), higher marketing and advertising (Barth et al., 2001), and higher growth (Moyer Chatfield & Sisneros, 1989; Chung & Jo, 1996), with greater analysts coverage. Analysts are interested in following such firms as they can profit from trading their private information or in-depth analysis valuable to investors (Moyer et al., 1989; Chung, McInish, Wood & Wyhowski, 1995; Ahn, Cai, Hamao & Ho, 2005). With extensive knowledge in accounting and finance, and substantial industry experience, financial analysts track firms' financial reporting and disclosures closely (Yu, 2008). Bhushan (1989) distinguishes the information intermediary and information provider roles of analysts in the capital markets. Analysts serve as information intermediaries when they repackage and transmit available information from a firm's disclosures and the business press into a more valuable report and sell it to investors. Analysts act as information providers when they compete with firms by providing disclosures to investors.

Existing literature argues that investors and firms benefit from analyst coverage.[39] For example, analyst coverage enhances a firm's visibility by increasing investors'

[39] A counter argument to this view is that analysts are accused of exerting pressure on management to opportunistically beat analysts' forecasts that may otherwise be penalized by investors (Degeorge, Patel & Zeckauser, 1999). However, Yu (2008) finds that firms with more analyst coverage have lower levels of abnormal discretionary accruals. Further, there is a line of literature arguing that analysts' lack of independence can compromise the role of governance (Kothari et al., 2009). For instance, analysts may need to favour management for access to private information, or issue favourable rating so that the client renews coverage, that can lead to conflict of interests (Lin & McNichols, 1998; Michaely & Womack, 1999; Dechow, Hutton & Sloan, 2000). Nevertheless, it is argued that analysts have incentives to protect their reputations (Covitz & Harrison, 2003), and this concern is further reduced after the passage of the *Regulation*

awareness of the stocks (Merton, 1987; Bushee & Noe, 2000). Analyst coverage also improves a firm's liquidity, by reducing adverse selection (Brennan & Subrahmanyam, 1995; Irvine, 2003). Further, analysts' private information becomes particularly valuable when financial statements provide less certain signals about firm value, as it assists investors in efficient asset allocation decisions (Healy & Palepu, 2001; Barth & Hutton, 2004). Analysts' external monitoring has a favourable impact on reducing a firm's agency conflicts and information asymmetry (Moyer et al., 1989; Lang, Lins & Miller, 2004), such as discovering corporate frauds (Dyck, Morse & Zingales, 2010) and reducing earnings management (Yu, 2008). Several studies have documented the positive impact of financial analysts on stock prices (Graham, Harvey & Rajgopal, 2005). For instance, Bowen, Chen and Cheng (2008) demonstrate that analyst coverage reduces underpricing in seasoned equity offerings. Roulstone (2003) documents a positive association between analyst coverage and liquidity (measured by bid-ask spread).

Brennan and Tamarowski (2000) argue that analyst coverage reduces information asymmetry not only between insiders and outsiders, but also between informed and uninformed traders, leading to more competitive informed trading in securities of these firms. Holden and Subrahmanyam (1992, 1994) and Foster and Visvanathan (1993, 1994, 1996) argue that greater competition among informed investors to obtain and trade profitably on private information renders more private information reflected in stock prices. In order to profit from trading against uninformed investors, informed investors exert

Fair Disclosure Act in 2000, which prohibits firms from making material non-public disclosures to selected groups of market participants (Bailey, Li & Zhong, 2003; Bushee, Matsumoto & Miller, 2004).

considerable effort to discover important firm-specific information, which in turn enhances the information efficiency of stock prices in general. Stock price informativeness, driven by such competition, can lower the level of private information by informed traders (Kyle, 1985), and information risk encountered by uninformed investors (Easley & O'Hara, 2004). Atkins, Ng and Verdi (2012) suggest that firms with more competitive informed trading are likely to experience a lower cost of equity capital.

Bentley et al. (2014) also observe that prospectors are associated with greater media coverage relative to defenders. Media coverage affects a firm's corporate governance and information environment. According to Becker (1968), media coverage can affect corporate governance in four ways: (1) publishing the news that affects the probability that a given action is known to a certain audience and thus carries a reputational cost; (2) increasing the reputational cost; (3) influencing the probability of enforcement; and (4) impacting the size of the penalty. Dyck and Zingales (2004) and Dyck et al. (2008) provide evidence in an international setting that the media plays a role in corporate governance and influences firms' behaviour. Miller (2006) finds that the media serves as an early information intermediary (i.e. watchdog) that provides the public with information about accounting fraud. Further, media collects, selects, certifies, and repackages information, thus reduces the cost investors have to pay to become informed (Dyck et al., 2008). Grullon et al. (2004) argue that firms with larger mass media exposure (e.g., achieved through advertising) have more liquid stocks that can attract more investors at lower financing costs. Barber and Odean (2008) also show that individual investors are net buyers of attention-grabbing stocks, for example, stocks in the news. Kross, Ro and Schroeder (1990) document that the accuracy of analysts' forecasts is greater for firms with higher levels of coverage in the Wall Street Journal.

Fang and Peress (2009) claim that the mass media can reduce informational frictions and affect stock pricing by reaching a broad population of investors. They find that stocks with no media coverage earn higher returns than stocks with high media coverage after controlling for market risk, size, book-to-market, momentum, and liquidity factors. These results are more pronounced among small stocks and stocks with high individual ownership, low analyst following, and high idiosyncratic volatility. They attribute their results to two explanations and support them with further tests: (1) the impediments-to-trade hypothesis which suggests that the no-media premium reflects a mispricing under the liquidity-related phenomenon; and (2) the investor recognition hypothesis by Merton (1987) which suggests that the no-media premium represents compensation for imperfect diversification. Bushee et al. (2010) find that press initiated coverage reduces information asymmetry around earnings announcements, and the results are robust after controlling for firm-initiated disclosures, market reactions to the announcement, and other information intermediaries (e.g., analyst coverage and institutional investors). They argue that through packaging, disseminating and creating new information, information disclosures by the business press can reduce the information advantage of privately informed traders as in Diamond and Verrechia (1991).

Further, prospectors need to heavily rely on external financing because of their tendencies towards lower profitability resulting in insufficient internal funds to finance extensive innovative activities (Hambrick, 1983; Ittner et al., 1997). Correspondingly, Bentley et al. (2014) observe that prospectors have greater incentives to lower information asymmetry through voluntary disclosures (e.g., more frequent management earnings guidance and press releases) as a tactic to reduce the cost of capital, relative to defenders.[40] Providing the benefits of disclosures exceed the costs (Verrechia, 1983), firms have incentives to voluntarily disclose information to enjoy economic benefits associated with lower bid-ask spreads, improved stock valuation and liquidity, greater visibility that attracts institutional investors and financial analysts, and lower cost of capital (Akerlof, 1970; Barry & Brown, 1985; Merton, 1987; Bhushan, 1989; Diamond & Verrecchia, 1991; Lang & Lundholm, 1993, 1996; Botosan, 1997; Sengupta, 1998).

Parallel to the aforementioned arguments regarding the benefits stemming from more analyst coverage, media coverage, and voluntary disclosures, Bentley et al. (2014) provide evidence that prospectors have smaller bid-ask spreads, lower analyst forecast dispersion, and higher analyst forecast accuracy, relative to defenders. This can mitigate their higher inherent-level of information asymmetry discussed in Subsection 3.1.1.

Several prospector attributes discussed previously, such as greater visibility, analyst following, and press coverage (Bhushan, 1989; O'Brien & Bhushan, 1990; Falkenstein, 1996; Grullon et al., 2004) can also attract institutional investors who act as external monitors, further reducing a firm's information asymmetry. The efficient monitoring hypothesis suggests that, given their expertise, resources, large and stable stakes in the

[40] In addition, other characteristics of prospectors also explain their incentives to provide greater voluntary disclosures. For instance, prospectors tend to adopt stock-based compensation plans (Rajagopalan & Finkelstein, 1992; Rajagopalan, 1997; Singh & Agarwal, 2002) that trigger greater voluntary disclosures to reduce information asymmetry (Noe, 1999; Aboody & Kasznik, 2000; Nagar, Nanda & Wysocki, 2003). In order to protect their career, managers in prospectors may also utilize voluntary disclosures to attribute poor performance to high executive turnover (Beyer et al., 2010; Warner, Watts & Wruck, 1998; Weisbach, 1988). Highly litigious firms have greater incentives to voluntary disclose information (Field, Lowry & Shu, 2005; Skinner, 1994), and Bentley et al. (2013) associate prospectors with greater financial reporting irregularities and thus a higher litigation risk.

firm, as well as easier access to board members and managers, institutional investors have incentives and can monitor management at lower cost, relative to retail or small atomistic investors (Shleifer & Vishny, 1986; Cready, 1988; Brous & Kini, 1994; Carleton, Nelson & Weisbach, 1998; Panousi & Papanikolaou, 2012).[41]

Extant studies provide evidence that institutional ownership affects financial reporting quality. For instance, Chung, Firth and Kim (2002) and Cornett, Marcus and Tehranian (2008) observe a positive effect of institutional investors in deterring managers from pursuing opportunistic earnings management through discretionary accrual choices. Ashbaugh-Skaife, Collins and Kinnery Jr (2007) find that concentrated institutional ownership is one of the factors driving firms to disclose internal control deficiencies. Ramalingegowda and Yu (2012) find that greater institutional ownership leads to more conservative financial reporting, and this causality is more pronounced among firms with more growth options and higher information asymmetry.

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[41] It is also possible that institutional investors play a passive rather than active monitoring role, if they have short term objectives and act like traders to hold or sell the stocks according to their portfolio rebalancing needs, instead of intervening firm decisions (Elyasiani & Jia, 2010). Two contrasting hypotheses dispute the efficient monitoring hypothesis (Pound, 1988). The conflict-of-interest hypothesis suggests that institutional investors, due to a short term focus (e.g., other profitable business relationships with the firm), vote with management even this is against their fiduciary interests. The strategic-alignment hypothesis suggests that institutional investors may cooperate with managers to extract private interests (e.g., receive more investment banking business) at the detriment of minority shareholders (Brickley, Lease & Smith Jr, 1988; Cornett, Marcus, Saunders & Tehranian, 2007). Brickley et al. (1988) classify institutional investors into three groups according to whether they have potential business relationships with the investee firms and, hence, their sensitivity to management pressure: (1) pressure-insensitive (e.g., public pension funds, mutual funds); (2) pressure-sensitive (e.g., insurers, banks, non-bank trusts owning at least one percent of a firm's stock); and (3) pressure-indeterminate (e.g., corporate pension funds, brokerage houses, investment counsel firms, institutions owning less than one percent of a firm's stock). Brickley et al. (1988) find that only pressure-insensitive institutions, that are free of conflicts of interests, can be active monitors and more likely to vote against the management. Pressure-sensitive institutions act as passive investors because they do not want to risk losing their business relationships with the investee firms.

Institutional investors also promote transparency and hence stock price informativeness (Hartzell & Starks, 2003; Piotriski & Roulstone, 2004). For instance, El-Gazzar (1998) finds that price reactions around earnings announcements are smaller for firms with greater institutional ownership, suggesting that institutional investors provide timely information through trading. Tasker (1998) argues that firms with institutional ownership are likely to hold conference calls to bridge the information gap between the firm and the market. Ajinkya, Bhojraj and Sengupta (2005) claim that firms with greater institutional ownership are more likely to issue a management forecast and are inclined to forecast more frequently. In addition, these forecasts tend to be more specific, accurate and less optimistically biased. Boehmer and Kelley (2009) offer evidence that greater institutional ownership enhances the informational efficiency of prices (i.e. stock intraday prices closely track fundamental values and follow a random walk) that can facilitate better financing and investment decisions. Rubin and Smith (2009) demonstrate that institutional owners' skills in gathering and processing information reduce stock volatility and make prices more informative. Elyasiani and Jia (2010) find that stable institutional ownership is associated with greater firm performance (i.e. greater industry adjusted ROA and Tobin’s Q), improved governance (i.e. greater executive incentive-compensation ratio), and reduced information asymmetry (i.e. lower stock residual volatility).

Collectively, it appears that prospectors exhibit a richer external information environment, relative to defenders, as a consequence of greater analyst coverage, media coverage, voluntary disclosures, and institutional holdings, which is in a sharp contrast to the discussion surrounding a firm's inherent information asymmetry in Subsection 3.1.1. As noted by Bentley et al. (2014), the interrelationships between business strategy and information environment is complex. Clearly, this introduces a tension as to whether prospectors or defenders are perceived by investors as carrying more information risk.

3.2 Other Risks Emanating from Business Strategy

It is acknowledged that business strategy can also frame firms' exposures to business risks, such as product specificity, environmental uncertainty and production efficiency. For instance, in the entrepreneurial dimension, business strategy determines a firm's product specificity risk through decisions made on product nature. Prospectors selling high specificity products, characterized with idiosyncrasy and high risk of product obsolescence, are exposed to the risk of low profitability, driven by speedy innovation and competition dynamism, as opposed to defenders selling low specificity products (Williamson, 1979; Levy, 1989; Bowen, DuCharme & Shores, 1995; Kotha & Nair, 1995; Ittner et al., 1997). Business strategy also determines whether a firm achieves growth through market expansion or penetration, and this affects the degree of environmental uncertainty.[42] Prospectors with a market expansion strategy and growth through constant innovation exposes themselves to environmental uncertainty, as they lack information to accurately predict the outcome for each innovation (Milliken, 1987; Klein, 1989; Noordewier, John & Nevin, 1990; Ittner & Larcker, 2001), and are exposed to high risk of costly failure (Saleh & Wang, 1993). In contrast, defenders with a market penetration growth strategy underpinned by strategic decision making based on relevant information available from existing operations, are less subject to the risk of costly failure. Further, business strategy affects a firm's ability to correctly specify production volume in the

[42] Subsection 3.1.1 discusses managerial behavioural issues driven by environmental uncertainty that can lead to information risk, rather than the environmental uncertainty *per se*.

engineering dimension. Prospectors emphasizing innovation face demand unpredictability for new products, leading to the risk of over- or under- production that reduces a firm's efficiency and profitability, compared to defenders serving stable market niches (Walker & Weber, 1984; Balakrishnan & Wernerfelt, 1986; Heide & John, 1990).

Business risks are not information risk. Generally, investors can diversify away business risks through holding a well-diversified portfolio (Fama, 1991). Nevertheless, several anomalies associated with firm characteristics (business risks) are observed in asset pricing studies (as briefly discussed in Section 2.1). For instance, Nguyen and Swanson (2009) and Frijns et al. (2012) find that efficiency (a prominent attribute of defenders), measured through a stochastic frontier approach and a data envelopment analysis, is priced by investors. Specifically, they find that efficient firms (presumably lower distress risk) are associated with lower required returns.

In summary, this chapter reasons business strategy as an *ex ante* and fundamental-broad information risk factor that shapes a firm's inherent and external information environment. While inherent and external information environment are closely related to the quality and quantity of information simultaneously considered by investors in asset pricing under the framework of Easley and O'Hara (2004) discussed in the previous chapter, it remains unexplored whether investors associate a prospector or defender business strategy with an overall higher level of fundamental-broad information risk when both aspects of information are taken into consideration. The next chapter presents the research questions and hypotheses of this thesis.

CHAPTER 4: RESEARCH QUESTIONS AND HYPOTHESIS DEVELOPMENT

Based on the related literature discussed in Chapters 2 and 3, this chapter presents the research questions of the thesis and formulates the hypotheses for testing. The thesis, poses the first research question: Is business strategy a priced fundamental-broad information risk factor? Beyer et al. (2010) suggest that the hypothesis of whether financial reporting and disclosures affect asset pricing or cost of capital depends critically on whether information risk is diversifiable (which can only be empirically tested) and the proxy for information risk. Core et al. (2008) argue that existing information risk proxies such as financial reporting and disclosure quality only represent a subset of information risk. They suggest future studies use a fundamental or broad information risk proxy when testing the pricing of information risk. Responding to their call, this thesis employs an *ex ante* and fundamental-broad information risk proxy, that is business strategy, to investigate the pricing of information risk.

According to Easley et al. (2002) and Easley and O'Hara (2004), uninformed investors are less able to effectively organize their stock portfolios due to the lack of information available to them, relative to informed investors. Hence, in bad times uninformed investors hold too many bad-news stocks, and in good times they hold too few good-news stocks, leading to the argument that information risk is not diversifiable, and thus quantity and quality of information affect equity pricing. If true, the expectation is that this non-diversifiability problem manifests more profoundly for firms that portray higher information risk emanating from business strategy, since business strategy is a fundamental-broad information risk. Rational investors, in equilibrium, are likely to demand a higher premium for holding stocks that exhibit higher information risk emanating from business strategy, to compensate for additional risk-bearing in their investment.

Business strategy is selected at a preliminary stage of a firm's history and is less likely to change considerably due to long-term resource commitments (Snow & Hambrick, 1980; Hambrick, 1983; Burgelman, 2002). Business strategy therefore has far-reaching impacts on a firm's entrepreneurial, engineering and administrative decisions (Miles & Snow, 1978, 2003) that influence its inherent and external information environment (Bentley et al., 2013; Bentley et al., 2014). Inherently, business strategy drives three fundamental determinants of information risk suggested by Jensen and Meckling (1976): (1) the level of managerial discretion; (2) the level of monitoring and control; and (3) the complexity of a firm’s operating environment through the alignment between entrepreneurial, engineering and administrative decisions. Therefore, prospectors and defenders which respectively embrace an innovation and efficiency strategy (Miles & Snow, 1978) are expected to exhibit different levels of inherent information risk. Prospectors that focus on product innovation usually grant their high human capital individuals with a greater degree of autonomy (Miles & Snow, 2003). These individuals have greater capacity to abuse discretion afforded, due to: the control difficulty under a decentralization policy; firms’ greater tolerance towards their opportunism as a consequence of replacement difficulty; and ineffective monitoring due to low behavioural programmability, less formalised technology and the lack of debt governance (Alchian & Demsetz, 1972; Klein et al., 1978; Williamson, 1979; Fama, 1980; Brüderl et al., 1992; Rajagopalan, 1997; Colf, 2002; Naiker et al., 2008; Raes et al., 2011). Further, such firms operate in a more uncertain business environment that complicates financial estimates (Bentley et al., 2013) and intensifies performance and remuneration uncertainties, leading managers to extract private interests or engage in opportunistic financial reporting (Jensen & Meckling, 1976; Smith & Watts, 1992; Skinner & Sloan, 2002).

By contrast, defenders that focus on cost-efficient products serving a stable market niche usually grant managers and employees less autonomy under a centralization policy (Miles & Snow, 1978). Subsequently, the managers and employees have less capacity to self-serving actions. Further, defender managers exhibit lower opportunism due to the ease of replacement and effective monitoring attributable to high behavioural programmability, more formalised technology and the availability of debt governance (Ittner et al., 1997; Rajagopalan, 1997). Further, these firms operate in a more stable business environment that reduces managerial opportunism (Naiker et al., 2008).

Based on three factors of financial reporting irregularities under the framework of *SAS No. 99* (AICPA, 2002; Hogan et al., 2008), Bentley (2012) and Bentley et al. (2013) suggest that prospectors are more likely to exhibit higher inherent information asymmetry than defenders, due to greater incentives (e.g., rapid and sporadic growth, greater need for external financing, and poorer financial performance), opportunities (e.g., lack of monitoring, internal control deficiencies, less stable and more complex organizational structure), and rationalizations (e.g., individualistic and egoism based ethical climate and culture) to misreport.

Several studies provide supporting evidence for the higher inherent information asymmetry of prospectors relative to defenders. For instance, R&D firms are associated with higher information asymmetry due to greater uncertainty about the firm that can lead to mispricing (Aboody & Lev, 2000; Barth et al., 2001). Bentley et al. (2013) find that prospectors display higher financial reporting irregularity and require more audit effort. Further, Higgins et al. (2013) find that prospectors are more aggressive in their tax position, as opposed to defenders. Firms with more aggressive tax avoidance are associated with a higher implied cost of equity capital, due to: (1) increasing investors' uncertainty in evaluating a firm's future cash flows; (2) their managers are more likely to engage in rent extraction; and (3) these firms are exposed to greater litigation risk that can reduce their future cash flows (Hutchens & Rego, 2013; Goh et al., 2013). A few studies associate isolated attributes of business strategy to required returns or cost of capital. For instance, Shangguan (2005) and Hedge and Mishra (2014) find that R&D expenditures, indicative of uncertainty and asymmetric information about the commercial success of innovative activities, are positively associated with the cost of equity capital.[43] Penman and Zhang (2002) attribute the R&D premium to conservative accounting treatment of R&D that misleads investors. Although not motivated through the angle of information risk, Nguyen and Swanson (2009) and Frijns et al. (2012) observe lower required returns for efficient firms (i.e. more likely defenders).

Nonetheless, Bentley et al. (2014) introduce the complex interrelationships between business strategy and information environment. It is argued that prospectors exhibit a richer information environment relative to defenders. This is because several attributes of

[43] Nevertheless, patented innovations enhance the probability that risky growth options would be converted into less risky asset-in-place (Berk, Green & Naik, 1999; Morellec & Shürhoff, 2011) and reduce uncertainty and information frictions about the commercial success of innovative activities (Holmstrom, 1989; Griliches, 1990), which can lower the discount rate and thus the cost of equity capital. In support, Hedge and Mishra (2014) offer evidence that a firm's cost of equity capital decreases with patented innovations (proxied by the annual number of patent grants and citation counts). Further, they find that patented innovations are related to lower stock return volatility, lower information asymmetry, greater analyst coverage, higher future capital spending, and lower financial leverage.

prospectors such as R&D intensity, marketing and advertising, and growth opportunities, are associated with greater visibility (Grullon et al., 2004; Chordia et al., 2007) that affects investor recognition. Merton (1987), under an incomplete information framework, claims that investor recognition (i.e. the number of investors who know about a particular stock) affects firm value, holding fundamentals constant. Investors only know about a subset of securities and will require higher returns to compensate them for holding securities that they are less familiar with (Lehavy & Sloan, 1998). Huang and Wei (2012) provide supporting evidence that advertising intensity (i.e. a prominent characteristic of prospectors) is related to lower implied cost of equity capital. Further, R&D and advertising activities are also possible channels to attract analyst coverage, media coverage, and institutional holders that can improve firm liquidity and reduce firm information asymmetry (Amihud & Mendelson, 1986b; Bhushan, 1989; Falkenstein, 1996; Barth et al., 2001; Miller, 2006; Dyck et al., 2008; Bushee et al., 2010; Patton & Verardo, 2012). Bentley et al. (2014) show that prospectors are associated with smaller bid-ask spreads, lower analyst forecast dispersion, and higher analyst forecast accuracy, relative to defenders. They attribute these outcomes to greater analyst coverage, media coverage and more frequent voluntary disclosures of prospectors *vis-à-vis* defenders.

In summary, defenders with less inherent information asymmetry and a poorer external information environment can be viewed as portraying better quality but less quantity of information; whereas prospectors with greater inherent information asymmetry and a richer external information environment can be conceptualized as displaying poorer quality but greater quantity of information. According to Easley et al. (2002) and Easley and O'Hara (2004), investors simultaneously price quality and quantity of information.

Research is yet to determine whether and how investors react to information risk emanating from business strategy through equity pricing (except for isolated characteristics examined that can lead to incomplete inferences). Clearly, there is a tension in the literature as to whether prospectors or defenders are exposed to an overall higher level of fundamental-broad information risk, and are thus required a higher rate of return by investors. These competing arguments render the formation of a directional hypothesis difficult. Consequently, the first hypothesis is formulated in null as follows:[44]

$H1_{null}$: *Business strategy, representing an ex ante and fundamental-broad information risk, is not priced by investors.*

The second research question of this thesis is conditioned on the first research question. It is possible that Core et al.'s (2008) suggestion of maximizing the chances of information risk pricing through a fundamental-broad information risk proxy not being supported, as they have neglected the potential offsetting effect of the information risk on asset prices a suggested by Ogneva (2012). Ogneva (2012) shows a negative correlation between Core et al.'s (2008) measure of accruals quality and future cash flow shocks. She disentangled realized returns into cash flow shocks and returns excluding cash flow shocks and observed that low (high) accruals quality firms are exposed to lower (higher) cash flow shocks. These lower cash flow shocks offset the higher expected returns of lower accruals quality firms, and these higher cash flow shocks offset the lower expected returns of higher accruals quality firms. After excluding cash flow shocks, she documents that low accruals quality firms are associated with a higher required rate of return.

[44] Similarly, considering that the effect of business strategy on a firm's overall information environment is unclear *ex ante*, Bentley et al. (2014, p.12) state their second hypothesis in the null form (i.e. "*Prospector business strategies are associated with equal levels of information asymmetry compared to Defender business strategies*").

The concern of offsetting pricing applies to this thesis as the fundamental-broad information risk proxy is operationalized by Bentley et al.'s (2013) business strategy scores using various variables. If the first hypothesis is not rejected, suggesting insignificant pricing of business strategy representative of a fundamental-broad information risk proxy, the thesis poses the second research question: Is there an offsetting pricing effect from variables or components of business strategy? Easley et al. (2002) and Easley and O'Hara (2004) argue that both quality and quantity of information are relevant to equity pricing. Conceptually, the innovation and efficiency components of business strategy capture quality and quantity of information, respectively. Greater innovation, through research and development and marketing and advertising, exposes a firm to greater managerial opportunism, less monitoring and more complex operating environment that can compromise the quality of information (Smith & Watts, 1992; Colf, 2002; Skinner & Sloan, 2002; Naiker et al., 2008). For instance, innovative firms exhibit greater incentives (e.g., rapid and sporadic growth, greater need for external financing, and poorer financial performance), opportunities (e.g., lack of monitoring, internal control deficiencies, less stable and more complex organizational structure), and rationalizations (e.g., individualistic and egoism based ethical climate and culture) to engage in financial reporting irregularity (Bentley, 2012; Bentley et al., 2013) and aggressive tax avoidance that exacerbates tax and information risks (Higgins et al., 2013). Several studies also associate innovative firms with greater information asymmetry (e.g., Aboody & Lev, 2000; Barth et al., 2001), and hence a higher cost of capital (Hegde & Mishra, 2014). Therefore, the innovation component that reflects poorer information quality is expected to be priced by investors.

On the other hand, greater efficiency at the expense of less research and development and marketing and advertising potentially reduces a firm’s visibility, due to less analyst coverage, media coverage, voluntary disclosures and institutional holding, that can lead to less external monitoring and a poorer external information environment (Grullon et al., 2004; Chordia et al., 2007; Elyasiani & Jia, 2010). Efficient firms are thus associated with greater bid-ask spreads, greater analyst forecast dispersion, and lower analyst forecast accuracy relative to innovative firms (Bentley et al., 2014). Eventually, efficiency that captures reduced information quantity and less investor recognition can lead to a higher cost of capital (Amihud & Mendelson, 1986a; Merton, 1987; Huang & Wei, 2012). Possibly, the variables or components used to construct the business strategy measure capture different forms of information risk and can be priced by investors in different manners. Particularly, the pricing of inherent information risk (i.e. poorer quality of information) and external information risk (i.e. less quantity of information) stemming from innovation and efficiency components of business strategy, respectively, offset each other, leading to an insignificant pricing of business strategy in aggregate (i.e. a higher average return associated with poorer information quality stemming from greater innovation offsets a lower average return associated with increased information quantity stemming from greater innovation, and vice versa).

Traditional asset pricing theory views idiosyncratic risk, including information risk, as diversifiable and hence irrelevant to equity pricing (Fama, 1991). The argument supporting the non-pricing of idiosyncratic risk is that it can be diversified away in the construction of investment portfolios (Sharpe, 1964; Lintner, 1965; Black, 1972). Studies such as Hughes et al. (2007) and Lambert et al. (2007) dispute Easley et al. (2002) and Easley and O'Hara (2004) that information risk is diversifiable in a larger economy or already impounded in market risk premium. The traditional finance view thus suggests that since variables or components of business strategy are not priced *a priori*, there is no offsetting pricing effect. Similarly, these competing arguments render the formulation of a directional second hypothesis difficult. Therefore, the second hypothesis is stated in null as follows:

$H2_{null}$: *There is no offsetting pricing effect from variables or components of business strategy*.

CHAPTER 5: RESEARCH METHODOLOGY

5.0 Introduction

The previous chapter poses the research questions of the thesis and formulates hypotheses for testing. This chapter presents the research methodology. Specifically, Section 5.1 introduces the cross-sectional model used to test the hypotheses. Section 5.2 discusses the operationalization of business strategy. Data sources are detailed within each section. For the sake of brevity, the model explanations in this chapter and the two subsequent chapters (i.e. Chapters 5, 6, and 7) focus on business strategy as the test variable (i.e. addressing the first research question of whether business strategy constitutes a priced fundamental-broad information risk factor). The main and sensitivity test models used to test the second research question (i.e. whether there is an offsetting pricing effect from variables or components of business strategy) in Chapter 8 are similar but with the test variable being replaced by an individual measure or component measures of business strategy. The signs of pricing of these variables or components are compared to determine if there is an offsetting pricing effect.

5.1 Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and Business Strategy

This thesis modifies several asset pricing tests used by McInnis (2010) to test the hypotheses. In the main test, similar to prior studies (e.g., Fama & French, 1992, 1993; Core et al., 2008; McInnis, 2010), a cross-sectional regression of monthly excess returns on the Fama-French three factors and business strategy is run every month from 1 January

1972 to 31 December 2010, to examine whether business strategy is associated with average returns. The model is expressed in Model 5.1.

$$R_i - R_F = \alpha_0 + \alpha_1 BETA_i + \alpha_2 SIZE_i + \alpha_3 BM_i + \alpha_4 BS_i + \varepsilon_i \qquad \text{(Model 5.1)}$$

R_i - R_F is a firm's monthly excess return measured in percentages, calculated as a firm's raw monthly stock return (from the Centre for Research in Security Prices [CRSP] monthly stock file) minus the risk-free rate proxied by the one-month Treasury bill rate (from the Fama-French files at Wharton Research Data Services [WRDS]). $BETA_i$ is the slope coefficient from the regression of a firm's monthly raw returns on the monthly value-weighted market return (from the CRSP monthly index file) over a rolling five-year window ending in the current fiscal year. A minimum requirement of 18 monthly returns over the rolling five-year interval is imposed for the estimation of *BETA*. $SIZE_i$, BM_i and BS_i are estimated using data from the Compustat Industrial Annual File. $SIZE_{i,}$ is the natural logarithm of the market value of equity [*CSHO**PRCC_F*], measured at the end of the current fiscal year. BM_i is the natural logarithm of the ratio of book value of equity to market value of equity [log(*CEQ*) less $SIZE_i$], measured at the end of the current fiscal year. BS_i is the variable surrogating a firm's *ex ante* and fundamental-broad information risk based on business strategy. It is a discrete score ranging from 6 to 30, constructed as the sum of quintile ranks of six variables per SIC 2-digit industry and year based on Bentley et al. (2013). Its measurement is detailed in Section 5.2.[45] If prospectors

[45] Amihud and Mendelson (1986b) suggest that liquidity is considered by investors in asset pricing, as investors require compensation for bearing transaction costs from investing illiquid stocks (i.e. higher bid-ask spread). Smaller firms are subject to market thinness leading to liquidity concerns, thus investors require higher returns. Thus, liquidity risk may be captured by *SIZE*. Further, bid-ask spread has been used in prior research as a proxy for information risk (LaFond & Watts, 2008). Also, as discussed in Subsection 3.1.2, business strategy determines the levels of analyst coverage, media coverage, and institutional holders that

(defenders) exhibit an overall higher level of information risk, then a greater BS_i indicates an increasing (a decreasing) magnitude in fundamental-broad information risk.

All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end.[46] For instance, a December-year-end firm gets a new $BETA_i$, $SIZE_i$, BM_i, and BS_i measure the following April. Time-series average parameter estimates for each variable from 468 monthly cross-sectional regressions will be presented, with standard errors and *t*-statistics computed using the Fama and Macbeth (1973) method to account for cross-sectional dependence in the data.[47] Based on Fama and French (1992, 1993), *BETA* is expected to be insignificant; *SIZE* is expected to be significantly and negatively associated with average returns; and *BM* is expected to be significantly and positively associated with average returns. The sign of coefficient on *BS* is unpredicted since it can be insignificant (i.e. fundamental-broad information risk proxied by business strategy is not priced, or there is an offsetting pricing effect of information risks emanating from innovation and efficiency components of business strategy), or significant and positive (i.e. for firms with a prospector strategy displaying higher overall fundamental-broad information risk), or significant and negative (i.e. for firms with a defender strategy displaying higher overall fundamental-broad information risk), given diverse perspectives drawn from the existing literature as discussed in Chapters 3 and 4.

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influence firm liquidity and information risk (Bhushan, 1989; Falkenstein, 1996; Barth et al., 2001; Miller, 2006; Dyck et al., 2008; Bushee et al., 2010; Patton & Verardo, 2012). Hence, testing business strategy (*BS*), in an indirect way, incorporates the liquidity effect in the model.

[46] Although the U.S. Securities and Exchange Commission (SEC) requests firms to file their 10-K reports within 90 days of fiscal year ends, Fama and French (1992) observe 19.8% of firms with non-compliance. Further, Alford, Jones and Zmijewski (1994) report that 40% of firms with a December fiscal year end make their financial reports public in April rather than by 31st March. Thus, a four-month gap is preferred to ensure accounting variables are known before the returns, as these accounting variables are used to explain returns.

[47] Cross-sectional dependence refers to the high cross-sectional correlation of residuals over long time windows induced by common market shocks (Huang & Hueng, 2008; Gray et al., 2009). Petersen (2009) provides evidence that the Fama-Macbeth (1973) procedure can effectively address the econometric concern of the time effect.

5.2 Operationalizing Business Strategy

To classify firms into high and low *ex ante* and fundamental-broad information risk consistent with two extreme strategic types in the Miles and Snow (1978) typology, namely prospectors and defenders, this thesis follows Bentley et al. (2013) in constructing a firm's business strategy score (*BS*) using data from the Compustat Industrial Annual File. *BS* is a discrete score ranging from 6 to 30, constructed as the sum of quintile ranks of the six variables per SIC 2-digit industry and year. The six variables are research intensity, marketing and advertising efforts, and historical growth or investment opportunities that capture the entrepreneurial dimension, operational efficiency and capital intensity or technological efficiency that capture the engineering dimension, and organizational stability that captures the administrative dimension, as summarized in Table 5.1.

<<<INSERT TABLE 5.1 ABOUT HERE>>>

Following Ittner et al. (1997) and Bentley et al. (2013), all variables are computed using a rolling prior five-year period. Existing literature shows that firms commit their resources and attempt to maintain their strategic positions over a long term period to gain competitive advantage (Miles & Snow, 1978, 2003). Therefore, using a rolling prior five-year window period to compute the variables can minimize the random influence of external events on each variable computed to reach a smoothing effect that more accurately captures business strategy (Zajac & Shortell, 1989; Thomas & Ramaswamy, 1996).

Research intensity (*RDS5*), reflective of a firm's tendency to search for new products and markets (Snow & Hrebiniak, 1980; Thomas & Ramaswamy, 1996; Naiker et al., 2008), is measured as the ratio of research and development expenditures [*XRD*] to sales [*SALE*] computed over a rolling prior five-year average. Prospectors with reputations as innovative leaders in the market will increase R&D intensity to explore new products and market opportunities (Hambrick, MacMillan & Barbosa, 1983; Ittner & Larcker, 1997). In contrast, defenders with little or no focus on new product or market development have lower research intensity. This is because they emphasize continuous improvement of existing products with standardized inputs (Miles & Snow, 1978; Smith et al., 1989). Conceivably, prospectors (defenders) exhibit a higher (lower) value in *RDS5*.

Marketing and advertising efforts (*SGA5*), measured as the ratio of selling, general and administrative expenses [*XSGA*] to sales [*SALE*] computed over a rolling prior five-year average, signal a firm's promotion activities and focus on exploiting new products (Naiker et al., 2008; Bentley et al., 2013).[48] Prospectors heavily rely on marketing and advertising to introduce customers their new differentiated products (Levy, 1989; Ittner et al., 1997). In contrast, regular customers are already familiar about defenders' well established cost-efficient products, therefore defenders rely less on marketing and advertising (McDaniel & Kolari, 1987; Kotha & Nair, 1995). Prospectors (defenders) are expected to have a higher (lower) value of *SGA5*.[49]

The third variable included is historical growth or investment opportunities (*REV5*), measured as one-year percentage change in total sales [*SALE*] computed over a rolling

[48] Pantzalis and Park (2009) raise the concern that less than 20 percent of firms in Compustat report their advertising expenditures. Thus, this study utilizes selling, general and administrative expenditure (SG&A, inclusive of marketing and advertising expenditure) that needs to be reported by firms to capture firm-level of marketing and advertising activities, which is in line with Bentley et al. (2013).

[49] In addition, the level of SG&A expense can be representative of the degree of decentralization and hence administration complexity. This is because coordination and operations are more costly for prospectors that grant lower level management with a degree of autonomy, relative to defenders that adopt a centralization policy (Miles & Snow, 1978; Rajagopalan, 1997). In a separate stream of literature, Chen, Lu and Sougiannis (2012) associate agency problems with SG&A cost asymmetry, where managers are quick to increase SG&A expense when demand increases but they are slow to reduce SG&A expense when demand falls, as SG&A expense is a means to extract private interests. Therefore *SGA5* captures the administrative dimension to a certain extent.

prior five-year average (Bentley et al., 2013).[50] Prospectors tend to experience high growth rates by market expansion via regularly pioneering new products. In contrast, defenders stick to the existing stable market domain and achieve growth through market penetration (Miles & Snow, 1978; Segev, 1989; Shortell & Zajac, 1990; Ittner et al., 1997; Said, HassabElnaby & Wier, 2003). Smith et al. (1989) juxtapose that the growth pattern of defenders is stable, while that of prospectors is spurt. Consequently, prospectors (defenders) are more likely to have a higher (lower) value of *REV5*.

Operational efficiency (*EMPS5*), which is the ratio of the number of employees [*EMP*] to sales [*SALE*] computed over a rolling prior five-year average, indicates a firm's ability to produce and distribute products and services efficiently (Bentley et al., 2013). Highly standardized business operations and clearly stipulated procedures enable employees in defenders to generate a higher level of sales, relative to the same number of employees in prospectors who engage in innovative activities characterized with uncertainty and loosely defined procedures that can lead to wasteful activities (Ittner et al., 1997; Miles & Snow, 2003; Said et al., 2003; Naiker et al., 2008). Thus, it is expected that prospectors (defenders) have a higher (lower) of *EMPS5*.

The fifth variable incorporated to compute *BS* is capital intensity (*CAP5*) reflective of a firm's technological efficiency, measured as net property, plant, and equipment [*PPENT*] to total assets [*AT*] computed over a rolling prior five-year average (Bentley et al., 2013). Defenders are more automated and capital intensive to achieve inputs

[50] Prior studies capture a firm's growth potential with the market-to-book ratio (e.g., Ittner et al., 1997; David, Hwang, Pei & Reneau, 2002; Naiker et al., 2008). To avoid a high correlation of *BS* with the book-to-market ratio in the Fama-French three factor model, this thesis employs change in total revenue over a rolling prior five-year average to compute *BS*, consistent with Bentley et al. (2013).

minimization and outputs maximization, that ultimately lead to economies of scale (McDaniel & Kolari, 1987; Langerak, Nijssen, Frambach & Gupta, 1999). In contrast, prospectors that continuously explore new market opportunities are less automated and capital-intensive, pay less attention to technology improvement, and they are more flexible and regularly replace their technologies (Hambrick, 1983; Segev, 1989). Therefore, it is expected to observe a higher (lower) *CAP5* for defenders (prospectors).

Finally, organizational stability (*TEMP5*), measured as the standard deviation of the total number of employees [*EMP*] computed over a rolling prior five-year period (Bentley et al., 2013), is included to capture *BS*. Employees in prospectors have shorter tenure as they move across firms based on the availability of projects, and also because they possess general skills that afford them to easily switch between firms. Further, senior management in prospectors can be hired externally (Miles & Snow, 1978; Thomas & Ramaswamy, 1996). Conversely, employees in defenders do not generally possess a wide range of skills that allow them to move across firms and they are trained extensively to get familiar with the business operations, rendering them more "sticky" to the firm (Naiker et al., 2008). Further, senior management is usually promoted within defenders who need to possess intimate knowledge of the firm and its production capacity (Thomas & Ramaswamy, 1996). Prior studies (e.g., Grant, 1996; Shaw et al., 2005; Kacmar et al., 2006; Morrow & McElroy, 2007) argue that employee turnover creates the need for knowledge transfer that leads to inefficiency. This is because firms incur costs, time and effort to train new employees to get familiar with job duties of departed employees. Prospectors (defenders) are more likely to display a higher (lower) value of *TEMP5*.

To remain in the sample, a firm-year observation is required to have data available to compute all the above-mentioned six variables as they collectively capture a firm's business strategy from the entrepreneurial (*RDS5*, *SGA5*, *REV5*), engineering (*EMPS5*, *CAP5*) and administrative (*TEMP5*) dimensions. Using an aggregate rather than a single variable can better capture the information risk nature of business strategy. These variables are ranked into quintiles per year and two-digit SIC industry to acknowledge the co-existence of different strategies in the same industry, and to control for the potential year-industry effect so that less biased quintiles can be constructed. *RDS5*, *SGA5*, *REV5*, *EMPS5*, and *TEMP5* are ranked in an ascending manner, while *CAP5* is ranked in a descending manner, with the intention that a higher (lower) value of these variables reflects prospector (defender) characteristics. The quintile-ranked scores of these six variables are summed every year, ranging from 6 to 30, to indicate a firm's business strategy: defender (6-12); analyzer (13-23); prospector (24-30). A greater *BS* indicates an increasing (a decreasing) degree in fundamental-broad information risk, if investors associate prospectors (defenders) with an overall higher level of information risk, after simultaneously taking quantity and quality of information into pricing consideration. The next chapter presents empirical results for the first research question to shed light on whether business strategy is a priced fundamental-broad information risk factor.

CHAPTER 6: RESULT ANALYSIS: IS BUSINESS STRATEGY A PRICED FUNDAMENTAL-BROAD INFORMATION RISK FACTOR?

6.0 Introduction

The previous chapter outlines the main model used to test the first hypothesis and discusses the operationalization of Bentley et al.'s (2013) business strategy score as the proxy for a firm's fundamental-broad information risk. This chapter reports empirical results for the first research question to shed light on whether business strategy constitutes a priced fundamental-broad information risk factor. Section 6.1 outlines the sample formation. Section 6.2 provides descriptive information for variables used in the main model. Section 6.3 documents the regression results.

6.1 Sample Selection

Panel A of Table 6.1 outlines the sample selection procedure for this study. Following Bentley et al. (2013), it begins with 256,238 firm-years spanning 1966-2010 with data available from the Compustat Annual file, after removing firm-years with duplications, missing historical SIC codes, and zero or negative sales, assets, and book-to-market.[51] Next, 55,224 firm-years in utilities (SIC 4900–4999) and financial (SIC 6000–6999) industries are also excluded, as these highly regulated industries are subject to different accounting rules (Barton & Simko, 2002; Gunny & Zhang, 2013; Bentley et al., 2013). It is also common for asset pricing studies to exclude financial firms because it is

[51] It is common for asset pricing studies to exclude firms with negative book-to-market (Fama & French, 1992, 1993). Jan and Ou (2012) suggest that firms with negative book value of equity are associated with significant R&D expenditures. Concerning that a number of potential prospectors may be excluded from the sample, Bentley et al. (2013) maintain firms with negative book-to-market when constructing business strategy scores. However, they note that their results are robust to the exclusion of negative book-to-market firms.

usual for them to have high financial leverage; whereas, high financial leverage for non-financial firms indicates distress (Fama & French, 1992). Subsequently, 113,148 firm-years with insufficient rolling prior five-year period data to compute all six variables used to construct business strategy score (*BS*) are excluded. The sample selection eventually yields 87,866 firm-years from 1972 to 2010 available for the execution of this study.[52]

<<<INSERT TABLE 6.1 ABOUT HERE>>>

Notably, among 87,866 firm-years, there are 6,608 defender firm-years, 7,290 prospector firm-years, and 73,968 analyzer firm-years, which represent 7.52, 8.30 and 84.18 percent of the full sample, respectively. Panel B of Table 6.1 presents industry membership of the sample firm-years for the full sample and the sub-samples of prospectors and defenders. The industry distribution is similar to Bentley et al. (2013) and supports Miles and Snow (1978, 2003) that three types of viable business strategies co-exist in different industries. It is observed that, generally, the percentages of prospectors and defenders are identical not only in each industry but also to the percentage of the total sample in each industry. For instance, the smallest industry segment is agriculture, forestry and fishing sector which consists of 0.43 percent of the full sample, 0.33 percent of the prospector sub-sample, and 0.42 percent of the defender sub-sample, respectively. Conversely, the manufacturing sector is the largest industry segment represented in the full sample (61.05 percent), as well as in the sub-samples of prospectors (66.27 percent) and defenders (74.65 percent).

[52] The final sample begins with 1972 because the computation of *BS* relies on rolling prior-five year data.

6.2 Descriptive Statistics

Descriptive statistics for the raw values of the six variables used to compute *BS* for the full sample and the sub-samples of prospectors and defenders are presented in Panels A and B of Table 6.2, respectively. Most statistics resemble those reported by Bentley et al. (2013). The means and medians indicate that, as anticipated, prospectors exhibit higher research intensity (higher *RDS5*), more marketing and advertising efforts (higher *SGA5*), higher historical growth or investment opportunities (higher *REV5*), lower operational efficiency (higher *EMPS5*), lower capital intensity or technological efficiency (lower *CAP5*), and less organizational stability (higher *TEMP5*), relative to defenders. *t*-statistics (Wilcoxon *Z*-statistics) indicate that the differences between the means (medians) of those six variables for the sub-samples of prospectors and defenders are all significant at the 1 percent level.

<<<INSERT TABLE 6.2 ABOUT HERE>>>

Panel C of Table 6.2 reports descriptive statistics for variables used in the main model for the full sample. Those statistics are very similar to those reported in McInnis (2010). R_i-R_F has a mean (median) of 1.3873 (0.2985); while the mean (1.0866) and median (1.0288) of *BETA* is close to 1. The mean (median) for *SIZE* and *BM* are 5.3977 (5.3127) and -0.4338 (-0.4078), respectively. The distribution of the test variable, *BS*, is also close to Bentley et al. (2013),[53] with a mean (median) of 18.3782 (18.0000) and an inter-quartile range between 16.0000 and 21.0000.

[53] The descriptive statistics for business strategy scores reported by Bentley et al. (2013) are as follows: 17.78 (mean), 18.00 (median), 15.00 (Quartile 1), 20.00 (Quartile 3).

Pearson and Spearman correlations between independent variables are presented at the lower and upper diagonal of Panel D, Table 6.2 respectively. The highest correlation observed is between *BM* and *SIZE* (Spearman correlation -0.5132). The significant correlations between *BS* and the Fama-French three factors indicate that firms pursuing a prospector strategy tend to be larger, have lower book-to-market (i.e. higher growth), and higher beta.

Panel E shows the correlations between individual business strategy measures and the Fama-French three factors. All individual business strategy measures are significantly correlated with *BM*. It shows that high *BM* firms (i.e. low growth firms) tend to have less research intensity, less marketing and advertising efforts, less historical growth and investment opportunities, less operational efficiency, greater capital intensity or technological efficiency, and greater organizational stability. Among the individual business strategy measures, *REV5* exhibits the highest correlation with *BM* (Pearson -0.1879; Spearman -0.2189), thereby justifying the computation of a modified business strategy measure exclusive of *REV5* (*BS2*) and the execution of principal component analysis to derive the innovation (*FINV*) and efficiency (*FEFF*) factors based on the five remaining measures of *BS2* in the later analysis.

6.3 Empirical Results

680,224 firm-month observations are used to run Model 5.1, after matching 87,866 firm-year observations with necessary data to execute this cross-sectional regression of monthly excess returns on the Fama-French three factors (*BETA*, *SIZE*, *BM*) and business strategy (*BS*) from 1 January 1972 to 31 December 2010. Time series average of the parameter estimates from the 468 monthly cross-sectional regressions in Model 5.1 are presented in Table 6.3. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach to account for cross-sectional correlation in the error terms.

<<<INSERT TABLE 6.3 ABOUT HERE>>>

As suggested by results in Table 6.3, the coefficient of *BS*, in a model without controlling for the Fama-French three factors, is positive (0.0071). A positive coefficient on *BS* suggests that investors associate prospectors with an overall higher level of fundamental-broad information risk, after simultaneously considering the quality and quantity of information in their price setting processes. However, the positive coefficient on *BS* is insignificant (*t*-statistic = 0.11). After controlling for the Fama-French three factors, the coefficient on *BS* remains positive (0.0123) but insignificant (*t*-statistic = 1.08). Similar to prior studies (e.g., Fama & French, 1992, 1993; Core et al., 2008; McInnis, 2010), the coefficient on *BETA* is insignificant, while the coefficient on *SIZE* (*BM*) is negative (positive) and significant. It is also observed that the R^2 for Model 5.1 is 3.82 (4.21) percent with the exclusion (inclusion) of *BS*. Results in Table 6.3 suggest that business strategy, either in isolation or in conjunction with the Fama-French three factors, is not associated with average returns. In other words, $H1_{null}$ is not rejected; business strategy, representing an *ex ante* and fundamental-broad information risk proxy, is not priced by investors. *Prima facie*, this lends support to the traditional finance school of thought that firm-specific risk including information risk is diversifiable and thus irrelevant to equity pricing. The subsequent chapters employ more analyses based on portfolio constructions to test the robustness of the result, and explore alternative explanations for the results obtained.

CHAPTER 7: SENSITIVITY ANALYSIS: IS BUSINESS STRATEGY A PRICED FUNDAMENTAL-BROAD INFORMATION RISK FACTOR?

7.0 Introduction

The previous chapter reports the empirical results for the cross-sectional regression of monthly excess returns on the Fama-French three factors and business strategy scores (*BS*) computed based on Bentley et al. (2013). While preliminary results show that business strategy, representing an *ex ante* and fundamental-broad information risk factor, is not priced by investors, more analyses are warranted to test the robustness of the results. This chapter presents the results of several robustness checks for the first research question, particularly time-series portfolio regressions of monthly excess returns on the Fama-French three factors, where portfolios are sorted based on business strategy scores (Section 7.1), and a two-stage cross-sectional regression (Section 7.2). Section 7.3 performs sub-period analyses to mitigate the concern of a structural break for using data spanning around 40 years. Since Bentley et al.'s (2013) *BS* encompasses a measure capturing historical growth (*REV5*) which is similar to book-to-market (*BM*) or *HML* in the Fama-French factor, a sensitivity analysis is conducted based on a modified *BS* excluding *REV5* (*BS2*) and reported in Section 7.4.

7.1 Time-series Business Strategy Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

The cross-sectional test employed in the previous chapter has been criticised given that realized returns are noisy, particularly at the firm level. McInnis (2010) argues that it is difficult to purely relate the candidate risk factor to realized returns in the presence of uncaptured confounding firm-specific events or factors. To mitigate this concern, following

Black, Jensen and Scholes (1972) and McInnis (2010), time-series portfolio regressions of monthly excess returns on the Fama-French three factors are conducted, as expressed in Model 7.1. Each month, from 1 January 1972 to 31 December 2010, firms are sorted into four portfolios based on their most recent business strategy scores (*BS*): defender (6-12); lower analyzer (13-17); upper analyzer (18-23); prospector (24-30). The use of portfolios can considerably reduce firm-specific noise in realized returns (McInnis, 2010). More stable returns allow one to detect any pricing pattern related to information risk surrogated by business strategy.

$$R_{p,t} - R_{F,t} = \alpha + b_1 (R_{M,t}-R_{F,t}) + b_2 SMB_t + b_3 HML_t + \varepsilon_{p,t} \qquad \text{(Model 7.1)}$$

$R_{p,t}$ -$R_{F,t}$ refers to portfolio monthly excess returns calculated as the value-weighted monthly return on the portfolio less the risk-free rate proxied by the one-month Treasury bill rate.[54] $R_{M,t}$-$R_{F,t}$ is the market risk premium calculated as the value-weighted monthly market return less the risk-free rate proxied by the one-month Treasury bill rate. SML_t is the value-weighted size-mimicking monthly portfolio return (i.e. the excess return of a portfolio that longs in small stocks and shorts in big stocks). HML_t is the value-weighted book-to-market-mimicking monthly portfolio return (the excess return of a portfolio that longs in high book-to-market stocks and shorts in low book-to-market stocks). R_M, R_F,

[54] Frequent (e.g., monthly) rebalancing can cause bid-ask spread bounces begetting biases that can be systematically correlated with firm size (Blume & Stambaugh, 1983). Moreover, it also increases transaction costs and questions the implementability of the investment strategy (Core et al., 2008). To address this concern, time-series portfolio regressions of 12 month buy-and-hold monthly excess returns on the Fama-French three factors are conducted. Results generated from this alternative specification remain qualitatively and quantitatively similar, and are reported in Appendix 7.1.

SMB and *HML* are obtained from Kenneth R. French's database through WRDS. Monthly returns are measured in percentages.

Firms are sorted into four portfolios each month based on their most recent *BS*. The choice of four portfolios is different from conventional choices of five or ten portfolios that are based on quintile- or decile- sorting (e.g., Blume & Stambaugh, 1983; Sloan, 1996; Pástor & Stambaugh, 2003; Aboody et al., 2005). This is because the study aims to juxtapose, if any, the pricing of information risk emanating from defender and prospector strategies. Bentley et al. (2013) is the only study that has established a more comprehensive way of classifying firms into these strategic types based on range of scores. It will be problematic for this study to sort firms into five portfolios, as to a certain extent, a number of analyzers will be "forcefully" classified as defenders or prospectors due to more ambiguous cut-off points, thereby a hedge portfolio strategy constructed subsequently is noisy since it contains the third type of business strategy (i.e. upper-end and lower-end analyzers). Similarly, if firms are sorted into ten portfolios, a number of lower-end prospectors and upper-end defenders will be omitted from constructing the hedge portfolio of two extreme strategies. Neglecting these issues can contaminate the inference. Therefore, while Bentley et al. (2013) has set the range of scores for defenders (6-12) and prospectors (24-30) which are treated as the two extreme portfolios and used to construct the hedge portfolio in this thesis; analyzers which represent the middle category are further pigeonholed into two categories (13-17 deemed as the lower category and 18-23 deemed as the upper category) to render portfolio constructions for robustness tests in this chapter more even, given a wider range of scores from 13 to 23 set in Bentley et al. (2013).

The intercept (α) in Model 7.1 is the variable of interest which represents excess returns unexplained by the risk factors controlled in the model (Core et al., 2008; McInnis, 2010). According to Black et al. (1972) and Cochrane (2005), α is expected to be zero under a properly specified factor model (i.e. there are no omitted risk factors). Conversely, under a model with omitted risk factors, α is expected to be significantly different from zero, since some excess returns cannot be explained by existing risk factors (e.g., market, *SMB*, *HML*), and this could suggest either the omitted risk factor is priced or there is mispricing (Core et al., 2008). Further, α is expected to be greater for portfolios with greater exposure to that risk factor. Therefore, if business strategy is priced and represents an information risk factor compensated in average returns, and this factor is orthogonal to the Fama-French three factors, α is expected to increase (decrease) as the portfolios move from defender to prospector strategies, and α under the hedge portfolio is expected to be significant and positive (negative), whereby investors associate prospectors (defenders) with an overall higher level of fundamental-broad information risk. On the other hand, α under the hedge portfolio is expected to be insignificant if business strategy does not constitute a priced fundamental-broad information risk factor, which can be attributed to either the diversifiable nature of information risk or the offsetting pricing effect of information risks emanating from innovation and efficiency components of business strategy.

Table 7.1 reports the results for the four time-series portfolio regressions and an additional hedge portfolio regression in the last column. The hedge portfolio is constructed by longing portfolio 4 of prospectors and shorting portfolio 1 of defenders, and reflects the monthly difference in returns between firms with the highest and lowest fundamental-broad information risk.

<<<INSERT TABLE 7.1 ABOUT HERE>>>

Model 7.1.1 is a variant of Model 7.1 which includes only the intercept to shed light on the average monthly returns for each portfolio. There is a monotonic decreasing pattern in average returns from the defender to prospector portfolios. α in each individual portfolio is also positive and significant at the 5 percent level or lower. A negative α under the hedge portfolio (-0.1014) suggests that in each month, defenders earn around 10 basis points more excess returns than prospectors, but the difference is not statistically significant (*t*-statistic = -0.59). In other words, on a univariate basis, although there is a negative association between business strategy and average returns (i.e. defenders are associated with greater overall fundamental-broad information risk), such a relation is insignificant.

Model 7.1.2 is also a variant of Model 7.1 which includes the intercept and the market risk premium (R_M-R_F). α continues to show a monotonic decrease moving from the defender to prospector portfolios. α is positive and significant in the defender, lower analyzer and upper analyzer portfolios, yet positive and insignificant for the prospector portfolio. The magnitude of negative α under the hedge portfolio (-0.2236) is greater compared to that in Model 7.1.1 (-0.1014). Although, it suggests that, controlling for R_M-R_F, defenders earn around 22 basis points more excess monthly returns than prospectors, the difference is statistically insignificant (*t*-statistic = -1.35). R_M-R_F yields increasingly significant positive coefficients when the portfolio progresses from defender to prospector.

This is similar to the correlations presented in Panel D of Table 6.2, where prospectors have larger beta.

Model 7.1.3 incorporates all of the variables from Model 7.1. After controlling for the Fama-French three factors, there is no clear trend in excess returns. α for the defender and upper analyzer (lower analyzer and prospector) portfolios are negative (positive), but none are significantly different from zero. Interestingly, the sign of α for the hedge portfolio becomes positive, which is in a sharp contrast to the models controlling only for the intercept (Model 7.1.1), and the intercept and market risk premium (Model 7.1.2). Albeit a positive α (0.0618) suggests that, prospectors earn around 6 basis points more excess monthly Fama-French adjusted returns than defenders (i.e. overall, prospectors are associated with greater fundamental-broad information risk), the difference is statistically insignificant (*t*-statistic = 0.42). The coefficients on R_M-R_F remain positive and significant for each portfolio and indicate an increasing trend. The coefficients on *SMB* are significant in each portfolio (except for the hedge portfolio) without a clear pattern. The coefficients of *HML* are positive and significant in each portfolio (except for the prospector portfolio where the coefficient is negative but insignificant) and demonstrate a monotonic decrease. The significant and negative coefficient on *HML* under the hedge portfolio is in line with correlations presented in Panel D of Table 6.2 that prospectors (defenders) tend to have higher (lower) growth and are more likely to be growth (value) firms.

The Gibbons, Ross and Shanken (GRS) (1989) *F*-statistic tests the null hypothesis that intercepts in the four portfolios of business strategy (i.e. defender, lower and upper analyzers, prospector) under Model 7.1.3 are jointly zero. The GRS *F*-statistic of 0.80 (*p*-value = 0.5273) suggests that the null hypothesis cannot be rejected (i.e. all intercepts are jointly zero). In conjunction with high R^2 (around 80 percent or better) and individually insignificant α, the Fama-French three factor model employed to test the pricing of business strategy portfolios is well-specified (Core et al., 2008; McInnis, 2010). Generally, the results generated under this hedge portfolio test do not suggest any significant positive abnormal (Fama-French adjusted) return can be generated if an investor longs stocks of prospectors and shorts stocks of defenders, nor significant negative abnormal (Fama-French adjusted) return for longing stocks of defenders and shorting stocks of prospectors. When $H1_{null}$ cannot be rejected, it strengthens the inference in the main test that business strategy is not a priced fundamental-broad information risk factor.[55]

7.2 Two-stage Cross-sectional Regression

Following prior studies, this thesis also adopts a two-stage cross-sectional regression approach that has been widely employed in the literature to test whether a candidate risk factor is priced (e.g., Cochrane, 2005; Petkova, 2006; Core et al., 2008; Kim & Qi, 2010; McInnis, 2010). Prior to this, for the sake of comparisons, a time-series regression model in the spirit of Francis et al. (2005) that examines a contemporaneous association between excess returns and the Fama-French three factor and business strategy factor returns is performed, as expressed in Model 7.2. Core et al. (2008) argue that the Francis et al. (2005) approach is insufficient to establish that the candidate variable (i.e. accruals quality in their study) as a priced risk factor, whereby the average factor loading

[55] Results, reported in Panel A of Appendix 7.2, are robust to controlling the Carhart's (1997) momentum factor (*UMD*). *UMD*, obtained from Kenneth R. French's database through WRDS, is the excess return of a portfolio that longs stocks with highest past returns and shorts stocks with lowest past returns.

merely indicates that firms in the contemporaneous regressions have exposure to the proposed risk factor.

$$R_{i,t} - R_{F,t} = \alpha + b_{RM\text{-}RF}\,(R_{M,t}\text{-}R_{F,t}) + b_{SMB}\,SMB_t + b_{HML}\,HML_t + b_{PMD}\,PMD_t + \varepsilon_{i,t} \quad \text{(Model 7.2)}$$

$R_{i,t}$ -$R_{F,t}$ refers to a firm's monthly excess returns, calculated as a firm's raw monthly stock return minus the risk-free rate proxied by the one-month Treasury bill rate. $R_{M,t}$-$R_{F,t}$ refers to the market risk premium estimated as the value-weighted monthly market return less the risk-free rate proxied by the one-month Treasury bill rate. SML_t is the value-weighted size-mimicking monthly portfolio return. HML_t is the value-weighted book-to-market-mimicking monthly portfolio return. PMD_t is the value-weighted business strategy-mimicking monthly portfolio return by subtracting the value weighted return of stocks in the defender portfolio from the value-weighted return of stocks in the prospector portfolio. The results for such time-series regressions at the firm level are presented in Panel A of Table 7.2.

<<<INSERT TABLE 7.2 ABOUT HERE>>>

Panel A of Table 7.2 presents average coefficients from firm-specific regressions across 5,238 firms with a minimum of 18 monthly return observations over the sample period. *t*-statistics are estimated from the standard errors of the average coefficients. McInnis (2010) argues that *t*-statistics under this approach are inflated due to a potential cross-correlation in the slope coefficients across firms. The coefficients on the Fama-French three factors are positive and significant, however they just indicate that firms have positive exposure to these factors rather than to be taken as pricing evidence. The coefficient of *PMD* is positive (0.0003) which indicates that firms have positive exposure to business strategy factor returns (i.e. overall, prospectors are perceived to have greater fundamental-broad information risk), however this exposure is clearly weak and insignificant (t-statistic = 0.02).

Following Core et al. (2008) and McInnis (2010), a more appropriate test, that is the two-stage cross-sectional regression approach, at the portfolio level is thus employed to directly test the pricing of information risk proxied by business strategy.[56] According to Black et al. (1972) and Fama and Macbeth (1973), the use of portfolio helps reduce the errors-in-variables problem emanating from firm-specific estimation.[57] The two stages of the regression model, Models 7.3 and 7.4, are as follows:

$$R_{p,t} - R_{F,t} = \alpha + \beta_{RM\text{-}RF}\,(R_{M,t}\text{-}R_{F,t}) + \beta_{SMB}\,SMB_t + \beta_{HML}\,HML_t + \beta_{PMD}\,PMD_t + \varepsilon_{p,t} \quad \text{(Model 7.3)}$$

$$R_{p,t} - R_{F,t} = \gamma + \lambda_1\beta_{p,RM\text{-}RF} + \lambda_2\beta_{p,SMB} + \lambda_3\beta_{p,HML} + \lambda_4\beta_{p,PMD} + u_t \quad \text{(Model 7.4)}$$

Model 7.3 represents the first-stage 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns ($R_{p,t}$-$R_{F,t}$, calculated as the monthly portfolio value-weighted return minus the risk-free rate proxied by the one-month Treasury bill rate) on the Fama-French three factors and business strategy factor ($R_{M,t}$-$R_{F,t}$, SMB_t, HML_t, and PMD_t, as defined for Model 7.2) to generate estimated factor betas (i.e. $\beta_{p,RM\text{-}RF}$, $\beta_{p,SMB}$, $\beta_{p,HML}$, and

[56] Kim and Qi (2010) note the trade-off between using individual stocks and using portfolios in the two-stage cross-sectional regression, where tests using portfolios (individual stocks) reduce (increase) the errors-in-variables bias due to the use of estimated betas rather than true betas, but have weaker (stronger) power in examining the explanatory power of betas for the cross-sectional variation of average returns.
[57] An error-in-variables problem can potentially bias the standard errors of the second-stage regression coefficients, since betas in the second-stage regression are estimated betas from the first-stage (García Lara et al., 2010).

$\beta_{p,PMD}$) used as independent variables in the second-stage regression (Model 7.4). In performing the two-stage cross-sectional regression analysis, the thesis follows McInnis (2010) by sorting stocks into book-to-market and the variable of interest. Specifically, each month, firms are independently sorted into quintiles based on book-to-market (*BM*) to produce variation in average returns, and four portfolios of *BS* (i.e. defender, lower analyzer, upper analyzer, and prospector) to ensure sufficient variation in the variable of interest among the test assets which can increase the power to test if *BS* is a priced fundamental-broad information risk factor (Core et al., 2008). The 20 *BM-BS* portfolios are then created from the intersection of these sorts.

Model 7.4 represents the second-stage monthly cross-sectional regressions of excess value-weighted portfolio returns ($R_{p,t}$-$R_{F,t}$) on portfolio factor loadings which are estimated betas from Model 7.3 (i.e. $\beta_{p,RM\text{-}RF}$, $\beta_{p,SMB}$, $\beta_{p,HML}$, and $\beta_{p,PMD}$). $\beta_{q,RM\text{-}RF}$ is the portfolio beta related to the R_M-R_F factor; $\beta_{p,SMB}$ is the portfolio beta related to the *SMB* factor; $\beta_{p,HML}$ is the portfolio beta related to the *HML* factor; and $\beta_{p,PMD}$ is the portfolio beta related to the *PMD* factor. $H1_{null}$ (i.e. business strategy is not a priced fundamental-broad information risk factor) cannot be rejected if the coefficient on $\beta_{p,PMD}$ (λ_4) is insignificant, which can be attributed to either the diversifiable nature of information risk or the offsetting pricing effect of information risks emanating from innovation and efficiency components of business strategy. Conversely, a significant and positive (negative) λ_4 suggests that business strategy represents a priced fundamental-broad information risk factor, and specifically investors associate prospectors (defenders) with an overall higher level of fundamental-broad information risk.

Panel B of Table 7.2 presents average factor loadings across 20 portfolios from estimating Model 7.3 (i.e. the first stage of two-stage cross-sectional regression). *t*-statistics are estimated from the standard errors of the average coefficients. The average loadings on the Fama-French three factors are positive and significant. Nevertheless, the average loading on *PMD* is negative (-0.0862) and insignificant (*t*-statistic = -1.05).[58] Panel C of Table 7.2 reports time-series average of the coefficients from the 468 monthly second stage cross-sectional regression (Model 7.4). *t*-statistics are computed based on the Fama-Macbeth (1973) approach to mitigate concerns about cross-sectional dependence in the data. The coefficients for $\beta_{RM\text{-}RF}$ (-1.5447) and β_{HML} (0.5026) are significant at the 10 percent level (*t*-statistics = -1.71 and 1.83, respectively). β_{SMB} has a positive (0.1603) but insignificant coefficient (*t*-statistic = 0.57). The coefficient on β_{PMD} is negative (-0.0922) whereby investors associate defenders with greater overall fundamental-broad information risk, but such loading is insignificant (*t*-statistic = -0.50). Therefore, $H1_{null}$ is not rejected.[59] Consistent with the results generated under the main test (Section 6.3) and hedge portfolio test (Section 7.1), the results from the two-stage cross-sectional regression provide no

[58] Appendix 7.3 shows average excess returns for the 20 portfolios sorted on *BM* and *BS* over the sample period to provide preliminary insight if there is any clear pattern in average returns based on these sorts. There are no clear patterns in average excess returns for each level of *BM*, moving from defender to prospector portfolios. Nevertheless, for all levels of *BM* (except for the second lowest level of *BM*), prospectors show greater average excess returns than defenders.

[59] Following other studies (e.g., Core et al., 2008; Ogneva, 2012), the two-stage cross sectional regression analysis is replicated by considering size as another sorting group. Stocks are sorted into five *BM* portfolios (based on quintile), four portfolios of *BS* (i.e. defender, lower analyzer, upper analyzer, and prospector) and two size portfolios (based on median) each month. The intersection of this sorting creates 40 *BM-BS-SIZE* portfolios. The results, reported in Appendix 7.4, indicate that there is no pricing evidence for business strategy, as the coefficients for *PMD* (-0.1275) in Panel A and β_{PMD} (-0.9290) in Panel B are both insignificant (t-statistics = -1.51 and -1.19, respectively). Therefore, the results are consistent with the main findings generated using 20 *BM-BS* portfolios.

support for business strategy as an incrementally priced fundamental-broad information risk factor.[60]

A limitation of the two-stage cross-sectional regression is that portfolio loadings in the first stage may introduce more noise than firm-specific characteristics like *SIZE*, *BM*, or *BS*, as McInnis (2010) claims that such measurement error can bias the coefficients in the second stage toward zero (as evident by insignificant coefficient on β_{SMB} in Panel C, Table 7.2). Further, Core et al. (2008) view that a significant coefficient on the risk factor in the two-stage cross-sectional regression is a necessary but not sufficient condition for the risk factor to be priced, as it can be interpreted as the evidence of risk (Fama & French, 1993) or mispricing (Daniel, Hirshleifer & Subrahmanyam, 2001). Considering that each of the three tests performed so far (i.e. the main test as in Chapters 5 and 6, and two sensitivity tests as in Sections 7.1 and 7.2) has strengths and weaknesses, they will all be replicated for sub-period analyses and an analysis based on a modified business strategy measure in the following sections, and for each analysis for the second research question in the next chapter.

7.3 Sub-period Analyses

Technology advancement has reshaped how firms conduct their business, and firms tend to engage in a greater level of research and development in the post-1990 period (Singh, Glen, Zammit, De-Hoyos, Singh & Weisse, 2005; Griffith, Harrison & van Reenen, 2006). The technology boom may increase the number of prospectors. The results obtained so far are potentially subject to a structural break by using data spanning around 40 years.

[60] Results, reported in Panels B to D of Appendix 7.2, remain similar after controlling for the Carhart's (1997) momentum factor (*UMD*).

To mitigate this concern, the sampling years of 1972-2010 are divided into two periods, which are 1972-1989 and 1990-2010, for sub-period analyses. Pre-1990 and post-1990 observations account for 39 and 61 percent, respectively, of the final sample firm-years.

Results for the pre-1990 period analyses are reported in Table 7.3. Results of a cross-sectional regression of monthly excess returns on the Fama-French three factors and *BS* in Panel A, indicate that in the pre-1990 period, *BS* is not priced as it is not significantly associated with average returns (0.0059, *t*-statistic = 0.36). The hedge portfolio tests in Panel B show a monotonic decrease in α moving from the defender to prospector portfolios, and α for the hedge portfolio are negative (-0.3726 and -0.4349, respectively) and significant at the 10 percent level (*t*-statistic = -1.65 and -1.98, respectively), under a model that incorporates only intercept (Model 7.1.1) and a model that incorporates intercept and market risk premium (Model 7.1.2). There is weak pricing evidence that in the pre-1990 period investors associate prospectors with lower fundamental-broad information risk and require lower risk premium relative to defenders. However, when *SMB* and *HML* are further controlled for (Model 7.1.3), α (-0.1808) becomes insignificant (*t*-statistic = -0.87). Panel C replicates Francis et al. (2005) and shows a significantly negative *PMD* (-0.1086, *t*-statistic= -5.00), implying that prospectors have negative exposure to returns (i.e. lower fundamental-broad information risk). But again, this does not necessarily indicate that *BS* is priced. Results reported in Panels D and E under a two-stage cross-sectional regression suggest that the negative coefficients on *PMD* (-0.0599) and β_{PMD} (-0.2618) are insignificant (*t*-statistics = -0.65 and -1.02, respectively). This corroborates the prior results that there is no evidence for showing business strategy as a priced fundamental-broad information risk factor in the pre-1990 period.

<<< INSERT TABLE 7.3 AROUND HERE >>>

Table 7.4 reports the results for the post-1990 period analyses. As with the pre-1990 period, Panel A suggests that *BS* is not priced as there is no significant association between *BS* and average returns (0.0179, *t*-statistic = 1.12) in the post 1990-period. Results on the hedge portfolio tests reported in Panel B suggest a monotonic increase of α moving from the defender to prospector portfolios for Model 7.1.1, suggesting prospectors are associated with higher fundamental-broad information risk, but α under the hedge portfolio is insignificant (0.1241, *t*-statistic = 0.49). There are no clear patterns for α under Models 7.1.2 and 7.1.3. Besides, α for the hedge portfolio is negative and insignificant (-0.0721, *t*-statistic = -0.30) for Model 7.1.2, and positive and insignificant (0.1772, *t*-statistic = 0.88) for Model 7.1.3. Despite firm-specific *BS* factor loading (*PMD*) is positive (0.0346) where investors associate prospectors with higher fundamental-broad information risk, it is insignificant (*t*-statistic = 1.02), as suggested by Panel C. Two-stage cross-sectional regression results reported in Panels D and E, with insignificant *PMD* (-0.0622, *t*-statistic = -0.77) and β_{PMD} (0.0489, *t*-statistic = 0.19), suggest that in the post 1990-period, there is no evidence indicating that fundamental-broad information risk proxied by business strategy is priced by investors. Collectively, the sub-period analyses fail to reject $H1_{null}$.[61]

[61] Internal and external information risk may vary with economic cycle which in turn affects equity pricing. An additional analysis is performed to examine if the pricing of information risk proxied by business strategy and its components varies across market phases. Based on Bätje and Menkhoff (2013), the following periods are deemed bearish (high volatility and falling price index): December 1972 to September 1974, December 1976 to February 1978, May 1981 to July 1982, June 1983 to May 1984, August 1987 to November 1987, May 1990 to October 1990, August 2000 to September 2002, and October 2007 to February 2009. Periods falling outside of these ranges are deemed bullish (low volatility and rising price index). Doing this results in a sample period from 1 January 1972 to 31 December 2010 with 109 bearish months and 359 bullish months.
Generally, analysis using *BS* and a modified business strategy measure exclusive of historical growth or investment opportunities (*BS2*) reported in Appendices 7.5 and 7.6, respectively, show some evidence that

<<< INSERT TABLE 7.4 AROUND HERE >>>

7.4 Analyses based on a Modified Business Strategy Measure Exclusive of Historical Growth or Investment Opportunities

Given that the measure reflective of a firm's historical growth or investment opportunities (*REV5*) is similar to the Fama-French's book-to-market and *HML* (and it is significantly priced by investors as suggested by Section 8.1 and Table 8.3), a modified measure of Bentley et al.'s (2013) business strategy (*BS2*) is constructed by excluding *REV5* to mitigate the concerns of multicollinearity arising from these variables. *BS2* is thus a score ranging from 5 to 25, and firms are classified into: defender (5-10); lower analyzer (11-15); upper analyzer (16-19); and prospector (20-25). Table 7.5 reports analyses conducted based on *BS2*. The exclusion of *REV5* to compute *BS2* also increases firm-year observations from 87,866 to 93,344.[62]

<<< INSERT TABLE 7.5 AROUND HERE >>>

Results of a cross-sectional regression of monthly excess returns on the Fama-French three factors and *BS2* reported in Panel A, indicate a positive coefficient on *BS2* (0.0190), whereby investors associate prospectors with an overall higher level of fundamental-broad information risk, after simultaneously incorporating the quality and

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investors associate defenders (prospectors) with a higher fundamental-broad information risk and thus require higher average returns in the bearish (bullish) periods. Further, Appendix 7.7 provides some evidence that more innovative firms are associated with lower (higher) average returns in the bearish (bullish) periods. Whereas, Appendix 7.8 offers some evidence that more efficient firms are associated with higher average returns in both bearish and bullish periods.

[62] The number of firm-specific, time-series regressions for replicating Francis et al. (2005) in Panel C of Tables 8.10, 8.11 and 8.12 also increases from 5,238 to 5,485.

quantity of information in their price setting processes. However, the positive coefficient on *BS2* is insignificant (*t*-statistic = 1.44), implying that *BS2* is not priced by investors. Notably, the magnitude of coefficient and the level of significance are greater compared to those reported using *BS* under Section 6.3 (i.e. 0.0123, *t*-statistic = 1.08). The hedge portfolio tests in Panel B under Model 7.1.1 show that α are positive and significant at least at the 5 percent level but there is no clear patterns in α moving from the defender to prospector portfolios. Further, α for the hedge portfolio is negative (-0.0788) and insignificant (*t*-statistic = -0.53). Under Model 7.1.2, α are positive and significant at the 5 percent level for the defender, lower analyzer and upper analyzer portfolios, and there is a clear decreasing patterns in α moving from the defender to prospector portfolios. α for the hedge portfolio is negative (-0.1863) yet insignificant (*t*-statistic = -1.30). Under Model 7.1.3, neither α are significant in any of the business strategy portfolios, nor they show a clear pattern. α for the hedge portfolio is positive (0.0329) yet insignificant (*t*-statistic = 0.25), and hence *BS2* is not priced by investors. Replicating Francis et al. (2005), Panel C shows a positive and significant firm-specific *BS2* factor loading (*PMD2*) at the 1 percent level (0.1265, *t*-statistic= 6.04), implying that prospectors exhibit positive exposure to returns. Notably, firm-specific *BS* factor loading (*PMD*) reported in Section 7.2 is positive but insignificant (i.e. 0.0003, *t*-statistic = 0.02). Panels D and E report two-stage cross-sectional regression analyses. The coefficients on *PMD2* (-0.0249) and β_{PMD2} (0.1207) are both insignificant (*t*-statistics = -0.29 and 0.51, respectively), therefore *BS2* is not priced by investors. Collectively, the analysis based on *BS2* fails to reject $H1_{null}$ and reinforces the prior results that there is no evidence that investors price an *ex ante* and fundamental-broad information risk factor surrogated by business strategy.

In summary, the results so far suggest that $H1_{null}$ in this thesis cannot not rejected. Business strategy, despite serving as an *ex ante* and fundamental-broad proxy for information risk, is not priced. These analyses show that business strategy lacks ability to explain variation in average returns at both firm- and portfolio- levels. The subsequent chapter examines the second research question and explores plausible explanations for these results (i.e. diversifiable nature of information risk versus offsetting pricing effect).

CHAPTER 8: RESULT ANALYSIS: IS THERE AN OFFSETTING PRICING EFFECT FROM VARIABLES OR COMPONENTS OF BUSINESS STRATEGY?

8.0 Introduction

The previous chapter reports results from robustness checks that confirm the main analysis for the first research question, whereby $H1_{null}$ cannot be rejected. As such, business strategy, representing an *ex ante* and fundamental-broad information risk factor, is not priced by investors. This chapter performs analysis to answer the second research question, as to whether the insignificant pricing of fundamental-broad information risk proxied by business strategy can be alternatively explained by the offsetting pricing effect of variables or components of business strategy. The motivation for the second research question is based on Ogneva (2012) who offers an offsetting pricing argument for Core et al.'s (2008) results. Ogneva (2012) suggests that a negative correlation between Core et al.'s (2008) measure of accruals quality and future cash flow shocks accounts for insignificant pricing of accruals quality. Disentangling realized returns into cash flow shocks and returns excluding cash flow shocks, she finds that low (high) accruals quality firms are exposed to lower (higher) cash flow shocks which offset the higher (lower) expected returns of such firms. After excluding cash flow shocks, she documents that low accruals quality firms are associated with a higher required rate of return.

Section 8.1 reports analyses on whether individual measures of *BS* are priced. Section 8.2 explores if components of *BS* identified through the principal component analysis (*PCA*) are priced by investors. Section 8.3 reports analysis on whether two components of a modified measure of business strategy exclusive of historical growth or investment opportunities (*BS2*) identified through the *PCA*, which can be grouped as innovation and efficiency factors, are priced by investors. Several tests conducted in the previous chapters are employed in performing these analyses, namely: (1) cross-sectional regression of monthly excess returns on the Fama-French three factors and individual measure or component of business strategy measure; (2) time-series individual measure or component of business strategy portfolio regressions of monthly excess returns on the Fama-French three factors; and (3) two-stage cross-sectional regression.[63] The signs of pricing of these variables or components would be compared to determine if there is an offsetting pricing effect. Section 8.4 reports analyses when selling, general, and administrative expenditure is replaced by marketing and advertising expenditure as a measure for marketing and advertising efforts. Section 8.5 reports industry analysis.

8.1 Pricing Evidence of Individual Measure of Business Strategy

Since *BS* is constructed based on six measures, this section investigates whether each individual measure is priced. This is because the non-pricing of *BS* may be due to the offsetting pricings emanating from these variables. Table 8.1 reports individual business strategy measure analyses based on research intensity (*RDS5*). A higher *RDS5* indicates greater research intensity. Results of a cross-sectional regression of monthly excess returns on the Fama-French three factors and *RDS5* in Panel A suggest that *RDS5* is priced by

[63] Recall that in the previous chapter, firms are sorted into four *BS* portfolios (i.e. defender, lower analyzer, upper analyzer and prospector) when performing time-series portfolio regressions of monthly excess returns on the Fama-French three factors, and into 20 *BM-BS* portfolios (i.e. the intersection of five *BM* and four *BS* portfolios) for two-stage cross-sectional regression analysis. In this chapter, for analyses on individual (Section 8.1) and component (Sections 8.2 and 8.3) business strategy measures, firms are sorted into five portfolios when implementing time-series portfolio regressions of monthly excess returns on the Fama-French three factors, and into 25 *BM*-individual or component business strategy portfolios (i.e. the intersection of five *BM* and five individual or component business strategy portfolios) for two-stage cross-sectional regression analysis, since each individual variable is quintile ranked as Bentley et al. (2013).

investors, as there is a positive association between *RDS5* and average returns that is significant at the 5 percent level (0.0856, *t*-statistic = 2.35). Results on the hedge portfolio tests reported in Panel B suggest α are mostly significant in each *RDS5* quintile portfolio, but no clear patterns moving from the lowest to highest *RDS5* quintile portfolios, under a model that incorporates only intercept (Model 7.1.1) and a model that incorporates intercept and market risk premium (Model 7.1.2). α for the hedge portfolio is positive (0.0116) yet insignificant (*t*-statistic = 0.08) under Model 7.1.1, and negative (-0.0930) yet insignificant under Model 7.1.2 (*t*-statistic = -0.65). When *HML* and *SMB* are further included as in Model 7.1.3, there is no clear pattern of α moving across the *RDS5* quintile portfolios. However, α for the hedge portfolio is positive (0.2012) and significant at the 10 percent level (*t*-statistic = 1.69). The highest *RDS5* quintile firms earn around 20 basis points more excess monthly Fama-French adjusted returns than the lowest *RDS5* quintile firms, thus *RDS5* is priced by investors. Panel C reports analysis in the vein of Francis et al. (2005). It indicates that firm-specific *RDS5* factor loading (*HLRDS5*) is positive (0.0813) and significant at the 1 percent level (*t*-statistic = 3.97), thereby higher *RDS5* firms have positive exposure to returns. However, the results for two-stage cross-sectional regression sorted based on 25 *BM-RDS5* portfolios reported in Panels D and E, with insignificant *HLRDS5* (-0.1073, *t*-statistic = -1.48) and β_{HLRDS5} (0.0963, *t*-statistic = 0.59), suggest no evidence that *RDS5* is priced by investors. Overall, there is evidence suggesting that investors unfavourably price research intensity (i.e. higher average returns). This is in line with prior studies that associate R&D firms with higher excess returns or cost of equity capital (e.g., Aboody & Lev, 2000; Penman & Zhang, 2002; Shangguan, 2005; Hedge & Mishra, 2014).[64]

<<< INSERT TABLE 8.1 AROUND HERE >>>

Table 8.2 reports individual business strategy measure analysis based on marketing and advertising efforts (*SGA5*). A higher *SGA5* signifies greater marketing and advertising efforts. Panel A reports the results of a cross-sectional regression of monthly excess returns on the Fama-French three factors and *SGA5*. Investors price *SGA5*, as it is positively and significantly associated with average returns at the 5 percent level (0.0544, *t*-statistic = 2.10). The hedge portfolio tests in Panel B show no patterns in α moving from the lowest to highest *SGA5* portfolios, and α in each *SGA5* quintile portfolio is significant at least at the 5 percent level, under Models 7.1.1 and 7.1.2. However, α for the hedge portfolio are positive (0.0844 and 0.0295, respectively) and insignificant (*t*-statistics = 0.64 and 0.33, respectively), under Models 7.1.1 and 7.1.2. Under Model 7.1.3, α shows a nearly increasing pattern across *SGA5* portfolios, and is only significant in the highest *SGA5* portfolio. α for the hedge portfolio is positive (0.2343) and significant at the 5 percent level (*t*-statistic = 2.22), implying that *SGA5* is priced by investors. The highest *SGA5* quintile firms generate around 23 basis points more excess monthly Fama-French adjusted returns than the lowest *SGA5* quintile firms. Panel C shows a positive and significant firm-specific *SGA5* factor loading (*HLSGA5*) at the 1 percent level (0.1135, *t*-statistic = 4.84), implying

[64] Albeit there is no pricing evidence for *RDS5* and *SGA5* under the two-stage cross sectional regression, these variables are priced under the monthly cross-sectional regression test and the hedge portfolio test (See Panels A and B of Tables 8.1 and 8.2, respectively). The pricing conclusion for *RDS5* and *SGA5* is based on the majority (two out of three) asset pricing tests being satisfied.

that higher *SGA5* firms have positive exposure to returns. The results for two-stage cross-sectional regression sorted based on 25 *BM-SGA5* portfolios reported in Panels D and E, however, show insignificant coefficients for *HLSGA5* (-0.0753, *t*-statistic = -1.12) and β_{HLSGA5} (0.5985, *t*-statistic = 1.22), therefore *SGA5* is not priced by investors. Overall, there is evidence indicating that investors unfavourably price marketing and advertising efforts (i.e. higher average returns). This is in sharp contrast to Huang and Wei (2012) who associate advertising intensity to lower implied cost of equity capital. The conflicting results can be attributed to different methodologies employed (i.e. asset pricing versus implied cost of equity capital), and the measurement of advertising intensity using selling, general and administrative expenditure (SG&A) as per Bentley et al. (2013) rather than advertising expenditure. SG&A clearly captures more than marketing and advertising efforts. The findings, however, also provide support for Chen et al. (2012) who relate SG&A cost asymmetry to agency problems where managers are quick (slow) to increase (decrease) SG&A expense when demand increases (falls) as a channel to extract private rent, that can lead to information risk.

<<< INSERT TABLE 8.2 AROUND HERE >>>

Individual business strategy measure analysis based on historical growth or investment opportunities (*REV5*) is reported in Table 8.3. A higher *REV5* reflects greater historical growth or investment opportunities. Panel A reports the results of a cross-sectional regression of monthly excess returns on the Fama-French three factors and *REV5*. It shows a negative yet insignificant association between *REV5* and average returns (-0.0472, *t*-statistic = -1.51), thus *REV5* is not priced by investors. Results on the hedge portfolio tests reported in Panel B suggest significant α in most *REV5* quintile portfolios, without clear patterns moving from the lowest to highest *REV5* quintile portfolios, under Models 7.1.1 and 7.1.2. α for the hedge portfolio are negative (-0.1125 and -0.1514, respectively) and significant (*t*-statistics = -1.75 and -1.85, respectively) under Models 7.1.1 and 7.1.2. Under Model 7.1.3, α is mostly insignificant in each *REV5* quintile portfolio, nor it shows a clear moving pattern. α for the hedge portfolio under Model 7.1.3 is positive (0.0244) but insignificant (*t*-statistic = 0.10), implying that *REV5* is not priced by investors. Panel C indicates that firm-specific *REV5* factor loading (*HLREV5*) is negative (-0.2846) and significant at the 1 percent level (*t*-statistic = -11.53), thereby higher *REV5* firms have negative exposure to returns. Panels D and E report the results for two-stage cross-sectional regression sorted based on 25 *BM-REV5* portfolios. They show negative coefficients which are significant at the 10 percent level on *HLREV5* (-0.1301, *t*-statistic = -1.98) and β_{HLREV5} (-0.2889, *t*-statistic = -1.71), suggesting that *REV5* is priced by investors. Overall, there is evidence showing that investors favourably price historical growth or investment opportunities (i.e. lower average returns). This is similar to Fama and French (1992, 1993) that high book-to-market (i.e. low growth) firms earn more excess returns than low book-to-market (i.e. high growth) firms. While this triggers a concern that *BS* incorporating *REV5* may be highly correlated with *BM* or *HML* in the Fama-French three factor model, a modified version of *BS* is constructed by excluding *REV5* (i.e. *BS2*) and the results for this analysis reported in Section 7.5 shows that $H1_{null}$ is not rejected.

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Table 8.4 reports individual business strategy measure analyses based on operational efficiency (*EMPS5*). A higher *EMPS5* is indicative of lower operational efficiency. Panel A presents the results of a cross-sectional regression of monthly excess returns on the Fama-French three factors and *EMPS5*. The coefficient on *EMPS5* is negative yet insignificant (-0.0274, *t*-statistic = -0.70), therefore *EMPS5* is not priced by investors. The hedge portfolio tests in Panel B show no patterns in α moving from the lowest to highest *EMPS5* portfolios under Models 7.1.1, 7.1.2 and 7.1.3. α for the hedge portfolio are negative (-0.0610 and -0.0971, respectively) and insignificant (*t*-statistics = -0.67 and -0.88, respectively), under Models 7.1.1 and 7.1.2. Nevertheless, under Model 7.1.3, α for the hedge portfolio is negative (-0.2037) and significant at the 5 percent level (*t*-statistic = -2.36), suggesting that investors price *EMPS5*. Interestingly, the lowest *EMPS5* quintile firms generate around 20 basis points more excess monthly Fama-French adjusted returns than the highest *EMPS5* quintile firms (i.e. more efficient firms are riskier as suggested by this analysis).

Contradictorily, Panel C shows a positive and significant firm-specific *EMPS5* factor loading (*HLEMPS5*) at the one percent level (0.3766, *t*-statistic= 13.02), implying that higher *EMPS5* firms have positive exposure to returns. Further, the results for two-stage cross-sectional regression sorted based on 25 *BM-EMPS5* portfolios reported in Panels D and E, show a significantly positive coefficient for *HLEMPS5* (0.1997, *t*-statistic = 2.89) for the first stage analysis, and a positive but insignificant coefficient on $\beta_{HLEMPS5}$ (0.0151, *t*-statistic = 0.13) for the second stage analysis, therefore *EMPS5* is not priced by investors. Overall, only the hedge portfolio tests controlling for the Fama-French three factors indicate that investors unfavourably price operational efficiency (i.e. higher average returns). This is in sharp contrast to Nguyen and Swanson (2009) and Frijns et al. (2012) who document that efficient firms (presumably lower distress risk) are associated with lower required returns. One can attribute such conflicting results to different measurements of operational efficiency as the number of employees scaled by sales as opposed to a measure of efficiency operationalized under a stochastic frontier approach or a data envelopment analysis (e.g., Nguyen & Swanson, 2009; Frijns et al., 2012).

<<< INSERT TABLE 8.4 AROUND HERE >>>

Table 8.5 reports individual business strategy measure analyses based on capital intensity or technological efficiency (*CAP5*). A higher *CAP5* signifies less capital intensity or technological efficiency (as this variable is ranked in a descending manner). Panel A presents the results of a cross-sectional regression of monthly excess returns on the Fama-French three factors and *CAP5*. The coefficient on *CAP5* is negative yet insignificant (-0.0161, *t*-statistic = -0.51), therefore *CAP5* is not priced by investors. The hedge portfolio tests in Panel B show no patterns in α progressing from the lowest to highest *CAP5* portfolios under Models 7.1.1, 7.1.2 and 7.1.3. α for the hedge portfolio is positive yet insignificant under Model 7.1.1 (0.0477, *t*-statistic = 0.36), negative yet insignificant under Model 7.1.2 (-0.0306, *t*-statistic = -0.16) under Model 7.1.2, and positive yet insignificant under Model 7.1.3 (0.0089, *t*-statistic = 0.17), therefore *CAP5* is not priced by investors. Panel C shows a positive and significant firm-specific *CAP5* factor loading (*HLCAP5*) at the one percent level (0.2734, *t*-statistic= 10.23), implying that higher *CAP5* firms exhibit positive exposure to returns. Further, the results for two-stage cross-sectional regression sorted based on 25 *BM-CAP5* portfolios reported in Panels D and E, show a significantly

positive coefficient for *HLCAP5* (0.0223, *t*-statistic = 0.32) for the first stage analysis, and a negative but insignificant coefficient on β_{HLCAP5} (-0.2179, *t*-statistic = -0.70) for the second stage analysis, implying that *CAP5* is not priced by investors. In sum, there is no evidence showing that capital intensity or technological efficiency is priced by investors. Different measurements of efficiency (net property, plant, and equipment scaled by total assets versus a measure of efficiency operationalized under a stochastic frontier approach or a data envelopment analysis) may account for such inconsistent results with Nguyen and Swanson (2009) and Frijns et al. (2012) who associate efficient firms with lower required returns.

<<< INSERT TABLE 8.5 AROUND HERE >>>

Individual business strategy measure analysis based on organizational stability (*TEMP5*) is reported in Table 8.6. A higher *TEMP5* is reflective of less organizational stability. The results of a cross-sectional regression of monthly excess returns on the Fama-French three factors and *TEMP5* are reported in Panel A. There is a positive yet insignificant association between *TEMP5* and average returns (0.0234, *t*-statistic = 0.66), therefore *TEMP5* is not priced by investors. Panel B reports results on the hedge portfolio tests. There are no clear patterns for α progressing from the lowest to highest *TEMP5* quintile portfolios, under Models 7.1.1, 7.1.2 and 7.1.3. α for the hedge portfolio under Model 7.1.1 is negative (-0.2346) yet insignificant (*t*-statistic = -1.39). A significantly negative α for the hedge portfolio (-0.2619, *t*-statistic = -1.71) under Model 7.1.2 suggests that investors view organizational stability unfavourably, whereby firms with greater organizational stability are associated with greater average returns, controlling for the market risk premium. Nevertheless, the negative coefficient on α for the hedge portfolio becomes insignificant under Model 7.1.3 (-0.1890, *t*-statistic = -1.58), when *SMB* and *HML* are further controlled for, implying that *TEMP5* is not priced by investors. Panel C indicates that firm-specific *TEMP5* factor loading (*HLTEMP5*) is negative (-0.3063) and significant at the 1 percent level (*t*-statistic = -16.99), thereby higher *TEMP5* firms exhibit negative exposure to returns. Panels D and E report the results for two-stage cross-sectional regression sorted based on 25 *BM-TEMP5* portfolios. They show a negative coefficient which is significant at the 5 percent level on *HLTEMP5* (-0.1544, *t*-statistic = -2.11) for the first stage analysis, and a negative but insignificant coefficient on $\beta_{HLTEMP5}$ (-0.2515, *t*-statistic = -1.51) for the second stage analysis, suggesting that *TEMP5* is not priced by investors. In sum, there is no strong evidence suggesting that investors price organizational stability.

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Taken together, individual business strategy measure analysis shows some evidence that investors price *RDS5*, *SGA5*, *REV5*, and *EMPS5*. Specifically, firms with greater research intensity, greater marketing and advertising efforts, lower historical growth or investment opportunities, and greater operational efficiency are associated with higher average returns. The different directions of pricing for these individual measures reject $H2_{null}$ and constitute an alternative explanation for insignificant pricing of business strategy presented in Chapters 6 and 7.[65]

[65] In an additional analysis, reported in Panel A of Appendix 8.1, the six individual measures of business strategy (*BS*) are simultaneously incorporated in the cross-sectional regression model employed for the main analysis. Similarly, results show that four of the six individual measures are significantly priced by investors and in different directions, thereby rejecting $H2_{null}$ and supporting the offsetting pricing argument for

8.2 Pricing Evidence of Components of Business Strategy Measure

Section 8.1 demonstrates pricing evidence for several individual business strategy measures, it is thus interesting to investigate how these variables are grouped into components by the principal component analysis (PCA) (i.e. whether they have any commonality) and whether these components are priced. A PCA conducted, based on Kaiser's Eigenvalue rule and Cattell's Scree test, suggests that three factors with Eigenvalues greater than 1 are retained. Two variables load on the first factor are research intensity (*RDS5*) and marketing and advertising efforts (*SGA5*), thus the quintile ranks of *RDS5* and *SGA5* are summed to construct a composite measure labelled *Factor 1* (*F1*). The second factor contains operational efficiency (*EMPS5*) and organizational stability (*TEMP5*), thus the quintile ranks of *EMPS5* and *TEMP5* are summed to construct a composite measure labelled *Factor 2* (*F2*). Finally, two variables load on the third factor are historical growth or investment opportunities (*REV5*) and capital intensity or technological efficiency (*CAP5*), thus the quintile ranks of *REV5* and *CAP5* are summed to construct a composite measure labelled *Factor 3* (*F3*). Therefore, *F1*, *F2* and *F3* are scores ranging from 2 to 10.

Table 8.7 reports *Factor 1* (*F1*) measure of business strategy analyses. A higher *F1* signifies greater research intensity and marketing and advertising efforts. Panel A reports the results of a cross-sectional regression of monthly excess returns on the Fama-French three factors and *F1*. Investors price *F1*, as it is positively and significantly associated with

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insignificant pricing of business strategy in aggregate. Specifically, the coefficients on *RDS5*, *SGA5* and *TEMP5* are positive (0.0927, 0.0449, and 0.0607, respectively) and significant (*t*-statistics = 2.34, 1.65, and 1.68, respectively), while the coefficient on *EMPS5* is negative (-0.0743) and significant (*t*-statistics = -2.60). The coefficients on *REV5* and *CAP5* are negative (-0.0181 and -0.0295, respectively) but insignificant (*t*-statistics = -0.82 and -1.25, respectively).

average returns at the 5 percent level (0.0869, *t*-statistic = 2.68). The hedge portfolio tests in Panel B show no patterns in α moving from the lowest to highest *F1* portfolios, and α in each *F1* quintile portfolio is mostly significant at least at the 5 percent level, under Models 7.1.1 and 7.1.2. However, α for the hedge portfolio is positive (0.0798) and insignificant (*t*-statistic = 0.64) under Model 7.1.1, and is negative (-0.0224) and insignificant (*t*-statistic = 0.00) under Model 7.1.2. Under Model 7.1.3, α shows an increasing pattern across *F1* portfolios, and is only significant in the highest *F1* portfolio. α for the hedge portfolio under Model 7.1.3 is positive (0.2923) and significant at the 5 percent level (*t*-statistic = 2.37), implying that investors price *F1*. The highest *F1* quintile firms augment around 29 basis points more excess monthly Fama-French adjusted returns than the lowest *F1* quintile firms. Panel C shows a positive and significant firm-specific *F1* factor loading (*HLF1*) at the 1 percent level (0.1108, *t*-statistic = 5.16), implying that higher *F1* firms exhibit positive exposure to returns. The results for two-stage cross-sectional regression sorted based on 25 *BM-F1* portfolios reported in Panels D and E, however, show insignificant coefficients for *HLF1* (-0.0661, *t*-statistic = -0.94) and β_{HLF1} (0.0727, *t*-statistic = 0.41), suggesting that *F1* is not priced. Overall, there is evidence indicating that investors unfavourably price *F1* (i.e. higher research intensity and marketing and advertising efforts are associated with higher average returns).

<<< INSERT TABLE 8.7 AROUND HERE >>>

Table 8.8 reports *Factor 2* (*F2*) measure of business strategy analyses. A higher *F2* reflects lower operational efficiency and less organizational stability. Panel A reports the results of a cross-sectional regression of monthly excess returns on the Fama-French three

factors and *F2*. It shows a negative yet insignificant association between *F2* and average returns (-0.0400, *t*-statistic = -1.59), thus *F2* is not priced by investors. Results on the hedge portfolio tests reported in Panel B suggest significant α in most *F2* quintile portfolios, without clear patterns progressing from the lowest to highest *F2* quintile portfolios, under Models 7.1.1 and 7.1.2. α for the hedge portfolio are negative (-0.2968 and -0.3445, respectively) and significant at least at the 5 percent level (*t*-statistics = -2.29 and -2.68, respectively) under Models 7.1.1 and 7.1.2. Under Model 7.1.3, α is mostly insignificant in each *F2* quintile portfolio, nor it shows a clear moving pattern. α for the hedge portfolio under Model 7.1.3 is negative (-0.3463) and significant (*t*-statistic = -2.82) at the 1 percent level, implying that investors price *F2*. The lowest *F2* quintile firms augment around 35 basis points more excess monthly Fama-French adjusted returns than the highest *F2* quintile firms (i.e. firms with greater operational efficiency and organizational stability are riskier). Panel C indicates that firm-specific *F2* factor loading (*HLF2*) is negative (-0.1469) and significant at the 1 percent level (*t*-statistic = -8.48), thereby higher *F2* firms have negative exposure to returns. Panels D and E report the results for two-stage cross-sectional regression sorted based on 25 *BM*-*F2* portfolios. They show negative but insignificant coefficients on *HLF2* (-0.0550, *t*-statistic = -0.82) and β_{HLF2} (-0.1880, *t*-statistic = -1.35), suggesting that *F2* is not priced by investors. Overall, there is some evidence indicating that investors price *F2*, whereby firms with greater operational efficiency and organizational stability are perceived riskier by investors and associated with higher average returns.

<<< INSERT TABLE 8.8 AROUND HERE >>>

Table 8.9 reports *Factor 3* (*F3*) measure of business strategy analyses. A higher *F3* signifies higher historical growth or investment opportunity and lower capital intensity or technological efficiency. Panel A presents the results of a cross-sectional regression of monthly excess returns on the Fama-French three factors and *F3*. The coefficient on *F3* is negative yet insignificant (-0.0487, *t*-statistic = -1.10), thus *F3* is not priced by investors. The hedge portfolio tests in Panel B show no patterns in α progressing from the lowest to highest *F3* portfolios under Models 7.1.1, 7.1.2 and 7.1.3. α for the hedge portfolio is negative yet insignificant under Model 7.1.1 (-0.1086, *t*-statistic = -1.34), and is negative and significant at the 5 percent level under Model 7.1.2 (-0.2433, *t*-statistic = -2.08) under Model 7.1.2. A significantly negative α for the hedge portfolio under Model 7.1.2 suggests that firms with greater historical growth or investment opportunities and lower capital intensity or technological efficiency are viewed favourably by investors, and are associated with lower average returns controlling for the market risk premium. Nonetheless, after controlling for *SMB* and *HML* under Model 7.1.3, the negative α for the hedge portfolio becomes insignificant (-0.0788, *t*-statistic = -0.91), and hence *F3* is not priced by investors. Contradictorily, Panel C shows a positive and significant firm-specific *F3* factor loading (*HLF3*) at the 1 percent level (0.0565, *t*-statistic= 2.95), implying that higher *F3* firms exhibit positive exposure to returns. Further, the results for two-stage cross-sectional regression sorted based on 25 *BM-F3* portfolios reported in Panels D and E, show a negative yet insignificant coefficient for *HLF3* (-0.0350, *t*-statistic = -0.57) for the first stage analysis, and a positive yet insignificant coefficient on β_{HLF3} (0.9792, *t*-statistic = 0.89) for the second stage analysis, suggesting that *F3* is not priced by investors. In sum, there is no evidence showing that *F3* is a priced risk factor.

<<< INSERT TABLE 8.9 AROUND HERE >>>

Collectively, components of business strategy measure analyses in this section provide some pricing that a higher value of *F1* representing greater research intensity and marketing and advertising efforts is associated with higher average returns, and a higher value of *F2* representing lower operational efficiency and less organizational stability is associated with lower average returns. No pricing evidence is, however, observed on *F3* representing historical growth or investment opportunities and capital intensity or technological efficiency. The different pricing directions of *F1* and *F2* reject $H2_{null}$ and support the offsetting pricing argument for insignificant pricing of business strategy presented in Chapters 6 and 7.[66]

8.3 Components Pricing of a Modified Business Strategy Measure Exclusive of Historical Growth or Investment Opportunities

The PCA and component pricing analyses are replicated based on the remaining five variables used to compute a modified measure of business strategy (i.e. *BS2*) exclusive of historical growth or investment opportunities (*REV5*). As discussed in Section 7.4, *REV5* is similar to the Fama-French book-to-market and *HML* factor which can trigger a potential multicollinearity issue. Further, *REV5* is significantly priced by investors as reported in Section 8.1 and Table 8.3. After excluding *REV5*, the PCA re-groups the five variables into

[66] In an additional analysis, reported in Panel B of Appendix 8.1, the three factors of business strategy measure (*BS*) identified through the PCA are simultaneously incorporated in the cross-sectional regression model employed for the main analysis. Similarly, results from this analysis show that the coefficient on *F1* is positive and significant (0.1508, *t*-statistic = 2.01). Nevertheless, the coefficient on *F2* is positive and insignificant (0.0513, *t*-statistic = 0.54), and the coefficient on *F3* is negative and insignificant (-0.0369, *t*-statistic = -1.50).

two components.[67] The first component comprises research intensity (*RDS5*) and marketing and advertising efforts (*SGA5*). Consistently, existing studies (e.g., Gupta & Wilemon, 1990; Naiker et al., 2008; Song & Song, 2010) associate R&D and marketing and advertising with innovativeness. Therefore, the quintile ranks of *RDS5* and *SGA5* are summed to construct an innovation factor denoted as *FINV*, that is a score ranging from 2 to 10. The second component comprises operational efficiency (*EMPS5*), capital intensity or technological efficiency (*CAP5*) and organizational stability (*TEMP5*). While operational efficiency and capital intensity or technological efficiency are clear indicators of efficiency (Thomas & Ramaswamy, 1996; Ittner et al., 2007; Bentley et al., 2013), prior studies also relate organizational stability to efficiency whereby employee turnover creates the need for knowledge transfer that leads to inefficiency, as new employees assume job duties of departed employees and firms incur costs, time and effort to train new employees (Grant, 1996; Shaw et al., 2005; Kacmar et al., 2006; Morrow & McElroy, 2007). Therefore, the quintile ranks of *EMPS5*, *CAP5* and *TEMP5* are summed to construct an efficiency factor denoted as *FEFF*, that is a score ranging from 3 to 15.

Table 8.10 reports the results for the analyses on *FINV*. A higher (lower) value of *FINV* indicates greater (less) research intensity and marketing and advertising efforts. The results obtained are similar to the analysis in Section 8.2 for *Factor 1* (*F1*) given the same variables loaded, despite the number of observations increases. Panel A reports the results

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[67] In an additional analysis, reported in Panel C of Appendix 8.1, the five individual measures of modified business strategy (i.e. *BS2*, exclusive of *REV5*) are simultaneously incorporated in the cross-sectional regression model employed for the main analysis. Similarly, results indicate that four of the five individual measures are significantly priced by investors and in different directions. This implies that $H2_{null}$ can be rejected and the insignificant pricing of business strategy can be explained by the offsetting pricing effect of individual measures used to construct business strategy. Specifically, the coefficients on *RDS5*, *SGA5* and *TEMP5* are positive (0.0824, 0.0417, and 0.0731, respectively) and significant (*t*-statistics = 2.42, 1.78, and 2.23, respectively), while the coefficient on *EMPS5* is negative (-0.0842) and significant (*t*-statistics = -4.59). The coefficient on *CAP5* is negative (-0.0175) yet insignificant (*t*-statistic = -0.92).

of a cross-sectional regression of monthly excess returns on the Fama-French three factors and *FINV*. Investors price *FINV* as it is positively and significantly associated with average returns at the 1 percent level (0.0895, *t*-statistic = 2.56). The hedge portfolio tests in Panel B show α are significant at the 1 percent level in each *FINV* quintile portfolios, along with a distinctively increasing pattern in α moving from the lowest to highest *FINV* portfolios under Model 7.1.1. However, α for the hedge portfolio is positive (0.1100) and insignificant (*t*-statistic = 0.66) under Model 7.1.1. Under Model 7.1.2, α are at least significant at the 10 percent level in each *FINV* quintile portfolios, but there is no pattern in α moving from the lowest to highest *FINV* portfolios. Similarly, α for the hedge portfolio is positive (0.0162) and insignificant (*t*-statistic = 0.10). Under Model 7.1.3, α shows an increasing pattern across *FINV* portfolios, and is only significant in the highest *FINV* quintile portfolio. α for the hedge portfolio is positive (0.3580) and significant at the 1 percent level (*t*-statistic = 2.70), implying that investors price *FINV*. The highest *FINV* quintile firms earn around 36 basis points more excess monthly Fama-French adjusted returns than the lowest *FINV* quintile firms (i.e. firms with greater *FINV* are riskier). Panel C shows a positive and significant firm-specific *FINV* factor loading (*HLFINV*) at the 1 percent level (0.1247, *t*-statistic = 5.87), implying that higher *FINV* firms exhibit positive exposure to returns. The results for two-stage cross-sectional regression sorted based on 25 *BM-FINV* portfolios reported in Panels D and E, however, show insignificant coefficients for *HLFINV* (-0.0650, *t*-statistic = -0.93) and β_{HLFINV} (0.1817, *t*-statistic = 0.97), implying that *FINV* is not priced by investors. Overall, there is evidence indicating that investors unfavourably price *FINV* (i.e. higher research intensity and marketing and advertising efforts are associated with higher average returns).

<<< INSERT TABLE 8.10 AROUND HERE >>>

The analyses on *FEFF* are reported in Table 8.11. A lower (higher) *FEFF* reflects greater (less) operational efficiency, organizational stability and capital intensity or technological efficiency. Panel A reports the results of a cross-sectional regression of monthly excess returns on the Fama-French three factors and *FEFF*. It shows a positive yet insignificant association between *FEFF* and average returns (0.0100, *t*-statistic = 0.24), implying that *FEFF* is not priced by investors. Results on the hedge portfolio tests reported in Panel B suggest significant α in most *FEFF* quintile portfolios, without clear patterns progressing from the lowest to highest *FEFF* quintile, under Models 7.1.1 and 7.1.2. α for the hedge portfolio are negative (-0.1905 and -0.2564, respectively) and significant (*t*-statistic = -2.19 and -3.12, respectively). Under Model 7.1.3, α is insignificant in each *FEFF* quintile portfolio, nor it shows a clear moving pattern. α for the hedge portfolio under Model 7.1.3 is negative (-0.2546) and significant at the 1 percent level (*t*-statistic = -3.07), implying that investors price *FEFF*. The lowest *FEFF* quintile firms augment around 25 basis points more excess monthly Fama-French adjusted returns than the highest *FEFF* quintile firms (i.e. firms with lower *FEFF* are riskier). Panel C indicates that firm-specific *FEFF* factor loading (*HLFEFF*) is positive (0.024) yet insignificant (*t*-statistic = 0.81). Panels D and E report the results for two-stage cross-sectional regression sorted based on 25 *BM-FEFF* portfolios. They show a positive but insignificant coefficient on *HLFEFF* (0.0735, *t*-statistic = 1.14) for the first stage analysis, and a negative coefficient on β_{HLFEFF} (-0.1980) which is significant at the 5 percent level (*t*-statistic = -2.10), suggesting that *FEFF* is a priced risk factor. Overall, at the portfolio level, there is evidence indicating that investors price *FEFF*, whereby firms with greater operational efficiency, organizational stability and capital intensity or technological efficiency are perceived riskier by investors and associated with higher average returns.

<<< INSERT TABLE 8.11 AROUND HERE >>>

It appears that after dropping *REV5*, asset pricing tests based on *FINV* and *FEFF* identified through the PCA show that both innovation and efficiency factors are priced by investors. Specifically, investors of firms with greater innovation and investors of firms with greater efficiency are both compensated with higher average returns.[68] This is less likely a sign of business risk pricing in equity as one should otherwise observe the contrasting component to be priced in an opposite way (i.e. higher (lower) average returns for firms with greater innovation (efficiency), or higher (lower) average returns for firms with greater efficiency (innovation)). The outcome tends to signify information risk pricing in equity that investors price the inherent information asymmetry of prospectors (i.e. greater innovation) and the poorer external information environment of defenders (i.e. greater efficiency) accordingly. As Easley and O'Hara (2004) claim that both quality and quantity of information are simultaneously priced by investors, the pricings of the two components of business strategy which mainly capture quality and quantity of information offset each other. In aggregate, as indicated by Sections 6.3, 7.1, 7.2 and 8.3, it leads to insignificant pricing of business strategy which serves as the fundamental-broad

[68] In an additional analysis, reported in Panel D of Appendix 8.1, the two factors of modified business strategy measure (*BS2*) identified through the PCA are simultaneously incorporated in the cross-sectional regression model employed for the main analysis. Similarly, results from this analysis show that the coefficient on *FINV* is positive and significant (0.0950, *t*-statistic = 2.72), whereas the coefficient on *FEFF* is negative and significant (-0.0362, *t*-statistic = -1.86). This analysis further rejects $H2_{null}$ and corroborates the offsetting pricing argument for insignificant pricing of business strategy in aggregate.

information risk proxy. Thus, $H2_{null}$ is rejected and the insignificant pricing of business strategy is explained by the offsetting information risk pricings emanating from business strategy components, rather than the diversifiability of information risk argument. The results are in line with Ogneva (2012) that the information risk proxy employed triggers an offsetting effect on asset prices that leads to insignificant pricing of the information risk proxy itself. [69]

8.4 Advertising Expenditure Replacing Selling, General, and Administrative Expenditure as a Measure for Marketing and Advertising Efforts

In the analysis conducted thus far, marketing and advertising efforts are measured with selling, general, and administrative expenditure over sales over a five-year rolling window (*SGA5*). *SGA5* incorporates more than a firm's marketing and advertising expenditure. As a multifaceted measure, *SGA5* can create inherent problems for interpretation. For instance, *SGA5* captures managerial opportunism because marketing intensity reflects product uniqueness that affects managerial discretion and the level of monitoring, and thus information quality (Williamson, 1979; Filatotchev & Nakajima, 2010; Bentley et al., 2013). *SGA5* also captures organizational slack that exacerbates

[69] The selection of the rolling window in computing business strategy variables may have an impact on the results documented in the thesis. As a robustness check, a rolling three-year window, rather than five-year, is used to compute business strategy variables. The results are consistent with the main analysis. The three asset pricing tests show no pricing evidence on an aggregate and modified business strategy measure computed over a rolling three-year window, denoted as *BSRW3* (Appendix 8.2) and *BS2RW3* (Appendix 8.3), respectively. Further, as indicated by Appendix 8.4, the monthly cross-sectional regression test (Panel A) and the hedge portfolio test under Model 7.1.3 (Panel B) show that the innovation component computed over a rolling three-year window period (*FINVRW3*) is priced by investors. The three asset pricing test results reported in Appendix 8.5 also show that the efficiency component computed over a rolling three-year window (*FEFFRW3*) is priced by investors. Consistently, the simultaneous pricing of these two components offset each other leading to insignificant pricing of business strategy.

operational inefficiency and agency conflicts that can lead to poorer long term performance (Chen et al., 2012). Both can lead to higher average returns required by investors through information and/or cash flow risks (Lambert et al., 2007).

To examine the construct validity of *SGA5* as a proxy for marketing and advertising efforts, the analysis is rerun with *ADV5* computed as the quintile rank (by SIC 2-digit industry and year) of the ratio of marketing and advertising expenses [*XAD*] to sales [*SALE*] computed over a rolling prior five-year average. Since many firms do not disclose marketing and advertising expenses, firm-year observations decrease from 87,866 to 16,701. Table 8.12 shows that *ADV5* is not priced by investors, since the coefficient on *ADV5* (0.0628) is insignificant (*t*-statistic = 1.34) in Panel A for the monthly cross-sectional regression test; the intercept for the hedge portfolio (-0.1189) is insignificant (*t*-statistic = -0.32) in Panel B for the hedge portfolio test under Model 7.1.3; and the coefficient on β_{HLADV5} (-0.4163) is insignificant (*t*-statistic = -0.91) in Panel E for the two-stage cross-sectional regression. This is inconsistent with Huang and Wei (2012) who find a negative association between advertising intensity and implied cost of equity.

<<< INSERT TABLE 8.12 AROUND HERE >>>

Following this, an aggregate business strategy measure is computed by replacing *SGA5* with *ADV5*, denoted as *BS3*. Similar to the main inferences in the thesis, Table 8.13 shows no pricing evidence for business strategy proxied by *BS3*, since the coefficient on *BS3* (0.0062) is insignificant (*t*-statistic = 0.21) in Panel A for the monthly cross-sectional regression test; the intercept for the hedge portfolio (-0.0701) is insignificant (*t*-statistic = -0.46) in Panel B for the hedge portfolio test under Model 7.1.3; and the coefficient on

β_{PMD3} (0.2700) is insignificant (*t*-statistic = 0.12) in Panel E for the two-stage cross-sectional regression.

<<< INSERT TABLE 8.13 AROUND HERE >>>

Results remain similar when a modified business strategy measure exclusive of historical growth or investment opportunities (*REV5*) is computed by replacing *SGA5* with *ADV5*, denoted as *BS4*. Table 8.14 shows no pricing evidence for business strategy proxied by *BS4*, since the coefficient on *BS4* (0.0217) is insignificant (*t*-statistic = 0.83) in Panel A for the monthly cross-sectional regression test; the intercept for the hedge portfolio (-0.4338) is insignificant (*t*-statistic = -1.13) in Panel B for the hedge portfolio test under Model 7.1.3; and the coefficient on β_{PMD4} (1.0468) is insignificant (*t*-statistic = 0.76) in Panel E for the two-stage cross-sectional regression.

<<< INSERT TABLE 8.14 AROUND HERE >>>

Consistent with the main findings in the thesis, there is pricing evidence for the innovation component when it is computed based on research intensity (*RDS5*) and marketing and advertising efforts proxied by *ADV5*, denoted as *FINV2*. Specifically, investors associate greater innovation reflective of poorer information quality with higher average returns. As indicated by Table 8.15, the coefficient on *FINV2* (0.1459) is significant at the 5 percent level (*t*-statistic = 2.45) in Panel A for the monthly cross-sectional regression test; the intercept for the hedge portfolio (0.5450) is significant at the 5 percent level (*t*-statistic = 2.14) in Panel B for the hedge portfolio test under Model 7.1.3;

and the coefficient on $\beta_{HLFINV2}$ (0.7680) is also significant at the 5 percent level (*t*-statistic = 2.05) in Panel E for the two-stage cross-sectional regression.

<<< INSERT TABLE 8.15 AROUND HERE >>>

In summary, there is no pricing evidence for *ADV5*. Results are qualitatively similar when *SGA5* is replaced by *ADV5* to compute the aggregate business strategy measure and modified business strategy measure exclusive of historical growth or investment opportunities with these measures are not priced by investors. As per the main results, the innovation component (*FINV*) comprising *RDS5* and *ADV5* is priced by investors.

8.5 Analysis by Industries

Different industries exhibit different levels of intangible investments, which can lead to different information environment. It is therefore appropriate to investigate if the pricing of business strategy and its components varies across industries. In executing this analysis, firms are classified into three broad industries: Manufacturing (two-digit SIC 20-39), Services (two-digit SIC 70-89) and Other. Firm-year observations from Manufacturing, Services and Other industries represent 61.05%, 12.03% and 26.92% of the full sample, respectively.

The analysis based on an aggregate business strategy measure (*BS*) is presented in Table 8.16. The monthly cross-sectional regression test reported in Panel A shows no pricing evidence for (*BS*) in the Manufacturing, Services and Other subsamples, as the coefficients on *BS* (0.0122, -0.0321, and -0.0131, respectively) are insignificant (*t*-statistics = 0.98, -1.18 and -0.85, respectively). Consistently, the hedge portfolio test reported in Panel B shows no pricing evidence for *BS* as the intercepts for the hedge portfolio (0.1628,

-0.1233, and -0.1738, respectively) are all insignificant (*t*-statistics = 0.82, -0.29 and -0.64, respectively) for the three subsamples. In Panel E, the two-stage cross-sectional regression test also shows no pricing evidence for business strategy as the coefficients on β_{PMD} (-0.0481, 0.5320 and -0.2962) are all insignificant (*t*-statistics = -0.22, 0.55 and -0.85, respectively) for the three subsamples.

<<< INSERT TABLE 8.16 AROUND HERE >>>

Next, the industry analysis based on a modified business strategy measure exclusive of historical growth or investment opportunities (*BS2*) is reported in Table 8.17. The monthly cross-sectional regression test reported in Panel A shows no pricing evidence for *BS2* in the Manufacturing, Services and Other subsamples, as the coefficients on *BS2* (0.0225, 0.0070, and 0.0049, respectively) are insignificant (*t*-statistics = 1.51, 0.24 and 0.28, respectively). Consistently, the hedge portfolio test reported in Panel B shows no pricing evidence for *BS2* as the intercepts for the hedge portfolio (0.1578, -0.5335, and -0.2491, respectively) are all insignificant (*t*-statistics = 1.00, -1.14 and -1.12, respectively) for the three subsamples. In Panel E, the two-stage cross-sectional regression test also shows no pricing evidence for business strategy as the coefficients on β_{PMD2} (0.2914, -0.0836 and -0.0937) are all insignificant (*t*-statistics = 0.88, -0.11 and -0.36, respectively) for the three subsamples.

<<< INSERT TABLE 8.17 AROUND HERE >>>

The industry analysis is also replicated with the innovation factor (*FINV*) and reported in Table 8.18. The monthly cross-sectional regression test reported in Panel A shows pricing evidence on *FINV* for the Manufacturing subsample, as the coefficient on *FINV* (0.1082) is significant at the 1 percent level (*t*-statistic = 2.73), indicating that more innovative manufacturing firms reflective of poorer information quality are associated with higher average returns. However there is no pricing evidence for *FINV* in the Services and Other subsamples, as the coefficients on *FINV* (-0.1573 and 0.0259, respectively) are insignificant (*t*-statistics = -0.97 and 0.51, respectively). Consistently, the hedge portfolio test reported in Panel B shows pricing evidence on *FINV* for the Manufacturing subsample, as the intercept for the hedge portfolio (0.4046) is significant at the 1 percent level (*t*-statistic = 2.82). However, there is no pricing evidence for *FINV* for the Services and Other subsamples as the intercepts for the hedge portfolio (0.1995 and -0.0631, respectively) are insignificant (*t*-statistics = 0.40 and -0.29, respectively). In Panel E, the two-stage cross-sectional regression test shows no pricing evidence for *FINV* as the coefficients on β_{HLFINV} (-0.1485, 0.6483 and 0.3027) are all insignificant (*t*-statistics = -0.42, 0.76 and 0.86, respectively) for the three subsamples.

<<< INSERT TABLE 8.18 AROUND HERE >>>

Finally, the industry analysis is replicated with the efficiency factor (*FEFF*) and reported in Table 8.19. The monthly cross-sectional regression test reported in Panel A shows no pricing evidence for *FEFF* in the Manufacturing, Services and Other subsamples, as the coefficients on *FEFF* (0.0195, 0.0182 and 0.0011, respectively) are insignificant (*t*-statistics = 0.30, 0.31 and 0.03, respectively). However, the hedge portfolio test reported in Panel B shows pricing evidence on *FEFF* for the Manufacturing subsample, as the intercept for the hedge portfolio (-0.2722) is significant at the 1 percent level (*t*-statistic = -

2.74), indicating that more efficient manufacturing firms characterized with reduced information quantity are associated with greater average returns. However, there is no pricing evidence for *FEFF* for the Services and Other subsamples as the intercepts for the hedge portfolio (-0.2354, and -0.2296, respectively) are insignificant (*t*-statistics = -0.91 and -1.61, respectively). In Panel E, the two-stage cross-sectional regression test shows no pricing evidence for *FEFF* as the coefficients on β_{HLFEFF} (-0.1204, 0.2304 and -0.1354) are all insignificant (*t*-statistics = -0.92, 0.53 and -0.84, respectively) for the three subsamples.

<<< INSERT TABLE 8.19 AROUND HERE >>>

In summary, consistent with the main results, no pricing evidence on business strategy in the three industry subsamples is found. There is evidence that investors associate both innovation and efficiency components with higher average returns in the Manufacturing subsample, thereby supporting the offsetting pricing effect. There is no pricing evidence on the innovation and efficiency components in the Services and Other subsamples, which can either be a reflection of investors' differentiating pricing across industries, or lack of sufficient observations for appropriately executing asset pricing tests.

The next chapter summarizes and makes concluding remarks for the thesis. It also discusses the limitation of the study and suggests avenues for future research.

CHAPTER 9: CONCLUSION

9.1 Summary

The pricing of information risk has been subject to extensive theoretical and empirical debates. Concerned that existing information risk proxies only capture a subset of information risk, Core et al. (2008) recommend that future studies employ a fundamental or broad information risk proxy when testing the pricing of information risk. Responding to their call, this thesis employs an *ex ante* and fundamental-broad information risk proxy, that is business strategy, to investigate the pricing of information risk. This thesis adopts the methodology of Bentley et al. (2013), which is based on the Miles and Snow (1978) strategic typology, to identify a firm's business strategy. Nevertheless, Core et al. (2008) have ignored that there could be offsetting effect of information risk on asset prices causing insignificant pricing of information risk, as Ogneva (2012) demonstrates through the offsetting effect of cash flow shocks on the pricing of accruals quality. Therefore if business strategy does not constitute a priced fundamental-broad information risk factor, the thesis aims to explore if there is any offsetting pricing effect from variables or components (e.g., innovation and efficiency) of business strategy, capturing different forms of information risk that may be priced by investors.

Business strategy fundamentally determines a firm's inherent and external information environment. Inherently, it affects the level of agency conflicts resulting in information asymmetry through managerial discretion afforded, the extent of monitoring and control, and the complexity of a firm's operating environment (Jensen & Meckling, 1976), that can subsequently affects the quality of disclosures, financial reporting and corporate governance. Bentley (2012) and Bentley et al. (2013) also articulate that business strategy can affect a firm's ethical climate and culture for fraudulent behaviour through incentive, opportunity, and rationalization. Further, Bentley et al. (2014) suggest business strategy as an underlying determinant of a firm's (external) information environment, as it affects investment activities and financing needs that influence the level of voluntary disclosures, analyst coverage and media coverage.

Firms with an efficiency-orientated defender business strategy exhibit less inherent information asymmetry and a poorer external information environment, and can thus be viewed as portraying better quality but less quantity of information. On the other hand, firms with an innovation-orientated prospector business strategy exhibit greater inherent information asymmetry and a richer external information environment, and can hence be conceptualized as displaying poorer quality but greater quantity of information. According to Easley et al. (2002) and Easley and O'Hara (2004), investors simultaneously price quality and quantity of information. This leads to a tension in the literature as to whether prospectors or defenders are exposed to an overall higher level of fundamental-broad information risk and are consequently required by investors a higher rate of returns. Possibly, there can also be an offsetting pricing effect of information risks emanating from innovation and efficiency components of business strategy, which signify higher inherent information risk (i.e. poorer quality of information) and higher external information risk (i.e. less quantity of information), respectively. This can lead to, in aggregate, insignificant pricing of information risk proxied by business strategy. Further, traditional asset pricing theory views idiosyncratic risk, including information risk, as diversifiable and irrelevant to equity pricing (Fama, 1991).

With 87,866 non-financial non-utility U.S. firm-year observations spanning 1972-2010, this thesis performs various asset pricing tests to test the hypotheses: (1) cross-sectional regression of monthly excess returns on the Fama-French three factors and business strategy related measures (aggregate, individual variable, or component); (2) time-series business strategy related measure portfolio regressions of monthly excess returns on the Fama-French three factors; and (3) two-stage cross-sectional regression. Results from the above tests show that business strategy constructed based on Bentley et al. (2013), as an *ex ante* and fundamental-broad measure of information risk as suggested by Core et al. (2008), is not priced by investors. Analyses are replicated in sub-periods with 1990 chosen as the cut-off point due to the technology boom to mitigate the concern of a structural break for employing 40 years of data. Results continue to show insignificant pricing of business strategy as a fundamental-broad measure of information risk. A modified measure of Bentley et al.'s (2013) business strategy is constructed by excluding the measure reflective of a firm's historical growth or investment opportunities (*REV5*). This is because *REV5* is significantly and favourably priced by investors (i.e. lower average returns), and it may be highly correlated with the book-to-market or *HML* as one of the Fama-French three factors. Analyses based on this modified measure corroborate the finding that business strategy, representing an *ex ante* and fundamental-broad information risk factor, is not priced by investors.

Before one can attribute the insignificant pricing of information risk proxied by business strategy to the traditional finance school of thought that idiosyncratic risk is diversifiable and thus irrelevant to equity pricing, further analysis is warranted to determine if there is an offsetting pricing effect of variables or components used to compute business strategy. Analyses of the individual measures of Bentley et al.'s (2013) business strategy provide evidence that the measure representative of a firm's research intensity or propensity to search for new products (*RDS5*), and the measure reflective of a firm's marketing and advertising efforts and focus on exploiting new products and services (*SGA5*), are unfavourably priced by investors. Specifically, firms with a higher value of *RDS5* and *SGA5* are compensated with higher average returns. Conversely, the measures capturing a firm's historical growth or investment opportunities (*REV5*), and a firm's operational efficiency or ability to produce and distribute products and services efficiently (*EMPS5*, recall that, a higher rank is associated with lower efficiency for this measure), are favourably priced by investors. Specifically, firms with higher values of *REV5* and *EMPS5* are compensated with lower average returns. Nonetheless, the analyses show no pricing evidence on the measure capturing a firm's capital intensity or technological efficiency (*CAP5*) and a firm's organizational stability (*TEMP5*). The different pricing directions for *RDS5*, *SGA5*, *REV5*, and *EMPS5* constitute a plausible explanation for the insignificant pricing of business strategy in aggregate.

A principal component analysis (PCA) is conducted to explore how these variables are grouped into components and examine if these components are priced by investors. These variables are loaded into three groups: (1) *RDS5* and *SGA5;* (2) *EMPS5* and *TEMP5*; and (3) *REV5* and *CAP5*. Asset pricing tests based on these groups indicate that the component of *RDS5* and *SGA5* is unfavourably priced by investors (i.e. higher average returns), and the component of *EMPS5* and *TEMP5* is favourably priced by investors (i.e. lower average returns). However, the component of *REV5* and *CAP5* is not priced by investors. Therefore, the different pricing directions of the first two components may explain the insignificant pricing of business strategy in aggregate.

To avoid the multicollinearity of *REV5* (which is significantly priced by investors) with the Fama-French book-to-market or *HML* factor, *REV5* is excluded and the PCA and component pricing analysis are replicated based on the remaining five variables used to construct a modified business strategy measure (*BS2*). Variables are re-grouped into two components suggested by the PCA: (1) *RDS5* and *SGA5* labelled as innovation factor; and (2) *EMPS5*, *CAP5* and *TEMP5* labelled as efficiency factor. Asset pricing tests show that both innovative and efficiency factors are unfavourably priced by investors. While firms with greater innovation and firms with greater efficiency are associated with higher average returns, this is more likely a demonstration of information risk as opposed to business risk pricing in equity, as one should otherwise observe the contrasting component to be priced in an opposite way under business risk pricing. Therefore, investors price the inherent information asymmetry of innovative component and the poorer external information environment of efficiency component accordingly. Since investors simultaneously price both quality and quantity of information (Easley and O'Hara, 2004), the pricings of the two business strategy components which mainly capture quality and quantity of information offset each other. In aggregate, it leads to insignificant pricing of business strategy which represents the fundamental-broad information risk proxy. Collectively, this thesis does not lend support to Core et al.'s (2008) suggestion that a fundamental-broad information risk proxy can maximize the likelihood of information risk being captured in the asset pricing models, but it supports Ogneva (2012) notions that the potential offsetting effect of the information risk proxy on asset prices can lead to insignificant pricing of such information risk proxy.

The thesis offers several contributions. It is the first study to show that there is no pricing evidence of information risk when an *ex ante* and fundamental-broad information risk proxy (i.e. business strategy) suggested by Core et al. (2008) is used. It questions whether prior empirical evidence on the pricing of information risk is subject to a correlated omitted variable issue (i.e. failing to control for business strategy), or the employment of an isolated and a less rigorous *ex post* information risk measure (e.g., financial reporting quality, disclosure quality, R&D, marketing and advertising). However, it needs not conclude that information risk is not priced by investors because various analysis conducted shows that the non-pricing evidence is due to the offsetting pricings of distinctive business strategy components, which encompass different types of information risk. This suggests that investors rationally react to different forms of information risk emanating from business strategy and simultaneously incorporate these into price setting process. It also supports Bentley et al.'s (2014) proposition that a firm's information environment is counterbalanced by the dynamic interplays of external monitoring mechanisms and information intermediaries (e.g., institutional investors, financial analysts, and the media). Moreover, this study expands business strategy literature by highlighting that firms adopting a particular business strategy (e.g., defender, analyzer, or prospector) are not advantaged in equity pricing over firms with alternative business strategies, given the trade-offs observed in the pricing of individual measures and components of business strategy.

From a practical viewpoint, results from this thesis are particularly of interest to: (1) portfolio managers in revising their investment strategies (i.e. abnormal returns based on an isolated measure of firm characteristic may not exist); (2) firm managers in revising their corporate governance practice to reduce inherent information asymmetry, and decisions to enrich informational flows in the capital market (e.g., purchasing analyst coverage); and (3) regulators in revising their policy settings relevant to corporate governance, financial reporting and disclosures as firms with different business strategies exhibit different forms of information asymmetry.

9.2 Limitations and Suggestions for Future Research

This study is subject to a few limitations. First, the results of this study subject to how business strategy is measured, as there is no definitive way of operationalizing it. Classification errors in business strategy can contribute to the non-pricing evidence documented in this study, and thus future studies can test the robustness of Bentley et al.'s (2013) business strategy measure and develop a more comprehensive one. Second, the study only controls for the Fama-French three factors in the asset pricing model to be aligned with Core et al. (2008) and McInnis (2010), and the Carhart’s momentum factor as a sensitivity analysis reported in Appendices, thus the results can be driven by correlated omitted variables (e.g. cash flows shocks) in the asset pricing models which future studies can explore. Third, while business strategy drives information risk, it can also capture other business risks unrelated to information risk. Disentangling information and business risks emanating from business strategy is difficult, yet can be an avenue for future research so that a better proxy can be used to test the pricing of information risk emanating from business strategy. Finally, investigating whether business strategy is associated with a firm's implied cost of equity and debt also constitute an area worth considered by future studies, given the limitations arising from the employment of realized returns in asset pricing studies.

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Table 5.1 Summary of Individual Business Strategy Measures

Dimension in the adaptive cycle	Variable	Measurement	Prospector	Defender
Entrepreneurial	Research intensity (*RDS5*)	The ratio of research and development expenditures [*XRD*] to sales [*SALE*] computed over a rolling prior five-year average.	High	Low
	Marketing and advertising efforts (*SGA5*)	The ratio of selling, general and administrative expenses [*XSGA*] to sales [*SALE*] computed over a rolling prior five-year average. *This measure also captures the administrative dimension to a certain extent.	High	Low
	Historical growth or investment opportunities (*REV5*)	One-year percentage change in total sales [*SALE*] computed over a rolling prior five-year average.	High	Low
Engineering	Operational efficiency (*EMPS5*)	The ratio of the number of employees [*EMP*] to sales [*SALE*] computed over a rolling prior five-year average.	High	Low
	Capital intensity or technological efficiency (*CAP5*)	Net property, plant, and equipment [*PPENT*] to total assets [*AT*] computed over a rolling prior five-year average.	Low	High
Administrative	Organizational stability (*TEMP5*)	The standard deviation of the total number of employees [*EMP*] computed over a rolling prior five-year period.	High	Low

RDS5, *SGA5*, *REV5*, *EMPS5*, and *TEMP5* are quintile ranked in an ascending manner per SIC 2-digit industry and year, but *CAP5* is quintile ranked in a descending manner per SIC 2-digit industry and year, so that a higher (lower) value of these variables captures prospector (defender) characteristics. These quintile ranks are summed to compute a firm's business strategy score (*BS*) in each year ranging from 6 to 30. The range of scores for each type of business strategy is as follows: defender (6-12); analyzer (13-23); prospector (24-30).

Table 6.1

Sample Selection and Industry Membership

Panel A: Sample Selection

	Firm-years
Compustat data for years between 1966 and 2010 (Firm-years with duplications, missing historical SIC codes, and zero or negative sales, assets, and book-to-market removed)	256,238
Less firm-years operating in Utilities and Financial Industries (SIC 4900-99 and 6000-99)	(55,224)
Less firm-years without sufficient rolling prior five-year period data to compute all six variables used to construct business strategy measures (*BS*)	(113,148)
Final firm-year observations with available *BS* between 1972 and 2010	87,866

Panel B: Industry Affiliation (Firm-years)

		Full Sample		**Prospectors**		**Defenders**	
Two-digit SIC code	**Industry affiliation**	**Number**	**Percent**	**Number**	**Percent**	**Number**	**Percent**
01-09	Agriculture, Forestry and Fishing	380	0.43	24	0.33	28	0.42
10-14	Mining	5,425	6.17	628	8.61	285	4.31
15-17	Construction	1,236	1.41	51	0.70	26	0.39
20-39	Manufacturing	53,639	61.05	4,831	66.27	4,933	74.65
40-48	Transportation and Communications	3,481	3.96	276	3.79	191	2.89
50-51	Wholesale Trade	4,612	5.25	340	4.66	223	3.37
52-59	Retail Trade	7,673	8.73	405	5.56	230	3.48
70-89	Services	10,572	12.03	674	9.25	632	9.56
99	Other	848	0.97	61	0.84	60	0.91
Total		87,866	100.00	7,290	100.00	6,608	100.00

This table presents sample selection procedure to construct business strategy score (Panel A) and industry distribution of the sample firms (Panel B).

Table 6.2

Descriptive Statistics and Correlation Matrices

Panel A: Descriptive Statistics for the Raw Values of the Six Variables Used to Compute Business Strategy Scores (*BS*) for the Full Sample (*n*=87,866)

Variable	Mean	Median	Q1	Q3	Std dev
RDS5	0.0695	0.0007	0.0000	0.0233	3.3611
SGA5	0.6764	0.2106	0.1263	0.3277	20.6101
REV5	12.1138	7.2145	1.4275	14.8548	28.1212
EMPS5	0.0141	0.0089	0.0050	0.0165	0.0539
CAP5	0.3132	0.2704	0.1551	0.4272	0.3503
TEMP5	1.3792	0.1905	0.0419	0.8040	5.5394

Panel B: Descriptive Statistics for the Raw Values of the Six Variables Used to Compute Business Strategy Scores (*BS*) for the Sub-samples of Prospectors (*n*=7,290) and Defenders (*n*=6,608)

	Prospectors		Defenders			
Variable	**Mean**	**Median**	**Mean**	**Median**	***t*-stat**	**Wilcoxon *Z*-stat**
RDS5	0.2241	0.0436	0.0001	0.0000	3.37***	86.29***
SGA5	1.3620	0.3551	0.1118	0.0933	4.07***	90.26***
REV5	34.9120	19.1556	3.0061	2.1843	50.94***	84.17***
EMPS5	0.0232	0.0145	0.0077	0.0053	18.99***	60.42***
CAP5	0.1967	0.1823	0.4969	0.4870	-109.18***	-82.15***
TEMP5	2.0132	0.4040	0.3392	0.0632	20.68***	47.56***

Panel C: Descriptive Statistics for Variables used in the Main Model (Full Sample)

Variable	Mean	5^{th}	25^{th}	Median	75^{th}	95^{th}
$R_i - R_F$	1.3873	-18.7500	-5.7966	0.2985	7.2727	23.2558
BETA	1.0866	0.0960	0.6647	1.0288	1.4205	2.2920
SIZE	5.3977	1.8297	3.6701	5.3127	6.9761	9.3587
BM	-0.4338	-1.7305	-0.9034	-0.4078	0.0740	0.7724
BS	18.3782	12.0000	16.0000	18.0000	21.0000	24.0000

Panel D: Pearson and Spearman Correlations

	BS	*BETA*	*SIZE*	*BM*
BS		**0.1598**	**0.1261**	**-0.1851**
BETA	**0.1361**		**0.0242**	0.0008
SIZE	**0.1269**	**0.0213**		**-0.5132**
BM	**-0.1781**	**-0.0167**	**-0.4921**	

Table 6.2 (Continued)

Panel E: Pearson and Spearman Correlations between Individual Business Strategy Measures and the Fama-French Three Factors

	RDS5	*SGA5*	*REV5*	*EMPS5*	*CAP5*	*TEMP5*	*BETA*	*SIZE*	*BM*
RDS5		**0.3442**	**0.0542**	**0.0610**	**0.1414**	**0.0452**	**0.1506**	**0.1307**	**-0.1325**
SGA5	**0.3396**		**-0.0071**	**0.1425**	**0.3517**	**-0.2127**	**0.0702**	**-0.1129**	**-0.1424**
REV5	**0.0552**	**-0.0084**		**-0.0168**	**-0.0093**	**0.1408**	**0.0874**	**0.2009**	**-0.2189**
EMPS5	**0.0590**	**0.1423**	**-0.0176**		**0.0662**	**0.0159**	**-0.0106**	**-0.2684**	**0.0731**
CAP5	**0.1386**	**0.3502**	**-0.0122**	**0.0655**		**-0.1729**	**0.0863**	**-0.2458**	**-0.0090**
TEMP5	**0.0409**	**-0.2164**	**0.1405**	**0.0206**	**-0.1766**		**0.0999**	**0.6769**	**-0.1337**
BETA	**0.1300**	**0.0781**	**0.0605**	**-0.0178**	**0.0817**	**0.0689**		**0.0501**	**-0.0353**
SIZE	**0.1377**	**-0.1102**	**0.2063**	**-0.2769**	**-0.2430**	**0.6603**	**0.0356**		**-0.4663**
BM	**-0.1335**	**-0.1487**	**-0.1879**	**0.0692**	**-0.0131**	**-0.1116**	**-0.0379**	**-0.4404**	

This table presents descriptive statistics and correlation matrices.

Panels A and B present descriptive statistics for the raw values of the six variables employed to compute a firm's business strategy score (*BS*) based on Bentley et al. (2013) using data from the Compustat Industrial Annual File, for the full sample and the sub-samples of prospectors and defenders, respectively. *BS* is a discrete score ranging from 6 to 30, constructed as the sum of quintile ranks of the following six variables per SIC 2-digit industry and year: (1) research intensity (*RDS5*) which is the ratio of research and development expenditures [*XRD*] to sales [*SALE*] computed over a rolling prior five-year average; (2) marketing and advertising efforts (*SGA5*) which is the ratio of selling, general and administrative expenses [*XSGA*] to sales [*SALE*] computed over a rolling prior five-year average; (3) historical growth or investment opportunities (*REV5*) which is one-year percentage change in total sales [*SALE*] computed over a rolling prior five-year average; (4) operational efficiency (*EMPS5*) which is the ratio of the number of employees [*EMP*] to sales [*SALE*] computed over a rolling prior five-year average; (5) capital intensity or technological efficiency (*CAP5*) measured as net property, plant, and equipment [*PPENT*] to total assets [*AT*] computed over a rolling prior five-year average; and (6) organizational stability (*TEMP5*) which is the standard deviation of the total number of employees [*EMP*] computed over a rolling prior five-year period. *RDS5*, *SGA5*, *REV5*, *EMPS5*, and *TEMP5* are ranked in an ascending manner, while *CAP5* is ranked in a descending manner, so that a higher (lower) value of these variables reflects prospector (defender) characteristics. The range of scores for each type of business strategy is as follows: defender (6-12); analyzers (13-23); prospectors (24-30). *t*-statistic (Wilcoxon *Z*-statistic) indicates the significance of the difference between the means (medians) of the six variables for the sub-samples of prospectors and defenders. ***, **, and * indicate the level of significance at the 1%, 5% and 10%, respectively.

Panel C presents the descriptive statistics on variables used in the main model for the full sample. R_i - R_F refers to a firm's monthly excess returns calculated as the raw stock return (from the CRSP monthly stock file) less the risk-free rate (from the Fama-French files at WRDS), and are measured in percentages. *BETA* is the slope coefficient from the regression of a firm's monthly raw returns on the monthly value-weighted market return (from the CRSP monthly index file) over a rolling five-year window ending in the current fiscal year end, wherein a minimum of 18 monthly returns over the rolling five-year interval is required to estimate *BETA*. *SIZE* and *BM* are calculated using data from the Compustat Industrial Annual File. *SIZE* is the natural logarithm of market value of equity [*CSHO*PRCC_F*], measured at the end of the current fiscal year. *BM* is the natural logarithm of the ratio of book value of equity to market value of equity [log(*CEQ*) less *SIZE*], measured at the end of the current fiscal year.

Panel D presents the Pearson (Spearman) correlation matrix at the lower (upper) diagonal. Panel E presents the Pearson (Spearman) correlations between individual business strategy measures and the Fama-French three factors at the lower (upper) diagonal. Correlations significant at the 5 percent level or lower (two-tailed) are bolded.

Table 6.3

Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and Business Strategy

	Intercept	***BETA***	***SIZE***	***BM***	***BS***	R^2
Coefficient	0.8372				0.0071	0.0174
t-stat	(0.90)				(0.11)	
Coefficient	1.2404	-0.0072	-0.0935	0.2587	0.0123	0.0421
t-stat	(4.13)***	(-0.06)	(-2.33)**	(3.31)***	(1.08)	
Coefficient	1.4177	-0.0002	-0.0889	0.2469		0.0382
t-stat	(4.51)***	(0.00)	(-2.15)**	(3.10)***		

This table presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and business strategy from 1 January 1972 to 31 December 2010 (680,224 firm-month observations). Refer to Table 6.2 for variable definitions. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *BS* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 7.1

Time-series Business Strategy Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	1 (Defender)	2 (Lower Analyzer)	3 (Upper Analyzer)	4 (Prospector)	Hedge (4-1)
Model 7.1.1					
Intercept (α)	0.8294	0.8006	0.7640	0.7281	-0.1014
t-stat	(3.07)***	(3.26)***	(2.92)***	(2.43)**	(-0.59)
Model 7.1.2					
Intercept (α)	0.3270	0.3252	0.2077	0.1033	-0.2236
t-stat	(2.05)**	(2.78)***	(2.06)**	(0.82)	(-1.35)
R_M-R_F	1.0012	1.0014	1.1086	1.2448	0.2436
t-stat	(29.75)***	(40.36)***	(52.02)***	(46.69)***	(6.97)***
Model 7.1.3					
Intercept (α)	-0.0237	0.0387	-0.0032	0.0381	0.0618
t-stat	(-0.19)	(0.44)	(-0.05)	(0.37)	(0.42)
R_M-R_F	1.0150	1.0198	1.0686	1.1396	0.1245
t-stat	(35.37)***	(51.62)***	(71.29)***	(49.01)***	(3.72)***
SMB	0.5521	0.4317	0.5192	0.5207	-0.0314
t-stat	(13.38)***	(15.22)***	(24.08)***	(15.57)***	(-0.65)
HML	0.5408	0.4638	0.2606	-0.0435	-0.5844
t-stat	(12.40)***	(15.50)***	(11.44)***	(-1.23)	(-11.48)***
R^2	0.7879	0.8797	0.9386	0.8868	0.2967
GRS *F*-statistic	0.80				
GRS-*P* value	0.5273				

This table presents results for time-series business strategy portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into four portfolios based on their business strategy scores (*BS*): defender (6-12); lower analyzer (13-17); upper analyzer (18-23); prospector (24-30). See Table 6.2 for a description of how *BS* is computed. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. Portfolio excess returns equal to the value-weighted return on the portfolio less the risk-free rate. R_M-R_F is the market risk premium calculated as the value-weighted market return less the risk-free rate. *SML* is the value-weighted size-mimicking portfolio return. *HML* is the value-weighted *BM*-mimicking portfolio return. R_M, R_F, *SMB* and *HML* are obtained from Kenneth R. French's website through WRDS. Monthly returns are measured in percentages. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS* (i.e. prospector) and sells portfolio 1 of *BS* (i.e. defender). ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 7.2

Business Strategy Factor Loadings and Two-stage Cross-sectional Regression

Panel A: Average Firm-Specific Factor Loadings

	Intercept	R_M-R_F	*SMB*	*HML*	*PMD*	R^2
Coefficient	0.0679	0.9998	0.8157	0.2438	0.0003	0.2528
t-stat	(1.75)*	(75.98)***	(45.92)***	(12.22)***	(0.02)	

Panel B: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BS*

	Intercept	R_M-R_F	*SMB*	*HML*	*PMD*	R^2
Coefficient	0.0265	1.0672	0.5674	0.3282	-0.0862	0.7792
t-stat	(1.02)	(115.62)***	(9.68)***	(4.75)***	(-1.05)	

Panel C: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	β_{RM-RF}	β_{SMB}	β_{HML}	β_{PMD}	R^2
Coefficient	2.2369	-1.5447	0.1603	0.5026	-0.0922	0.4189
t-stat	(2.44)**	(-1.71) *	(0.57)	(1.83)*	(-0.50)	

This table presents firm-specific business strategy factor loadings and regression results of the two-stage cross-sectional regression based on 20 *BM-BS* portfolios. For each month, from 1 January 1972 to 31 December 2010, a business strategy factor mimicking portfolio (*Prospector minus Defender* denoted as *PMD*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS* (i.e. defender) from the value-weighted return on stocks in the highest portfolio of *BS* (i.e. prospector). See Tables 6.2 and 7.1 for a description of how *BS* and stock returns are measured and definitions of the Fama-French three factors. Panel A presents average coefficients across 5,238 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *PMD*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel B presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMD*. The 20 portfolios are created by sorting stocks in to quintiles based on *BM* and four portfolios of *BS* (i.e. defender, lower analyzer, upper analyzer, and prospector) each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel C presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel B). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 7.3

Pre-1990 Sub-period Analyses

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and Business Strategy (*BS*)

	Intercept	***BETA***	***SIZE***	***BM***	***BS***	R^2
Coefficient	1.1811	-0.2716	-0.0637	0.2786	0.0059	0.0517
t-stat	(2.35)**	(-1.58)	(-1.05)	(2.17)**	(0.36)	

Panel B: Time-series *BS* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	**1 (Defender)**	**2 (Lower Analyzer)**	**3 (Upper Analyzer)**	**4 (Prospector)**	**Hedge (4-1)**
<u>Model 7.1.1</u>					
Intercept (α)	0.7485	0.6134	0.5771	0.3759	-0.3726
t-stat	(1.78)*	(1.58)	(1.41)	(0.86)	(-1.65)*
<u>Model 7.1.2</u>					
Intercept (α)	0.3595	0.2762	0.1577	-0.0754	-0.4349
t-stat	(1.61)	(1.68)*	(1.14)	(-0.50)	(-1.98)**
R_M-R_F	1.0333	1.0484	1.1139	1.1986	0.1654
t-stat	(23.29)***	(31.72)***	(40.38)***	(39.96)***	(3.79)***
<u>Model 7.1.3</u>					
Intercept (α)	0.1197	0.0958	-0.0165	-0.0612	-0.1808
t-stat	(0.70)	(0.74)	(-0.21)	(-0.49)	(-0.87)
R_M-R_F	0.9397	1.0020	1.0363	1.0695	0.1298
t-stat	(24.10)***	(33.73)***	(56.78)***	(37.57)***	(2.72)***
SMB	0.7655	0.5285	0.5938	0.4851	-0.2804
t-stat	(12.30)***	(11.26)***	(20.39)***	(10.68)***	(-3.68)***
HML	0.1953	0.2266	0.1306	-0.1689	-0.3642
t-stat	(2.91)***	(4.50)***	(4.16)***	(-3.45)***	(-4.44)***
R^2	0.8474	0.8982	0.9647	0.9259	0.2094
GRS *F*-statistic	1.36				
GRS-*P* value	0.2471				

Panel C: Average Returns and *BS* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***PMD***	R^2
Coefficient	-0.1470	0.9678	0.8993	0.1702	-0.1086	0.3037
t-stat	(-1.66)*	(47.38)***	(33.25)***	(3.33)***	(-5.00)***	

Table 7.3 (Continued)

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BS*

	Intercept	R_M-R_F	***SMB***	***HML***	***PMD***	R^2
Coefficient	-0.0126	1.0289	0.6833	0.1737	-0.0599	0.8450
t-stat	(-0.25)	(99.00)***	(8.66)***	(1.99)*	(-0.65)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	B_{PMD}	R^2
Coefficient	2.8624	-2.2327	-0.0455	0.6832	-0.2618	0.4529
t-stat	(2.32)**	(-1.77)*	(-0.11)	(1.81)*	(-1.02)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 for the pre-1990 period.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *BS* from 1 January 1972 to 31 December 1989. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *BS* measure each April. Parameter estimates are time-series averages of the parameters from the 216 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *BS* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 1989, all firm-years in the sample are sorted into four portfolios based on *BS*: defender (6-12); lower analyzer (13-17); upper analyzer (18-23); prospector (24-30). Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML*). The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS* (i.e. prospector) and sells portfolio 1 of *BS* (i.e. defender).

Panels C to E present firm-specific *BS* factor loadings and regression results of the two-stage cross-sectional regressions based on 20 *BM-BS* portfolios. For each month, from 1 January 1972 to 31 December 1989, a *BS* factor mimicking portfolio (*Prospector minus Defender* denoted as *PMD*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS* from the value-weighted return on stocks in the highest portfolio of *BS*. Panel C presents average coefficients across 2,470 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *PMD*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMD*. The 20 portfolios are created by sorting stocks into quintiles based on *BM* and four portfolios based on *BS* each month (i.e. defender, lower analyzer, upper analyzer, and prospector). *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 216 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 7.4

Post-1990 Sub-period Analyses

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and Business Strategy (*BS*)

	Intercept	***BETA***	***SIZE***	***BM***	***BS***	R^2
Coefficient	1.2914	0.2200	-0.1191	0.2416	0.0179	0.0341
t-stat	(3.62)***	(-1.31)	(-2.22)**	(2.55)**	(1.12)	

Panel B: Time-series *BS* Portfolio Regressions of Monthly Excess returns on the Fama-French Three Factors

Portfolio number	**1 (Defender)**	**2 (Lower Analyzer)**	**3 (Upper Analyzer)**	**4 (Prospector)**	**Hedge (4-1)**
<u>Model 7.1.1</u>					
Intercept (α)	0.8967	0.9614	0.9794	1.0208	0.1241
t-stat	(2.55)**	(3.08)***	(2.71)***	(2.50)**	(0.49)
<u>Model 7.1.2</u>					
Intercept (α)	0.3101	0.3852	0.2512	0.2380	-0.0721
t-stat	(1.37)	(2.33)**	(1.73)*	(1.23)	(-0.30)
R_M-R_F	0.9678	0.9507	1.1025	1.2916	0.3237
t-stat	(19.18)***	(25.80)***	(34.05)***	(29.88)***	(6.03)***
<u>Model 7.1.3</u>					
Intercept (α)	-0.0459	0.0820	0.0426	0.1312	0.1772
t-stat	(-0.26)	(0.75)	(0.43)	(0.84)	(0.88)
R_M-R_F	1.0031	0.9815	1.0683	1.1924	0.1893
t-stat	(24.94)***	(39.04)***	(46.32)***	(33.18)***	(4.08)***
SMB	0.5039	0.4263	0.5046	0.5704	0.0665
t-stat	(9.41)***	(12.73)***	(16.43)***	(11.92)***	(1.08)
HML	0.6896	0.5885	0.3185	0.0354	-0.6542
t-stat	(12.29)***	(16.78)***	(9.90)***	(0.71)	(-10.09)***
R^2	0.7663	0.8843	0.9180	0.8622	0.4093
GRS *F*-statistic	0.55				
GRS-*P* value	0.6958				

Panel C: Average Returns and *BS* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***PMD***	R^2
Coefficient	-0.0390	0.9990	0.8220	0.2918	0.0346	0.2464
t-stat	(-0.04)	(37.11)***	(2.94)***	(5.36)***	(1.02)	

Table 7.4 (Continued)

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BS*

	Intercept	R_M-R_F	*SMB*	*HML*	*PMD*	R^2
Coefficient	0.1024	1.0549	0.5415	0.4144	-0.0622	0.7380
t-stat	(2.67)**	(62.83)***	(11.20)***	(7.13)***	(-0.77)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	β_{RM-RF}	β_{SMB}	β_{HML}	B_{PMD}	R^2
Coefficient	1.7169	-0.9727	0.3314	0.3525	0.0489	0.3906
t-stat	(1.29)	(-0.76)	(0.91)	(0.90)	(0.19)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 for the post-1990 period.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *BS* from 1 January 1990 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *BS* measure each April. Parameter estimates are time-series averages of the parameters from the 252 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for *BS* portfolio time-series regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1990 to 31 December 2010, all firm-years in the sample are sorted into four portfolios based on *BS*: defender (6-12); lower analyzer (13-17); upper analyzer (18-23); prospector (24-30). Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS* (i.e. prospector) and sells portfolio 1 of *BS* (i.e. defender).

Panels C to E present firm-specific *BS* factor loadings and regression results of the two-stage cross-sectional regressions based on 20 *BM-BS* portfolios. For each month, from 1 January 1990 to 31 December 2010, a *BS* factor mimicking portfolio (*Prospector minus Defender* denoted as *PMD*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS* from the value-weighted return on stocks in the highest portfolio of *BS*. Panel C presents average coefficients across 4,026 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *PMD*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMD*. The 20 portfolios are created by sorting stocks into quintiles based on *BM* and four portfolios based on *BS* each month (i.e. defender, lower analyzer, upper analyzer, and prospector). *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 252 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 7.5

Modified Measure of Business Strategy (*BS2*)
Exclusive of Historical Growth or Investment Opportunities (*REV5*) Analyses

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *BS2*

	Intercept	***BETA***	***SIZE***	***BM***	***BS2***	R^2
Coefficient	1.0580	0.0347	-0.0785	0.2661	0.0190	0.0408
t-stat	(3.40)***	(0.31)	(-1.95)*	(3.76)***	(1.44)	

Panel B: Time-series *BS2* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	**1 (Defender)**	**2 (Lower Analyzer)**	**3 (Upper Analyzer)**	**4 (Prospector)**	**Hedge (4-1)**
Model 7.1.1					
Intercept (α)	0.7648	0.7669	0.7881	0.6860	-0.0788
t-stat	(3.05)***	(3.04)***	(3.00)***	(2.37)**	(-0.53)
Model 7.1.2					
Intercept (α)	0.2962	0.2650	0.2601	0.1100	-0.1863
t-stat	(2.22)**	(2.12)**	(2.42)**	(0.89)	(-1.30)
R_M-R_F	0.9978	1.0368	1.1242	1.2256	0.2278
t-stat	(35.12)***	(38.91)***	(49.24)***	(46.41)***	(7.45)***
Model 7.1.3					
Intercept (α)	0.0075	-0.0186	0.0914	0.0404	0.0329
t-stat	(0.07)	(-0.20)	(1.22)	(0.41)	(0.25)
R_M-R_F	1.0178	1.0468	1.0714	1.1291	0.1113
t-stat	(42.28)***	(49.32)***	(62.84)***	(50.18)***	(3.76)***
SMB	0.4518	0.4823	0.5460	0.5519	0.1001
t-stat	(13.10)***	(15.89)***	(22.35)***	(17.12)***	(2.36)**
HML	0.4918	0.4828	0.2331	0.0329	-0.4589
t-stat	(13.51)***	(15.05)***	(9.04)***	(0.97)	(-10.25)***
R^2	0.8299	0.8698	0.9221	0.8883	0.2868
GRS *F*-statistic	0.37				
GRS-*P* value	0.8331				

Panel C: Average Returns and *BS2* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***PMD2***	R^2
Coefficient	0.1330	0.9840	0.8424	0.2908	0.1265	0.2536
t-stat	(3.40)***	(82.31)***	(49.35)***	(14.62)***	(6.04)***	

Table 7.5 (Continued)

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BS2*

	Intercept	R_M-R_F	*SMB*	*HML*	*PMD2*	R^2
Coefficient	0.0408	1.0612	0.5651	0.3568	-0.0249	0.8164
t-stat	(1.37)	(133.28)***	(9.41)***	(5.14)***	(-0.29)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	B_{PMD2}	R^2
Coefficient	2.5475	-1.9086	0.1350	0.6147	0.1207	0.4361
t-stat	(2.03)**	(-1.59)	(0.55)	(2.94)***	(0.51)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of a modified measure of business strategy (*BS2*) exclusive of historical growth of investment opportunities (*REV5*), which is a score ranging from 5 to 25.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *BS2* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *BS2* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *BS2* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into four portfolios based on *BS2*: defender (5-10); lower analyzer (11-15); upper analyzer (16-19); prospector (20-25). Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS2* (i.e. prospector) and sells portfolio 1 of *BS2* (i.e. defender).

Panels C to E present firm-specific *BS2* factor loadings and regression results of the two-stage cross-sectional regressions based on 20 *BM-BS2* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *BS2* factor mimicking portfolio (*Prospector minus Defender 2* denoted as *PMD2*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS2* from the value-weighted return on stocks in the highest portfolio of *BS2*. Panel C presents average coefficients across 5,485 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *PMD2*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMD2*. The 20 portfolios are created by sorting stocks into quintiles based on *BM* and four portfolios based on *BS2* (i.e. defender, lower analyzer, upper analyzer, and prospector) each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.1

Individual Measure of Business Strategy Analyses: Research Intensity (*RDS5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *RDS5*

	Intercept	*BETA*	*SIZE*	*BM*	*RDS5*	R^2
Coefficient	0.9357	0.0507	-0.0606	0.3566	0.0856	0.0424
t-stat	(2.20)**	(0.43)	(-1.11)	(2.62)***	(2.35)**	

Panel B: Time-series *RDS5* Portfolio Regressions of Monthly Excess returns on the Fama-French Three Factors

Portfolio number	1	2	3	4	5	Hedge (5-1)
Model 7.1.1						
Intercept (α)	0.8030	0.7846	0.6847	0.8479	0.8146	0.0116
t-stat	(3.21)***	(3.20)***	(2.56)**	(3.30)***	(2.81)***	(0.08)
Model 7.1.2						
Intercept (α)	0.3200	0.2800	0.1841	0.3227	0.2230	-0.0930
t-stat	(2.53)**	(2.46)**	(1.31)	(3.03)***	(1.86)*	(-0.65)
R_M-R_F	0.9966	0.9964	1.05	1.07	1.2106	0.2140
t-stat	(37.77)***	(41.89)***	(35.42)***	(47.87)***	(47.83)***	(7.08)***
Model 7.1.3						
Intercept (α)	-0.0238	-0.0077	-0.1100	0.1100	0.1774	0.2012
t-stat	(-0.28)	(-0.10)	(-0.96)	(1.38)	(1.92)*	(1.69)*
R_M-R_F	1.0160	1.0000	1.0616	1.0520	1.0900	0.08
t-stat	(53.44)***	(55.34)***	(41.23)***	(56.75)***	(52.47)***	(2.91)***
SMB	0.5106	0.4700	0.4906	0.4500	0.5340	0.0234
t-stat	(18.68)***	(18.01)***	(13.27)***	(16.88)***	(17.82)***	(0.61)
HML	0.5299	0.4173	0.4628	0.2828	-0.0791	-0.6090
t-stat	(18.37)***	(15.19)***	(11.86)***	(10.05)***	(-2.50)**	(-14.95)***
R^2	0.8920	0.8970	0.8272	0.9027	0.9024	0.3982
GRS *F*-statistic	0.90					
GRS-*P* value	0.4613					

Panel C: Average Returns and *RDS5* Factor Loadings

	Intercept	R_M-R_F	*SMB*	*HML*	*HLRDS5*	R^2
Coefficient	0.1050	0.9849	0.8433	0.2660	0.0813	0.2533
t-stat	(2.64)***	(75.43)***	(48.83)***	(12.89)***	(3.97)***	

Table 8.1 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *RDS5*

	Intercept	R_M-R_F	***SMB***	***HML***	***HLRDS5***	R^2
Coefficient	0.0728	1.0501	0.5516	0.3078	-0.1073	0.8191
t-stat	(4.58)***	(146.41)***	(10.16)***	(5.13)***	(-1.48)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	B_{HLRDS5}	R^2
Coefficient	2.2942	-1.6674	0.2580	0.5317	0.0963	0.3684
t-stat	(1.02)	(-0.79)	(0.48)	(1.00)	(0.59)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of an individual measure of business strategy, namely research intensity (*RDS5*). *RDS5* is the quintile rank (by SIC 2-digit industry and year) of the ratio of research and development expenditures [*XRD*] to sales [*SALE*] computed over a rolling prior five-year average.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *RDS5* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *RDS5* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *RDS5* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *RDS5*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *RDS5* and sells portfolio 1 of *RDS5*.

Panels C to E present firm-specific *RDS5* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-RDS5* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *RDS5* factor mimicking portfolio (*High minus Low RDS5* denoted as *HLRDS5*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *RDS5* from the value-weighted return on stocks in the highest portfolio of *RDS5*. Panel C presents average coefficients across 5,238 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLRDS5*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLRDS5*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *RDS5* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.2

Individual Measure of Business Strategy Analyses: Marketing and Advertising Efforts (*SGA5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *SGA5*

	Intercept	***BETA***	***SIZE***	***BM***	***SGA5***	R^2
Coefficient	1.1939	0.0067	-0.0750	0.2923	0.0544	0.0414
t-stat	(3.81)***	(0.06)	(-1.79) *	(3.52)***	(2.10)**	

Panel B: Time-series *SGA5* Portfolio Regressions of Monthly Excess returns on the Fama-French Three Factors

Portfolio number	**1**	**2**	**3**	**4**	**5**	**Hedge (5-1)**
Model 7.1.1						
Intercept (α)	0.7705	0.7602	0.8179	0.7934	0.8549	0.0844
t-stat	(2.99)***	(2.97)***	(3.20)***	(2.96)***	(3.18)***	(0.64)
Model 7.1.2						
Intercept (α)	0.2647	0.2442	0.2952	0.2646	0.2942	0.0295
t-stat	(2.12)**	(2.16)**	(2.82)***	(2.23)**	(2.57)**	(0.33)
R_M-R_F	1.0351	1.0559	1.0697	1.1141	1.1171	0.0820
t-stat	(39.34)***	(44.36)***	(48.44)***	(44.36)***	(46.17)***	(2.96)***
Model 7.1.3						
Intercept (α)	-0.0536	-0.0483	0.0756	0.1128	0.1807	0.2343
t-stat	(-0.56)	(-0.65)	(1.05)	(1.27)	(1.96)*	(2.22)**
R_M-R_F	1.0821	1.0547	1.0354	1.0411	1.0390	-0.0431
t-stat	(50.14)***	(62.73)***	(63.62)***	(51.80)***	(50.04)***	(-1.80)*
SMB	0.3658	0.5096	0.5131	0.5724	0.4988	0.1330
t-stat	(11.79)***	(21.08)***	(21.93)***	(19.84)***	(16.71)***	(3.71)***
HML	0.5327	0.4334	0.2833	0.1623	0.0648	-0.4679
t-stat	(16.27)***	(16.99)***	(11.47)***	(5.33)***	(2.05)**	(-12.47)***
R^2	0.8685	0.9193	0.9240	0.8953	0.8883	0.3016
GRS *F*-statistic	2.45					
GRS-*P* value	0.0441					

Panel C: Average Returns and *SGA5* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***HLSGA5***	R^2
Coefficient	0.1053	1.0327	0.8039	0.2992	0.1135	0.2556
t-stat	(2.46)**	(52.56)***	(38.06)***	(14.44)***	(4.84)***	

Table 8.2 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *SGA5*

	Intercept	R_M-R_F	***SMB***	***HML***	***HLSGA5***	R^2
Coefficient	0.0890	1.0456	0.5826	0.3209	-0.0753	0.8262
t-stat	(4.23)***	(137.40)***	(10.52)***	(5.10)***	(-1.12)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	B_{HLSGA5}	R^2
Coefficient	1.8893	-0.9733	-0.5700	1.1318	0.5985	0.3827
t-stat	(1.06)	(-0.73)	(-0.47)	(1.21)	(1.22)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of an individual measure of business strategy, namely marketing and advertising efforts (*SGA5*). *SGA5* is the quintile rank (by SIC 2-digit industry and year) of the ratio of selling, general and administrative expenses [*XSGA*] to sales [*SALE*] computed over a rolling prior five-year average.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *SGA5* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *SGA5* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *SGA5* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *SGA5*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB,* and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *SGA5* and sells portfolio 1 of *SGA5*.

Panels C to E present firm-specific *SGA5* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-SGA5* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *SGA5* factor mimicking portfolio (*High minus Low SGA5* denoted as *HLSGA5*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *SGA5* from the value-weighted return on stocks in the highest portfolio of *SGA5*. Panel C presents average coefficients across 5,238 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLSGA5*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLSGA5*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *SGA5* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.3

Individual Measure of Business Strategy Analyses:
Historical Growth or Investment Opportunities (*REV5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *REV5*

	Intercept	*BETA*	*SIZE*	*BM*	*REV5*	R^2
Coefficient	1.4472	-0.0124	-0.0693	0.2738	-0.0472	0.0411
t-stat	(4.52)***	(-0.09)	(-1.39)	(2.92)***	(-1.51)	

Panel B: Time-series *REV5* Portfolio Regressions of Monthly Excess returns on the Fama-French Three Factors

Portfolio number	1	2	3	4	5	Hedge (5-1)
Model 7.1.1						
Intercept (α)	0.8188	0.9498	0.8133	0.7959	0.7063	-0.1125
t-stat	(2.75)***	(3.88)***	(3.37)***	(3.15)***	(2.55)**	(-1.75)*
Model 7.1.2						
Intercept (α)	0.2727	0.4644	0.3198	0.2556	0.1213	-0.1514
t-stat	(1.64)	(4.04)***	(3.25)***	(2.53)**	(1.10)	(-1.85)*
R_M-R_F	1.1505	0.9935	1.0099	1.0609	1.1658	0.0152
t-stat	(32.77)***	(40.98)***	(48.67)***	(49.85)***	(50.21)***	(1.02)
Model 7.1.3						
Intercept (α)	-0.0599	0.1747	0.0689	0.0556	-0.0355	0.0244
t-stat	(-0.51)	(2.10)**	(1.00)	(0.70)	(-0.43)	(0.10)
R_M-R_F	1.1035	1.0067	1.0171	1.0397	1.1021	-0.0015
t-stat	(41.29)***	(53.63)***	(65.24)***	(58.51)***	(58.68)***	(-0.09)
SMB	0.7847	0.4483	0.4052	0.4206	0.5176	-0.2671
t-stat	(20.45)***	(16.61)***	(18.08)***	(16.39)***	(19.16)***	(-7.81)***
HML	0.4693	0.4476	0.3821	0.2592	0.1484	-0.3210
t-stat	(11.59)***	(15.71)***	(16.15)***	(9.60)***	(5.20)***	(-9.35)***
R^2	0.8505	0.8900	0.9216	0.9070	0.9137	0.2198
GRS *F*-statistic	1.56					
GRS-*P* value	0.1813					

Panel C: Average Returns and *REV5* Factor Loadings

	Intercept	R_M-R_F	*SMB*	*HML*	*HLREV5*	R^2
Coefficient	0.1910	1.0161	0.7696	0.1541	-0.2846	0.2506
t-stat	(5.19)***	(84.80)***	(44.20)***	(7.65)***	(-11.53)***	

Table 8.3 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *REV5*

	Intercept	R_M-R_F	***SMB***	***HML***	***HLREV5***	R^2
Coefficient	0.0272	1.0565	0.5346	0.3574	-0.1301	0.8144
t-stat	(0.97)	(103.67)***	(10.53)***	(6.06)***	(-1.98)*	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	β_{RM-RF}	β_{SMB}	β_{HML}	B_{HLREV5}	R^2
Coefficient	2.0316	-1.5110	0.0038	0.8284	-0.2889	0.3683
t-stat	(1.98)*	(-1.41)	(0.01)	(2.57)**	(-1.71)*	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of an individual measure of business strategy, namely historical growth or investment opportunities (*REV5*). *REV5* is the quintile rank (by SIC 2-digit industry and year) of one-year percentage change in total sales [*SALE*] computed over a rolling prior five-year average.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *REV5* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *REV5* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *REV5* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *REV5*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *REV5* and sells portfolio 1 of *REV5*.

Panels C to E present firm-specific *REV5* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-REV5* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *REV5* factor mimicking portfolio (*High minus Low REV5* denoted as *HLREV5*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *REV5* from the value-weighted return on stocks in the highest portfolio of *REV5*. Panel C presents average coefficients across 5,238 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLREV5*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLREV5*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *REV5* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.4

Individual Measure of Business Strategy Analyses: Operational Efficiency (*EMPS5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *EMPS5*

	Intercept	*BETA*	*SIZE*	*BM*	*EMPS5*	R^2
Coefficient	1.7676	-0.0664	-0.1144	0.1942	-0.0274	0.0406
t-stat	(5.40)***	(-0.41)	(-2.87)***	(2.40)**	(-0.70)	

Panel B: Time-series *EMPS5* Portfolio Regressions of Monthly Excess returns on the Fama-French Three Factors

Portfolio number	1	2	3	4	5	Hedge (5-1)
Model 7.1.1						
Intercept (α)	0.8194	0.7369	0.8381	0.7698	0.7584	-0.0610
t-stat	(3.42)***	(2.90)***	(3.19)***	(2.84)***	(2.80)***	(-0.67)
Model 7.1.2						
Intercept (α)	0.3187	0.2276	0.2869	0.2160	0.2217	-0.0971
t-stat	(3.69)***	(2.18)**	(2.66)***	(1.73)*	(1.60)	(-0.88)
R_M-R_F	1.0247	1.0730	1.0981	1.1035	1.0696	0.0449
t-stat	(56.20)***	(48.46)***	(48.15)***	(41.87)***	(36.47)***	(2.00)**
Model 7.1.3						
Intercept (α)	0.1431	0.0296	0.0474	-0.0607	-0.0606	-0.2037
t-stat	(2.04)**	(0.35)	(0.60)	(-0.69)	(-0.69)	(-2.36)**
R_M-R_F	1.0223	1.0630	1.0817	1.0784	1.0033	-0.0191
t-stat	(64.54)***	(55.28)***	(61.21)***	(54.15)***	(50.57)***	(-1.06)
SMB	0.3122	0.3929	0.4775	0.5750	0.7445	0.4323
t-stat	(13.71)***	(14.23)***	(18.79)***	(20.08)***	(26.10)***	(15.88)***
HML	0.2582	0.2976	0.3349	0.3786	0.3317	0.0735
t-stat	(10.74)***	(10.21)***	(12.47)***	(12.51)***	(11.00)***	(2.66)***
R^2	0.9180	0.8934	0.9150	0.8986	0.8996	0.3581
GRS *F*-statistic	1.93					
GRS-*P* value	0.1021					

Panel C: Average Returns and *EMPS5* Factor Loadings

	Intercept	R_M-R_F	*SMB*	*HML*	*HLEMPS5*	R^2
Coefficient	0.2500	1.0241	0.6728	0.1934	0.3766	0.2536
t-stat	(6.84)***	(83.49)***	(34.15)***	(10.00)***	(13.02)***	

Table 8.4 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *EMPS5*

	Intercept	R_M-R_F	***SMB***	***HML***	***HLEMPS5***	R^2
Coefficient	0.0780	1.0553	0.4666	0.3653	0.1997	0.8312
t-stat	(3.52)***	(110.63)***	(10.24)***	(5.89)***	(2.89)***	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	$B_{HLEMPS5}$	R^2
Coefficient	6.4630	-5.9910	0.7752	0.8192	0.0151	0.3756
t-stat	(1.14)	(-1.06)	(1.33)	(2.08)**	(0.13)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of an individual measure of business strategy, namely operational efficiency (*EMPS5*). *EMPS5* is the quintile rank (by SIC 2-digit industry and year) of the ratio of the number of employees [*EMP*] to sales [*SALE*] computed over a rolling prior five-year average.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *EMPS5* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *EMPS5* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *EMPS5* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *EMPS5*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *EMPS5* and sells portfolio 1 of *EMPS5*.

Panels C to E present firm-specific *EMPS5* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-EMPS5* portfolios. For each month, from 1 January 1972 to 31 December 2010, an *EMPS5* factor mimicking portfolio (*High minus Low EMPS5* denoted as *HLEMPS5*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *EMPS5* from the value-weighted return on stocks in the highest portfolio of *EMPS5*. Panel C presents average coefficients across 5,238 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLEMPS5*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLEMPS5*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *EMPS5* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.5

Individual Measure of Business Strategy Analyses: Capital Intensity or Technological Efficiency (*CAP5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *CAP5*

	Intercept	***BETA***	***SIZE***	***BM***	***CAP5***	R^2
Coefficient	1.5110	-0.0126	-0.1002	0.2301	-0.0161	0.0408
t-stat	(4.77)***	(-0.10)	(-2.61)***	(3.08)***	(-0.51)	

Panel B: Time-series *CAP5* Portfolio Regressions of Monthly Excess returns on the Fama-French Three Factors

Portfolio number	**1**	**2**	**3**	**4**	**5**	**Hedge (5-1)**
Model 7.1.1						
Intercept (α)	0.7652	0.7152	0.7825	0.9308	0.8129	0.0477
t-stat	(3.09)***	(2.81)***	(3.18)***	(3.37)***	(2.84)***	(0.36)
Model 7.1.2						
Intercept (α)	0.2665	0.2145	0.2616	0.3489	0.2359	-0.0306
t-stat	(2.43)**	(1.88)*	(2.68)***	(2.94)***	(1.70)*	(-0.16)
R_M-R_F	1.0206	1.0547	1.0380	1.1426	1.1498	0.1292
t-stat	(44.14)***	(43.65)***	(50.40)***	(45.71)***	(39.27)***	(5.00)***
Model 7.1.3						
Intercept (α)	0.0015	-0.0145	0.0502	0.1273	0.0104	0.0089
t-stat	(0.02)	(-0.16)	(0.71)	(1.53)	(0.11)	(0.17)
R_M-R_F	1.0531	1.0468	1.0178	1.0855	1.0611	0.0080
t-stat	(54.02)***	(51.04)***	(64.28)***	(57.97)***	(50.52)***	(0.30)
SMB	0.3305	0.4390	0.4432	0.5945	0.7334	0.4029
t-stat	(11.79)***	(14.91)***	(19.46)***	(21.99)***	(24.28)***	(12.30)***
HML	0.4350	0.3478	0.2879	0.2397	0.2173	-0.2177
t-stat	(14.70)***	(11.19)***	(11.96)***	(8.42)***	(6.81)***	(-6.22)***
R^2	0.8841	0.8792	0.9225	0.9136	0.8990	0.3554
GRS *F*-statistic	1.10					
GRS-*P* value	0.3525					

Panel C: Average Returns and *CAP5* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***HLCAP5***	R^2
Coefficient	0.1612	0.9868	0.7816	0.2976	0.2734	0.2545
t-stat	(3.21)***	(56.00)***	(30.09)***	(15.68)***	(10.23)***	

Table 8.5 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *CAP5*

	Intercept	R_M-R_F	***SMB***	***HML***	***HLCAP5***	R^2
Coefficient	0.0444	1.0495	0.5514	0.3678	0.0223	0.8329
t-stat	(2.37)**	(125.91)***	(12.20)***	(5.71)***	(0.32)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	B_{HLCAP5}	R^2
Coefficient	3.6190	-3.3747	1.0261	0.2714	-0.2179	0.3718
t-stat	(1.25)	(-1.12)	(2.79)***	(0.87)	(-0.70)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of an individual measure of business strategy, namely capital intensity or technological efficiency (*CAP5*). *CAP5* is the quintile rank (by SIC 2-digit industry and year), in a descending manger, of a ratio of net property, plant, and equipment [*PPENT*] to total assets [*AT*] computed over a rolling prior five-year average.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *CAP5* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *CAP5* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *CAP5* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *CAP5*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *CAP5* and sells portfolio 1 of *CAP5*.

Panels C to E present firm-specific *CAP5* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-CAP5* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *CAP5* factor mimicking portfolio (*High minus Low CAP5* denoted as *HLCAP5*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *CAP5* from the value-weighted return on stocks in the highest portfolio of *CAP5*. Panel C presents average coefficients across 5,238 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLCAP5*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLCAP5*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *CAP5* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.6

Individual Measure of Business Strategy Analyses: Organizational Stability (*TEMP5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *TEMP5*

	Intercept	*BETA*	*SIZE*	*BM*	*TEMP5*	R^2
Coefficient	1.4019	0.0003	-0.1042	0.2242	0.0234	0.0417
t-stat	(4.51)***	(0.00)	(-2.41)**	(3.06)***	(0.66)	

Panel B: Time-series *TEMP5* Portfolio Regressions of Monthly Excess returns on the Fama-French Three Factors

Portfolio number	1	2	3	4	5	Hedge (5-1)
Model 7.1.1						
Intercept (α)	0.9013	0.8730	0.9128	0.8677	0.6667	-0.2346
t-stat	(3.26)***	(3.04)***	(3.40)***	(3.35)***	(2.65)***	(-1.39)
Model 7.1.2						
Intercept (α)	0.4013	0.3670	0.3878	0.3433	0.1394	-0.2619
t-stat	(2.29)**	(2.12)**	(2.94)***	(3.08)***	(1.58)	(-1.71)*
R_M-R_F	0.9818	1.0660	1.0745	1.0731	1.0790	0.0973
t-stat	(26.62)***	(29.09)***	(38.63)***	(45.69)***	(58.01)***	(2.96)***
Model 7.1.3						
Intercept (α)	0.1311	0.1669	0.1251	0.0888	-0.0579	-0.1890
t-stat	(1.08)	(1.40)	(1.50)	(1.11)	(-0.79)	(-1.58)
R_M-R_F	0.8651	0.9312	1.0087	1.0595	1.1070	0.2419
t-stat	(31.59)***	(34.60)***	(53.57)***	(58.80)***	(67.02)***	(8.43)***
SMB	0.9042	0.9149	0.7107	0.4927	0.2312	-0.6730
t-stat	(22.86)***	(23.68)***	(26.26)***	(19.02)***	(9.74)***	(-16.01)***
HML	0.2255	0.1750	0.3075	0.3615	0.3287	0.1033
t-stat	(5.42)***	(4.29)***	(10.76)***	(13.22)***	(13.12)***	(2.34)**
R^2	0.8150	0.8368	0.9079	0.9093	0.9190	0.3890
GRS *F*-statistic	3.16					
GRS-*P* value	0.0133					

Panel C: Average Returns and *TEMP5* Factor Loadings

	Intercept	R_M-R_F	*SMB*	*HML*	*HLTEMP5*	R^2
Coefficient	0.1142	1.0932	0.6827	0.2680	-0.3063	0.2563
t-stat	(3.24)***	(84.41)***	(36.38)***	(14.47)***	(-16.99)***	

Table 8.6 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *TEMP5*

	Intercept	R_M-R_F	***SMB***	***HML***	***HLTEMP5***	R^2
Coefficient	0.0768	1.0321	0.5839	0.3298	-0.1544	0.8002
t-stat	(2.03)*	(76.13)***	(14.06)***	(4.67)***	(-2.11)**	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	β_{RM-RF}	β_{SMB}	β_{HML}	$B_{HLTEMP5}$	R^2
Coefficient	0.8732	-0.3727	0.2340	0.5191	-0.2515	0.3770
t-stat	(0.75)	(-0.33)	(1.06)	(2.51)**	(-1.51)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of an individual measure of business strategy, namely organizational stability (*TEMP5*). *TEMP5* is the quintile rank (by SIC 2-digit industry and year) of the standard deviation of the total number of employees [*EMP*] computed over a rolling prior five-year period.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *TEMP5* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *TEMP5* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *TEMP5* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *TEMP5*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *TEMP5* and sells portfolio 1 of *TEMP5*.

Panels C to E present firm-specific *TEMP5* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-TEMP5* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *TEMP5* factor mimicking portfolio (*High minus Low TEMP5* denoted as *HLTEMP5*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *TEMP5* from the value-weighted return on stocks in the highest portfolio of *TEMP5*. Panel C presents average coefficients across 5,238 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLTEMP5*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLTEMP5*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *TEMP5* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.7

Factor 1 (*F1*) Measure of Business Strategy Analyses:
Research Intensity (*RDS5*) and Marketing and Advertising Efforts (*SGA5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *F1*

	Intercept	***BETA***	***SIZE***	***BM***	***F1***	R^2
Coefficient	1.1690	-0.0323	-0.0806	0.2965	0.0869	0.0418
t-stat	(3.88)***	(-0.27)	(-2.01)**	(3.71)***	(2.68)***	

Panel B: Time-series *F1* Portfolio Regressions of Monthly Excess returns on the Fama-French Three Factors

Portfolio number	**1**	**2**	**3**	**4**	**5**	**Hedge (5-1)**
<u>Model 7.1.1</u>						
Intercept (α)	0.7523	0.7905	0.8059	0.7575	0.8320	0.0798
t-stat	(2.95)***	(3.16)***	(3.17)***	(2.91)***	(2.78)***	(0.64)
<u>Model 7.1.2</u>						
Intercept (α)	0.2312	0.2921	0.2953	0.2392	0.2088	-0.0224
t-stat	(1.83)**	(2.55)**	(2.60)***	(2.18)**	(1.54)	(0.00)
R_M-R_F	1.0143	1.0199	1.0448	1.0919	1.2237	0.2074
t-stat	(38.17)***	(42.19)***	(43.60)***	(46.96)***	(42.77)***	(6.12)***
<u>Model 7.1.3</u>						
Intercept (α)	-0.1012	-0.0172	0.0053	0.0617	0.1911	0.2923
t-stat	(-1.11)	(-0.22)	(0.07)	(0.73)	(1.82)*	(2.37)**
R_M-R_F	1.0384	1.0380	1.0569	1.0487	1.0815	0.0432
t-stat	(50.55)***	(59.01)***	(57.92)***	(54.76)***	(45.90)***	(1.44)
SMB	0.4693	0.4634	0.4532	0.4938	0.5732	0.1039
t-stat	(15.81)***	(18.33)***	(17.28)***	(17.96)***	(16.85)***	(2.31)**
HML	0.5114	0.4828	0.4466	0.2322	-0.1758	-0.6872
t-stat	(16.38)***	(18.09)***	(16.13)***	(8.00)***	(-4.91)***	(-15.30)***
R^2	0.8778	0.9072	0.9036	0.8989	0.8837	0.4056
GRS *F*-statistic	1.80					
GRS-*P* value	0.1253					

Panel C: Average Returns and *F1* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***HLF1***	R^2
Coefficient	0.0360	1.0046	0.8200	0.3179	0.1108	0.2545
t-stat	(0.80)	(56.70)***	(43.23)***	(15.52)***	(5.16)***	

Table 8.7 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *F1*

	Intercept	R_M-R_F	***SMB***	***HML***	***HLF1***	R^2
Coefficient	0.0598	1.0576	0.5719	0.3160	-0.0661	0.8232
t-stat	(3.84)***	(155.30)***	(10.05)***	(5.06)***	(-0.94)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	β_{RM-RF}	β_{SMB}	β_{HML}	B_{HLF1}	R^2
Coefficient	0.5315	0.0065	0.3547	0.4133	0.0727	0.3860
t-stat	(0.64)	(0.01)	(1.14)	(1.50)	(0.41)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of the first factor (*F1*) of business strategy identified by the principal component analyses. *F1* is the sum of quintile ranks of research intensity (*RDS5*) and marketing and advertising efforts (*SGA5*), and thus it is a score ranging from 2 to 10.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *F1* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *F1* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *F1* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *F1*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *F1* and sells portfolio 1 of *F1*.

Panels C to E present firm-specific *F1* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-F1* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *F1* factor mimicking portfolio (*High minus Low F1* denoted as *HLF1*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *F1* from the value-weighted return on stocks in the highest portfolio of *F1*. Panel C presents average coefficients across 5,238 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLF1*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLF1*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *F1* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.8

Factor 2 (*F2*) Measure of Business Strategy Analyses: Operational Efficiency (*EMPS5*) and Organizational Stability (*TEMP5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *F2*

	Intercept	***BETA***	***SIZE***	***BM***	***F2***	R^2
Coefficient	1.5450	-0.0027	-0.0860	0.2427	-0.0400	0.0410
t-stat	(5.00)***	(-0.02)	(-2.12)**	(3.21)***	(-1.59)	

Panel B: Time-series *F2* Portfolio Regressions of Monthly Excess returns on the Fama-French Three Factors

Portfolio number	**1**	**2**	**3**	**4**	**5**	**Hedge (5-1)**
Model 7.1.1						
Intercept (α)	0.9742	0.8313	0.8508	0.7514	0.6774	-0.2968
t-stat	(3.56)***	(3.18)***	(3.44)***	(2.93)***	(2.51)**	(-2.29)**
Model 7.1.2						
Intercept (α)	0.4659	0.3291	0.3329	0.2244	0.1213	-0.3445
t-stat	(2.86)***	(2.60)***	(3.79)***	(2.16)**	(1.01)	(-2.68)***
R_M-R_F	1.0128	1.0582	1.0600	1.0785	1.1080	0.0952
t-stat	(29.50)***	(39.42)***	(57.15)***	(49.32)***	(43.84)***	(3.51)***
Model 7.1.3						
Intercept (α)	0.2000	0.1210	0.1585	-0.0252	-0.1464	-0.3463
t-stat	(1.63)	(1.32)	(2.37)**	(-0.34)	(-1.61)	(-2.82)***
R_M-R_F	0.9348	0.9974	1.0390	1.0752	1.1036	0.1689
t-stat	(33.94)***	(48.06)***	(69.03)***	(64.49)***	(53.92)***	(6.10)***
SMB	0.7618	0.6213	0.3833	0.4435	0.4794	-0.2824
t-stat	(19.24)***	(20.85)***	(17.71)***	(18.50)***	(16.29)***	(-7.09)***
HML	0.2917	0.2619	0.2328	0.3670	0.3928	0.1012
t-stat	(6.97)***	(8.33)***	(10.19)***	(14.51)***	(12.63)***	(2.41)**
R^2	0.8102	0.8823	0.9306	0.9211	0.8918	0.1421
GRS *F*-statistic	4.44					
GRS-*P* value	0.0014					

Panel C: Average Returns and *F2* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***HLF2***	R^2
Coefficient	0.1314	1.0308	0.8138	0.2408	-0.1469	0.2514
t-stat	(3.42)***	(78.76)***	(46.95)***	(12.69)***	(-8.48)***	

Table 8.8 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *F2*

	Intercept	R_M-R_F	***SMB***	***HML***	***HLF2***	R^2
Coefficient	0.0567	1.0352	0.5743	0.3700	-0.0550	0.7974
t-stat	(1.65)	(107.49)***	(12.44)***	(5.97)***	(-0.82)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	β_{RM-RF}	β_{SMB}	β_{HML}	B_{HLF2}	R^2
Coefficient	2.0108	-1.4075	0.1223	0.6688	-0.1880	0.3571
t-stat	(2.34)**	(-1.68)*	(0.34)	(2.25)**	(-1.35)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of the second factor (*F2*) of business strategy identified by the principal component analyses. *F2* is the sum of quintile ranks of operational efficiency (*EMPS5*) and organizational stability (*TEMP5*), and thus it is a score ranging from 2 to 10.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *F2* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *F2* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *F2* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *F2*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *F2* and sells portfolio 1 of *F2*.

Panels C to E present firm-specific *F2* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM*-*F2* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *F2* factor mimicking portfolio (*High minus Low F2* denoted as *HLF2*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *F2* from the value-weighted return on stocks in the highest portfolio of *F2*. Panel C presents average coefficients across 5,238 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLF2*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLF2*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *F2* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.9

Factor 3 (*F3*) Measure of Business Strategy Analyses: Historical Growth or Investment Opportunities (*REV5*) and Capital Intensity or Technological Efficiency (*CAP5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *F3*

	Intercept	*BETA*	*SIZE*	*BM*	*F3*	R^2
Coefficient	1.5124	-0.0303	-0.0833	0.2500	-0.0487	0.0411
t-stat	(4.89)***	(-0.22)	(-1.92)*	(3.08)***	(-1.10)	

Panel B: Time-series *F3* Portfolio Regressions of Monthly Excess returns on the Fama-French Three Factors

Portfolio number	1	2	3	4	5	Hedge (5-1)
Model 7.1.1						
Intercept (α)	0.8247	0.8161	0.7992	0.8203	0.7161	-0.1086
t-stat	(3.13)***	(3.33)***	(3.10)***	(3.21)***	(2.41)***	(-1.34)
Model 7.1.2						
Intercept (α)	0.3367	0.3180	0.2584	0.2794	0.0934	-0.2433
t-stat	(2.36)**	(3.05)***	(2.43)***	(2.80)***	(0.70)	(-2.08)**
R_M-R_F	1.0280	1.0193	1.0776	1.0777	1.2121	0.1841
t-stat	(33.97)***	(46.38)***	(48.01)***	(51.17)***	(42.94)***	(6.37)***
Model 7.1.3						
Intercept (α)	0.0139	0.0427	0.0129	0.0850	-0.0648	-0.0788
t-stat	(0.12)	(0.59)	(0.18)	(1.20)	(-0.66)	(-0.91)
R_M-R_F	1.0549	1.0342	1.0584	1.0388	1.1091	0.0542
t-stat	(40.72)***	(63.34)***	(64.31)***	(65.39)***	(50.06)***	(2.01)**
SMB	0.4607	0.4170	0.4985	0.4864	0.6565	0.1958
t-stat	(12.39)***	(17.77)***	(21.06)***	(21.29)***	(20.50)***	(5.00)***
HML	0.5286	0.4281	0.3400	0.2376	0.0766	-0.4521
t-stat	(13.47)***	(17.28)***	(13.60)***	(9.84)***	(2.27)**	(-10.72)***
R^2	0.8203	0.9170	0.9236	0.9273	0.8951	0.3178
GRS *F*-statistic	0.86					
GRS-*P* value	0.4886					

Panel C: Average Returns and *F3* Factor Loadings

	Intercept	R_M-R_F	*SMB*	*HML*	*HLF3*	R^2
Coefficient	0.1179	0.9935	0.8306	0.2596	0.0565	0.2518
t-stat	(3.14)***	(78.54)***	(47.37)***	(13.11)***	(2.95)***	

Table 8.9 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *F3*

	Intercept	R_M-R_F	***SMB***	***HML***	***HLF3***	R^2
Coefficient	0.0283	1.0560	0.5644	0.3685	-0.0350	0.8067
t-stat	(1.20)	(144.64)***	(11.21)***	(5.83)***	(-0.57)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	β_{RM-RF}	β_{SMB}	β_{HML}	B_{HLF3}	R^2
Coefficient	-10.0888	10.8794	-0.7802	0.3609	0.9792	0.3713
t-stat	(-0.99)	(1.02)	(-0.60)	(1.30)	(0.89)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of the third factor (*F3*) of business strategy identified by the principal component analyses. *F3* is the sum of quintile ranks of historical growth or investment opportunities (*REV5*) and capital intensity or technological efficiency (*CAP5*), and thus it is a score ranging from 2 to 10.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *F3* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *F3* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *F3* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *F3*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *F3* and sells portfolio 1 of *F3*.

Panels C to E present firm-specific *F3* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-F3* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *F3* factor mimicking portfolio (*High minus Low F3* denoted as *HLF3*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *F3* from the value-weighted return on stocks in the highest portfolio of *F3*. Panel C presents average coefficients across 5,238 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLF3*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLF3*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *F3* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.10

Analyses of Innovation Factor (*FINV*) of a Modified Measure of Business Strategy: Research Intensity (*RDS5*) and Marketing and Advertising Efforts (*SGA5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *FINV*

	Intercept	*BETA*	*SIZE*	*BM*	*FINV*	R^2
Coefficient	1.0357	0.0305	-0.0672	0.3140	0.0895	0.0416
t-stat	(3.30)***	(0.27)	(-1.66)*	(3.85)***	(2.56)**	

Panel B: Time-series *FINV* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	1	2	3	4	5	Hedge (5-1)
Model 7.1.1						
Intercept (α)	0.6965	0.7458	0.7602	0.7746	0.8065	0.1100
t-stat	(2.76)***	(2.89)***	(2.99)***	(3.05)***	(2.72)***	(0.66)
Model 7.1.2						
Intercept (α)	0.2118	0.2361	0.2606	0.2620	0.2280	0.0162
t-stat	(1.71)*	(1.81)*	(2.29)**	(2.60)***	(1.66)*	(0.10)
R_M-R_F	1.0320	1.0530	1.0631	1.0914	1.2307	0.1987
t-stat	(39.11)***	(37.78)***	(43.85)***	(50.82)***	(42.25)***	(5.78)***
Model 7.1.3						
Intercept (α)	-0.0888	-0.0643	-0.0088	0.1033	0.2692	0.3580
t-stat	(-1.00)	(-0.67)	(-0.11)	(1.44)	(2.53)**	(2.70)***
R_M-R_F	1.0480	1.0639	1.0728	1.0432	1.0817	0.0337
t-stat	(52.19)***	(48.41)***	(57.82)***	(64.32)***	(44.87)***	(1.12)
SMB	0.4916	0.5096	0.4601	0.5074	0.5753	0.0836
t-stat	(17.09)***	(16.21)***	(17.31)***	(21.83)***	(16.66)***	(1.94)*
HML	0.5080	0.5117	0.4506	0.2206	-0.1933	-0.7013
t-stat	(16.74)***	(15.40)***	(16.07)***	(9.00)***	(-5.31)***	(-15.42)***
R^2	0.3159	0.8667	0.9013	0.9244	0.8775	0.3942
GRS *F*-statistic	2.00					
GRS-*P* value	0.0920					

Panel C: Average Returns and *FINV* Factor Loadings

	Intercept	R_M-R_F	*SMB*	*HML*	*HLFINV*	R^2
Coefficient	0.0732	0.9944	0.8465	0.3084	0.1247	0.2538
t-stat	(1.80)*	(72.86)***	(46.59)***	(15.36)***	(5.87)***	

Table 8.10 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *FINV*

	Intercept	R_M-R_F	***SMB***	***HML***	***HLFINV***	R^2
Coefficient	0.0748	1.0637	0.5780	0.3140	-0.0650	0.8341
t-stat	(4.31)***	(142.66)***	(10.35)***	(5.06)***	(-0.93)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	β_{RM-RF}	β_{SMB}	β_{HML}	B_{HLFINV}	R^2
Coefficient	1.4456	-0.9147	0.3828	0.3920	0.1817	0.4018
t-stat	(1.13)	(-0.75)	(1.21)	(1.48)	(0.97)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of the innovation factor (*FINV*) of a modified measure of business strategy (i.e. excluding historical growth or investment opportunities (*REV5*)) identified by the principal component analyses. *FINV* is the sum of quintile ranks of research intensity (*RDS5*) and marketing and advertising efforts (*SGA5*), and thus it is a score ranging from 2 to 10.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *FINV* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *FINV* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *FINV* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *FINV*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *FINV* and sells portfolio 1 of *FINV*.

Panels C to E present firm-specific *FINV* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-FINV* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *FINV* factor mimicking portfolio (*High minus Low FINV* denoted as *HLFINV*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *FINV* from the value-weighted return on stocks in the highest portfolio of *FINV*. Panel C presents average coefficients across 5,485 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLFINV*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLFINV*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *FINV* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.11

Analyses of Efficiency Factor (*FEFF*) of a Modified Measure of Business Strategy: Operational Efficiency (*EMPS5*), Capital Intensity or Technological Efficiency (*CAP5*), and Organizational Stability (*TEMP5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *FEFF*

	Intercept	***BETA***	***SIZE***	***BM***	***FEFF***	R^2
Coefficient	1.5474	0.0042	-0.1097	0.1431	0.0100	0.0398
t-stat	(4.66)***	(0.03)	(-2.41)**	(1.32)	(0.24)	

Panel B: Time-series *FEFF* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	**1**	**2**	**3**	**4**	**5**	**Hedge (5-1)**
<u>Model 7.1.1</u>						
Intercept (α)	0.8307	0.7214	0.7710	0.7177	0.6403	-0.1905
t-stat	(3.50)***	(2.97)***	(3.06)***	(2.61)***	(2.39)**	(-2.19)**
<u>Model 7.1.2</u>						
Intercept (α)	0.3663	0.2305	0.2617	0.1652	0.1099	-0.2564
t-stat	(3.35)***	(2.40)**	(2.70)***	(1.26)	(0.94)	(-3.12)***
R_M-R_F	0.9888	1.0453	1.0872	1.1414	1.1284	0.1396
t-stat	(42.49)***	(51.09)***	(52.77)***	(40.83)***	(45.40)***	(8.01)***
<u>Model 7.1.3</u>						
Intercept (α)	0.1314	0.0465	0.0889	-0.0567	-0.1233	-0.2546
t-stat	(1.59)	(0.67)	(1.35)	(-0.56)	(-1.44)	(-3.07)***
R_M-R_F	0.9895	1.0220	1.0445	1.1028	1.1090	0.1195
t-stat	(52.81)***	(64.71)***	(70.13)***	(47.79)***	(57.07)***	(6.39)***
SMB	0.4360	0.4459	0.4997	0.5752	0.5199	0.0839
t-stat	(16.24)***	(19.71)***	(23.38)***	(17.43)***	(18.67)***	(3.13)***
HML	0.3871	0.2830	0.2405	0.3364	0.3667	-0.0204
t-stat	(13.67)***	(11.86)***	(10.67)***	(9.64)***	(12.49)***	(-0.72)
R^2	0.8849	0.9218	0.9353	0.8702	0.9026	0.1391
GRS *F*-statistic	3.20					
GRS-*P* value	0.0125					

Panel C: Average Returns and *FEFF* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***HLFEFF***	R^2
Coefficient	0.2131	0.9848	0.8622	0.2060	0.0240	0.2527
t-stat	(5.69)***	(80.91)***	(50.52)***	(10.61)***	(0.81)	

Table 8.11 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *FEFF*

	Intercept	R_M-R_F	*SMB*	*HML*	*HLFEFF*	R^2
Coefficient	0.0621	1.0394	0.5341	0.3771	0.0735	0.8350
t-stat	(2.48)**	(167.08)***	(10.63)***	(6.11)***	(1.14)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	B_{HLFEFF}	R^2
Coefficient	-1.2857	1.7012	0.5427	0.0696	-0.1980	0.3615
t-stat	(-0.77)	(1.00)	(1.59)	(0.22)	(-2.10)**	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of the efficiency factor (*FEFF*) of a modified measure of business strategy (i.e. excluding historical growth or investment opportunities (*REV5*)) identified by the principal component analyses. *FEFF* is the sum of quintile ranks of operational efficiency (*EMPS5*), capital intensity technological efficiency (*CAP5*) and organizational stability (*TEMP5*), and thus it is a score ranging from 3 to 15.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *FEFF* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *FEFF* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *FEFF* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *FEFF*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *FEFF* and sells portfolio 1 of *FEFF*.

Panels C to E present firm-specific *FEFF* factor loadings and regression results of the two-stage cross-sectional regression based on 25 *BM-FEFF* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *FEFF* factor mimicking portfolio (*High minus Low FEFF* denoted as *HLFEFF*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *FEFF* from the value-weighted return on stocks in the highest portfolio of *FEFF*. Panel C presents average coefficients across 5,485 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLFEFF*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLFEFF*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *FEFF* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.12

Individual Measure of Business Strategy Analyses: Marketing and Advertising Efforts using Marketing and Advertising Expenditure (*ADV5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *ADV5*

	Intercept	***BETA***	***SIZE***	***BM***	***ADV5***	R^2
Coefficient	1.0747	0.2723	-0.1075	0.1481	0.0628	0.1328
t-stat	(2.66)***	(1.76)*	(-1.56)	(0.73)	(1.34)	

Panel B: Time-series *ADV5* Portfolio Regressions of Monthly Excess returns on the Fama-French Three Factors

Portfolio number	**1**	**2**	**3**	**4**	**5**	**Hedge (5-1)**
<u>Model 7.1.1</u>						
Intercept (α)	1.1224	0.8625	0.9058	1.2424	0.9400	-0.1824
t-stat	(3.65)***	(2.78)***	(3.26)***	(3.74)***	(3.43)***	(-0.53)
<u>Model 7.1.2</u>						
Intercept (α)	0.4386	0.2527	0.3447	0.6558	0.4021	1.8814
t-stat	(2.61)***	(1.46)	(1.99)**	(2.71)***	(2.32)**	(0.01)
R_M-R_F	1.1307	1.1350	0.9747	1.0370	0.9628	-0.1679
t-stat	(31.35)***	(30.14)***	(26.03)***	(19.75)***	(25.54)***	(-3.99)***
<u>Model 7.1.3</u>						
Intercept (α)	0.3376	0.0769	0.1105	0.3412	0.2187	-0.1189
t-stat	(2.21)**	(0.48)	(0.71)	(1.49)	(1.30)	(-0.32)
R_M-R_F	1.0702	1.1326	0.9807	1.0707	0.9907	-0.0795
t-stat	(30.55)***	(30.36)***	(27.14)***	(20.31)***	(25.41)***	(-1.85)*
SMB	0.5100	0.4373	0.4776	0.4953	0.2587	-0.2514
t-stat	(9.98)***	(8.01)***	(9.07)***	(6.47)***	(4.57)***	(-3.68)***
HML	0.1378	0.3053	0.3972	0.5285	0.3215	0.1837
t-stat	(2.57)**	(5.37)***	(7.17)***	(6.55)***	(5.39)***	(2.84)***
R^2	0.7655	0.7406	0.6974	0.5527	0.6406	0.1013
GRS *F*-statistic	0.97					
GRS-*P* value	0.4208					

Panel C: Average Returns and *ADV5* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***HLADV5***	R^2
Coefficient	0.2683	0.9665	0.8455	0.2818	0.0077	0.2797
t-stat	(4.43)***	(44.25)***	(23.26)***	(8.14)***	(0.20)	

Table 8.12 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *ADV5*

	Intercept	R_M-R_F	***SMB***	***HML***	***HLADV5***	R^2
Coefficient	0.1672	1.0395	0.4511	0.3971	-0.0089	0.5876
t-stat	(3.16)***	(56.44)***	(7.36)***	(6.60)***	(-0.15)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	β_{HLADV5}	R^2
Coefficient	-4.0827	4.1151	1.9676	-0.3193	-0.4163	0.3185
t-stat	(-1.02)	(1.31)	(0.54)	(-0.14)	(-0.91)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of an individual measure of business strategy, namely marketing and advertising efforts (*ADV5*). *ADV5* is the quintile rank (by SIC 2-digit industry and year) of the ratio of marketing and advertising expenses [*XAD*] to sales [*SALE*] computed over a rolling prior five-year average.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *ADV5* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *ADV5* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *ADV5* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *ADV5*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *ADV5* and sells portfolio 1 of *ADV5*.

Panels C to E present firm-specific *ADV5* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-ADV5* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *ADV5* factor mimicking portfolio (*High minus Low ADV5* denoted as *HLADV5*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *ADV5* from the value-weighted return on stocks in the highest portfolio of *ADV5*. Panel C presents average coefficients across 1,391 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLADV5*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLADV5*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *ADV5* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 426 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.13

Analyses on Business Strategy Measure (*BS3*) Replacing Selling, General, and Administrative Expenditure (*SGA5*) with Marketing and Advertising Expenditure (*ADV5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *BS3*

	Intercept	***BETA***	***SIZE***	***BM***	***BS3***	R^2
Coefficient	0.9075	0.4880	-0.0909	0.1658	0.0062	0.1282
t-stat	(1.33)	(1.96)*	(-1.32)	(0.50)	(0.21)	

Panel B: Time-series *BS3* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	**1 (Defender)**	**2 (Lower Analyzer)**	**3 (Upper Analyzer)**	**4 (Prospector)**	**Hedge (4-1)**
<u>Model 7.1.1</u>					
Intercept (α)	0.8044	0.9757	0.8959	0.8453	0.0409
t-stat	(2.73)***	(3.65)***	(3.18)***	(2.11)**	(0.16)
<u>Model 7.1.2</u>					
Intercept (α)	0.4152	0.4153	0.2786	0.1657	-0.2495
t-stat	(1.68)*	(2.84)***	(1.85)*	(0.55)	(-0.94)
R_M-R_F	0.6732	0.9736	1.0557	1.1534	0.4802
t-stat	(12.63)***	(31.02)***	(32.53)***	(17.70)***	(6.22)***
<u>Model 7.1.3</u>					
Intercept (α)	0.1628	0.2058	0.1023	0.0927	-0.0701
t-stat	(0.70)	(1.63)	(0.72)	(0.32)	(-0.46)
R_M-R_F	0.7130	0.9985	1.0705	1.0610	0.3480
t-stat	(13.57)***	(34.61)***	(32.96)***	(15.93)***	(4.48)***
SMB	0.4835	0.4093	0.3272	0.6480	0.1645
t-stat	(6.32)***	(9.71)***	(6.93)***	(6.63)***	(1.40)
HML	0.5281	0.4361	0.3191	0.0649	-0.4632
t-stat	(6.48)***	(9.91)***	(6.41)***	(0.64)	(-3.39)
R^2	0.4123	0.7884	0.7615	0.5004	0.1397
GRS *F*-statistic	0.57				
GRS-*P* value	0.6836				

Panel C: Average Returns and *BS3* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***PMD3***	R^2
Coefficient	0.3066	0.9689	0.7720	0.3145	0.0677	0.2811
t-stat	(4.88)***	(45.66)***	(22.68)***	(8.78)***	(4.14)***	

Table 8.13 (Continued)

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BS3*

	Intercept	R_M-R_F	*SMB*	*HML*	*PMD3*	R^2
Coefficient	0.1224	0.9496	0.5234	0.3908	0.0810	0.5074
t-stat	(1.37)	(26.27)***	(7.51)***	(4.77)***	(0.89)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	β_{PMD3}	R^2
Coefficient	0.7568	0.1988	0.2336	-0.2177	0.2700	0.3981
t-stat	(0.23)	(0.06)	(0.10)	(-0.17)	(0.12)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 on an aggregate business strategy measure computed by replacing selling, general, and administrative expenditure (*SGA5*) with marketing and advertising expenditure (*ADV5*), denoted as *BS3*. *ADV5* is the quintile rank (by SIC 2-digit industry and year) of the ratio of marketing and advertising expenses [*XAD*] to sales [*SALE*] computed over a rolling prior five-year average.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *BS3* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *BS3* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *BS3* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into four portfolios based on *BS3*: defender (6-12); lower analyzer (13-17); upper analyzer (18-23); prospector (24-30). Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS3* (i.e. prospector) and sells portfolio 1 of *BS3* (i.e. defender).

Panels C to E present firm-specific *BS3* factor loadings and regression results of the two-stage cross-sectional regressions based on 20 *BM-BS3* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *BS3* factor mimicking portfolio (*Prospector minus Defender* denoted as *PMD3*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS3* from the value-weighted return on stocks in the highest portfolio of *BS3*. Panel C presents average coefficients across 1,391 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *PMD3*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMD3*. The 20 portfolios are created by sorting stocks into quintiles based on *BM* and four portfolios based on *BS3* each month (i.e. defender, lower analyzer, upper analyzer, and prospector). *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 396 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.14

Analyses on Modified Business Strategy Measure Exclusive of Historical Growth and Investment Opportunities Replacing Selling, General and Administrative Expenditure with Marketing and Advertising Expenditure (*BS4*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *BS4*

	Intercept	***BETA***	***SIZE***	***BM***	***BS4***	R^2
Coefficient	0.9686	0.2680	-0.1135	0.1244	0.0217	0.1325
t-stat	(2.24)**	(1.72)*	(-1.40)	(0.58)	(0.83)	

Panel B: Time-series *BS4* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	**1 (Defender)**	**2 (Lower Analyzer)**	**3 (Upper Analyzer)**	**4 (Prospector)**	**Hedge (4-1)**
<u>Model 7.1.1</u>					
Intercept (α)	0.9753	1.0441	1.0591	0.7338	-0.2416
t-stat	(3.35)***	(3.71)***	(3.62)***	(2.22)**	(-0.45)
<u>Model 7.1.2</u>					
Intercept (α)	0.5424	0.4604	0.4766	0.1309	-0.4115
t-stat	(2.35)**	(2.81)***	(2.59)***	(0.57)	(-1.06)
R_M-R_F	0.7816	1.0164	1.0297	1.0792	0.2976
t-stat	(15.55)***	(28.80)***	(25.76)***	(21.60)***	(4.98)***
<u>Model 7.1.3</u>					
Intercept (α)	0.3212	0.2436	0.2616	-0.1126	-0.4338
t-stat	(1.44)	(1.67)	(1.48)	(-0.52)	(-1.13)
R_M-R_F	0.7971	1.0189	1.0533	1.0497	0.2527
t-stat	(15.51)***	(30.37)***	(25.82)***	(20.99)***	(4.11)***
SMB	0.4160	0.4790	0.3364	0.5928	0.1768
t-stat	(5.57)***	(9.84)***	(5.68)***	(8.16)***	(2.23)**
HML	0.3844	0.3914	0.3619	0.3254	-0.0590
t-stat	(4.82)***	(7.61)***	(5.80)***	(4.25)***	(0.00)
R^2	0.442	0.7455	0.6545	0.5935	0.0722
GRS *F*-statistic	1.00				
GRS-*P* value	0.4064				

Panel C: Average Returns and *BS4* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***PMD4***	R^2
Coefficient	0.3640	0.9702	0.8081	0.2775	0.0491	0.2776
t-stat	(5.81)***	(45.92)***	(23.85)***	(7.83)***	(2.47)**	

Table 8.14 (Continued)

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BS4*

	Intercept	R_M-R_F	*SMB*	*HML*	*PMD4*	R^2
Coefficient	0.1520	0.9714	0.4962	0.4106	0.0375	0.5244
t-stat	(2.03)*	(38.18)***	(8.20)***	(6.78)***	(0.50)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	β_{PMD4}	R^2
Coefficient	8.6265	-5.1313	-9.7568	7.5937	1.0468	0.3831
t-stat	(0.56)	(-0.36)	(-0.78)	(0.60)	(0.76)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 on a modified business strategy measure exclusive of historical growth or investment opportunities computed by replacing selling, general, and administrative expenditure (*SGA5*) with marketing and advertising expenditure (*ADV5*), denoted as *BS4*. *ADV5* is the quintile rank (by SIC 2-digit industry and year) of the ratio of marketing and advertising expenses [*XAD*] to sales [*SALE*] computed over a rolling prior five-year average.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *BS4* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *BS4* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *BS4* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into four portfolios based on *BS4*: defender (5-10); lower analyzer (11-15); upper analyzer (16-19); prospector (20-25).. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS4* (i.e. prospector) and sells portfolio 1 of *BS4* (i.e. defender).

Panels C to E present firm-specific *BS4* factor loadings and regression results of the two-stage cross-sectional regressions based on 20 *BM-BS4* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *BS4* factor mimicking portfolio (*Prospector minus Defender* denoted as *PMD4*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS4* from the value-weighted return on stocks in the highest portfolio of *BS4*. Panel C presents average coefficients across 1,391 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *PMD4*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMD4*. The 20 portfolios are created by sorting stocks into quintiles based on *BM* and four portfolios based on *BS4* each month (i.e. defender, lower analyzer, upper analyzer, and prospector). *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 426 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.15

Analyses of Modified Innovation Factor (*FINV2*): Research Intensity (*RDS5*) and Marketing and Advertising Efforts (*ADV5*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *FINV2*

	Intercept	*BETA*	*SIZE*	*BM*	*FINV2*	R^2
Coefficient	0.9305	0.2515	-0.1237	0.1595	0.1459	0.1321
t-stat	(2.41)**	(1.61)	(-1.62)	(0.79)	(2.45)**	

Panel B: Time-series *FINV2* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	1	2	3	4	5	Hedge (5-1)
Model 7.1.1						
Intercept (α)	0.7129	0.9622	1.2810	0.9269	1.0281	0.3152
t-stat	(2.25)**	(3.42)***	(4.11)***	(2.73)***	(3.76)***	(1.14)
Model 7.1.2						
Intercept (α)	0.1361	0.4056	0.6995	0.3164	0.4707	0.3346
t-stat	(0.63)	(2.37)**	(3.27)***	(1.30)	(2.90)***	(1.23)
R_M-R_F	1.0333	1.0053	1.0281	1.0360	0.9976	-0.0356
t-stat	(21.99)***	(27.11)***	(22.14)***	(19.76)***	(28.23)***	(-0.79)
Model 7.1.3						
Intercept (α)	-0.0964	0.1915	0.3982	0.1396	0.4486	0.5450
t-stat	(-0.47)	(1.21)	(2.04)**	(0.59)	(2.74)***	(2.14)**
R_M-R_F	1.0316	1.0167	1.0327	1.0600	0.9691	-0.0625
t-stat	(21.99)***	(27.79)***	(22.85)***	(19.43)***	(25.57)***	(-1.25)
SMB	0.5273	0.4207	0.5784	0.3477	0.1508	-0.3765
t-stat	(7.71)***	(7.90)***	(8.82)***	(4.34)***	(2.74)***	(-4.54)***
HML	0.3977	0.3815	0.4645	0.3555	-0.0099	-0.4076
t-stat	(5.53)***	(6.80)***	(6.71)***	(4.29)***	(-0.17)	(-4.71)***
R^2	0.6079	0.6993	0.6260	0.5330	0.6594	0.0783
GRS *F*-statistic	2.35					
GRS-P value	0.0502					

Panel C: Average Returns and *FINV2* Factor Loadings

	Intercept	R_M-R_F	*SMB*	*HML*	*HLFINV2*	R^2
Coefficient	0.3699	0.9865	0.7835	0.2504	-0.0401	0.2752
t-stat	(6.04) ***	(48.13)***	(21.36)***	(6.85)***	(-1.62)	

Table 8.15 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *FINV2*

	Intercept	R_M-R_F	*SMB*	*HML*	*HLFINV2*	R^2
Coefficient	0.1734	1.0366	0.4672	0.3328	-0.0154	0.5399
t-stat	(3.21)***	(48.85)***	(7.73)***	(5.90)***	(-0.23)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	$\beta_{HLFINV2}$	R^2
Coefficient	-1.9158	2.7692	-0.4202	0.8996	0.7680	0.3257
t-stat	(-0.75)	(0.94)	(-0.27)	(0.84)	(2.05)**	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of the modified innovation factor (*FINV2*). *FINV2* is the sum of quintile ranks of research intensity (*RDS5*) and marketing and advertising efforts (*ADV5* replacing *SGA5*), and thus it is a score ranging from 2 to 10. *ADV5* is the quintile rank (by SIC 2-digit industry and year) of the ratio of marketing and advertising expenses [*XAD*] to sales [*SALE*] computed over a rolling prior five-year average.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *FINV2* from 1 January 1972 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *FINV2* measure each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *FINV2* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *FINV2*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *FINV2* and sells portfolio 1 of *FINV2*.

Panels C to E present firm-specific *FINV2* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-FINV2* portfolios. For each month, from 1 January 1972 to 31 December 2010, a *FINV2* factor mimicking portfolio (*High minus Low FINV2* denoted as *HLFINV2*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *FINV2* from the value-weighted return on stocks in the highest portfolio of *FINV2*. Panel C presents average coefficients across 1,391 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLFINV2*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLFINV2*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *FINV2* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 426 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.16
Industry Analyses on Business Strategy Measure (*BS*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *BS*

	Manufacturing		Services		Other	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
Intercept	1.1481	3.42***	1.8096	2.48**	1.4995	3.71***
BETA	0.1502	1.08	0.2953	1.41	-0.0672	-0.55
SIZE	-0.0972	-2.17**	-0.1054	-1.62	-0.0720	-1.61
BM	0.2461	2.87***	0.1195	0.82	0.3074	2.52**
BS	0.0122	0.98	-0.0321	-1.18	-0.0131	-0.85
R^2	0.0514		0.1027		0.0575	

Panel B: Time-series *BS* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

	Portfolio number	Intercept (α)	*t*-stat	R_M-R_F	*t*-stat	*SMB*	*t*-stat	*HML*	*t*-stat	R^2
Manufacturing	**1 (Defender)**	0.0315	0.23	1.0307	34.05***	0.5335	12.20***	0.5833	12.68***	0.8156
	2 (Lower Analyzer)	0.0657	0.84	1.0338	58.96***	0.3828	15.19***	0.4926	18.51***	0.9031
	3 (Upper Analyzer)	0.0503	0.71	1.0659	66.89***	0.4993	21.79***	0.2237	9.24***	0.9307
	4 (Prospector)	0.1943	1.64	1.1085	41.62***	0.5544	14.42***	-0.1883	-4.65***	0.8603
	Hedge (4-1)	0.1628	0.82	0.0778	2.03**	0.0208	0.48	-0.7716	-13.13***	0.3303
	GRS *F*-statistic	0.58								
	GRS-*P* value	0.6782								

	Portfolio number	Intercept (α)	*t*-stat	R_M-R_F	*t*-stat	*SMB*	*t*-stat	*HML*	*t*-stat	R^2
Services	**1 (Defender)**	0.0873	0.26	1.0987	14.11***	0.5810	5.06***	0.3447	2.92***	0.3939
	2 (Lower Analyzer)	0.2887	1.37	1.0207	21.62***	0.8728	12.75***	0.3806	5.30***	0.6371
	3 (Upper Analyzer)	-0.0245	-0.19	1.0402	35.55***	0.7459	17.58***	0.1250	2.81***	0.8213
	4 (Prospector)	-0.0340	-0.13	1.3000	21.26***	0.5389	6.05***	0.0133	0.14	0.5901
	Hedge (4-1)	-0.1213	-0.29	0.2013	2.03**	-0.0421	-0.18	-0.3314	-2.04**	0.0307
	GRS *F*-statistic	0.99								
	GRS-*P* value	0.4102								

Table 8.16 (Continued)

	Portfolio number	Intercept (α)	*t*-stat	R_M-R_F	*t*-stat	*SMB*	*t*-stat	*HML*	*t*-stat	R^2
Other	1 (Defender)	-0.1966	-0.78	0.9625	16.93***	0.6040	7.39***	0.5623	6.51***	0.4726
	2 (Lower Analyzer)	-0.0376	-0.28	1.0076	33.77***	0.4796	11.19***	0.4482	9.91***	0.764
	3 (Upper Analyzer)	-0.1662	-1.63	1.0955	47.70***	0.5114	15.49***	0.3876	11.11***	0.8682
	4 (Prospector)	-0.3705	-2.31**	1.1885	32.88***	0.4495	8.65***	0.3729	6.79***	0.7493
	Hedge (4-1)	-0.1738	-0.64	0.2260	3.70***	-0.1544	-1.76*	-0.1894	-2.04**	0.0497
	GRS *F*-statistic	2.81								
	GRS-*P* value	0.0245								

Panel C: Average Returns and *BS* Factor Loadings

	Manufacturing		Services		Other	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Intercept	0.0598	1.19	0.3531	3.17***	-0.0681	-0.99
R_M-R_F	1.0261	49.53***	0.9830	30.41***	0.9614	41.62***
SMB	0.8333	34.88***	0.7969	15.75***	0.8099	24.41***
HML	0.2302	9.04***	0.0295	0.53	0.3578	10.32***
PMD	-0.0064	-0.36	0.0706	3.18***	0.0137	1.03
R^2	0.2563		0.2605		0.2432	

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BS*

	Manufacturing		Services		Other	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Intercept	0.1237	2.14**	0.0433	0.36	-0.1706	-2.22**
R_M-R_F	1.0588	103.05***	1.0937	26.20***	1.0730	42.64***
SMB	0.5763	8.26***	0.7342	12.16***	0.5509	7.90***
HML	0.2850	4.56***	0.2280	2.68***	0.4744	6.99***
PMD	-0.0778	-0.98	-0.0732	-0.93	-0.1221	-1.47
R^2	0.7315		0.4302		0.5488	

Table 8.16 (Continued)

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Manufacturing		Services		Other	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
Intercept	0.5793	0.49	1.0863	1.14	-0.9070	-0.87
β_{RM-RF}	-0.1969	-0.17	-0.0387	-0.04	1.2117	1.22
β_{SMB}	0.9756	1.91*	-0.4495	-0.56	0.4455	0.53
β_{HML}	0.0212	0.05	0.8798	1.36	0.2495	0.33
β_{PMD}	-0.0481	-0.22	0.5320	0.55	-0.2962	-0.85
R^2	0.4191		0.3681		0.4174	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 on business strategy measure (*BS*) for three broad industries: Manufacturing (two-digit SIC 20-39), Services (two-digit SIC 70-89) and Other. Firm-year observations from Manufacturing, Services and Other industries represent 61.05%, 12.03% and 26.92% of the full sample, respectively.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *BS*. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *BS* measure each April. Parameter estimates are time-series averages of the parameters from the monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *BS* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, all firm-years in the sample are sorted into four portfolios based on *BS*: defender (6-12); lower analyzer (13-17); upper analyzer (18-23); prospector (24-30). The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts are jointly equal to zero. The row "Hedge 4-1" presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS* (i.e. prospector) and sells portfolio 1 of *BS* (i.e. defender).

Panels C to E present firm-specific *BS* factor loadings and regression results of the two-stage cross-sectional regressions based on 20 *BM-BS* portfolios. For each month, a *BS* factor mimicking portfolio (*Prospector minus Defender* denoted as *PMD*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS* from the value-weighted return on stocks in the highest portfolio of *BS*. Panel C presents average coefficients for firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *PMD*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMD*. The 20 portfolios are created by sorting stocks into quintiles based on *BM* and four portfolios based on *BS* each month (i.e. defender, lower analyzer, upper analyzer, and prospector). *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.17
Industry Analyses on Modified Business Strategy Measure Exclusive of Historical Growth or Investment Opportunities (*BS2*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *BS2*

	Manufacturing		Services		Other	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
Intercept	1.0041	3.20***	1.3555	2.28**	1.3095	3.64***
BETA	0.0153	0.11	0.8447	0.80	0.0373	0.31
SIZE	-0.0715	-1.67*	-0.4136	-0.95	-0.1142	-2.39**
BM	0.2863	3.44***	0.2720	1.39	0.2015	1.93*
BS2	0.0225	1.51	0.0070	0.24	0.0049	0.28
R^2	0.0503		0.1026		0.0573	

Panel B: Time-series *BS2* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

	Portfolio number	Intercept (α)	*t*-stat	R_M-R_F	*t*-stat	*SMB*	*t*-stat	*HML*	*t*-stat	R^2
Manufacturing	**1 (Defender)**	0.0349	0.31	1.0333	40.41***	0.4289	11.71***	0.5010	12.96***	0.8140
	2 (Lower Analyzer)	-0.0209	-0.27	1.0405	59.40***	0.4110	16.37***	0.4773	18.02***	0.9036
	3 (Upper Analyzer)	0.1597	2.04**	1.0653	60.00***	0.5386	21.17***	0.1870	6.97***	0.9159
	4 (Prospector)	0.1927	1.67*	1.1105	42.56***	0.5613	15.02***	-0.0887	-2.25**	0.8583
	Hedge (4-1)	0.1578	1.00	0.0772	2.16**	0.1324	2.58**	-0.5897	-10.90***	0.2807
	GRS *F*-statistic	1.67								
	GRS-*P* value	0.1551								
	Portfolio number	**Intercept (α)**	***t*-stat**	R_M-R_F	***t*-stat**	***SMB***	***t*-stat**	***HML***	***t*-stat**	R^2
Services	**1 (Defender)**	0.4353	1.47	0.9470	14.13***	0.8255	8.48***	0.3441	3.37***	0.4310
	2 (Lower Analyzer)	0.1731	1.21	1.0618	32.77***	0.6869	14.76***	0.3358	6.84***	0.7777
	3 (Upper Analyzer)	0.0349	0.27	1.0434	35.83***	0.7789	18.64***	0.0582	1.32	0.8279
	4 (Prospector)	-0.0982	-0.28	1.1810	14.84***	0.8885	7.70***	-0.0339	-0.28	0.4641
	Hedge (4-1)	-0.5335	-1.14	0.2340	2.04**	0.0630	0.39	-0.3780	-2.38**	0.0358
	GRS *F*-statistic	0.91								
	GRS-*P* value	0.4576								

Table 8.17 (Continued)

	Portfolio number	Intercept (α)	*t*-stat	R_M-R_F	*t*-stat	*SMB*	*t*-stat	*HML*	*t*-stat	R^2
Other	**1 (Defender)**	-0.0705	-0.35	0.9507	20.64***	0.5318	8.06***	0.5096	7.32***	0.5554
	2 (Lower Analyzer)	-0.0533	-0.44	1.0443	38.03***	0.5026	12.80***	0.4839	11.66***	0.801
	3 (Upper Analyzer)	-0.0794	-0.80	1.0984	48.54***	0.4597	14.18***	0.4025	11.77***	0.8657
	4 (Prospector)	-0.3196	-2.14**	1.1460	33.79***	0.5386	11.08***	0.3282	6.40***	0.7664
	Hedge (4-1)	-0.2491	-1.12	0.1953	3.89***	0.0068	0.09	-0.1814	-2.39**	0.0625
	GRS *F*-statistic	1.56								
	GRS-*P* value	0.1815								

Panel C: Average Returns and *BS2* Factor Loadings

	Manufacturing		Services		Other	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
Intercept	0.1246	2.45**	0.4186	3.86***	-0.0281	-0.40
R_M-R_F	1.0019	49.01***	0.9951	30.33***	0.9868	44.86***
SMB	0.8497	30.71***	0.8563	18.70***	0.8260	26.15***
HML	0.2668	10.63***	0.0225	0.42	0.3733	11.14***
PMD2	0.0912	4.47***	0.0480	2.52**	0.0035	0.20
R^2	0.2565		0.2578		0.2429	

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BS2*

	Manufacturing		Services		Other	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
Intercept	0.0928	2.55**	0.2474	2.08**	-0.1098	-1.81*
R_M-R_F	1.0598	108.39***	0.9993	39.99***	1.0551	61.21***
SMB	0.5525	8.87***	0.8615	12.25***	0.6004	8.03***
HML	0.3440	5.38***	0.2011	2.88***	0.4516	6.51***
PMD2	0.0037	0.04	0.0254	0.35	-0.0939	-1.11
R^2	0.7801		0.4060		0.5902	

Table 8.17 (Continued)

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Manufacturing		Services		Other	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
Intercept	-0.9645	-0.63	0.6003	0.43	1.2990	1.14
β_{RM-RF}	1.2994	0.84	-0.3502	-0.28	-0.8904	-0.82
β_{SMB}	0.9216	2.86***	0.8275	1.48	0.1834	0.42
β_{HML}	-0.0365	-0.08	0.1923	0.38	0.5079	1.24
β_{PMD2}	0.2914	0.88	-0.0836	-0.11	-0.0937	-0.36
R^2	0.4289		0.3266		0.4035	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 using a modified business strategy measure exclusive of historical growth or investment opportunities (*BS2*) for three broad industries: Manufacturing (two-digit SIC 20-39), Services (two-digit SIC 70-89) and Other. Firm-year observations from Manufacturing, Services and Other industries represent 60.80%, 12.16% and 27.04% of the full sample, respectively.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *BS2*. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *BS2* measure each April. Parameter estimates are time-series averages of the parameters from the monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *BS2* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, all firm-years in the sample are sorted into four portfolios based on *BS2*: defender (5-10); lower analyzer (11-15); upper analyzer (16-19); prospector (20-25). The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts are jointly equal to zero. The row "Hedge 4-1" presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS2* (i.e. prospector) and sells portfolio 1 of *BS2* (i.e. defender).

Panels C to E present firm-specific *BS2* factor loadings and regression results of the two-stage cross-sectional regressions based on 20 *BM-BS2* portfolios. For each month, a *BS2* factor mimicking portfolio (*Prospector minus Defender* denoted as *PMD2*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS2* from the value-weighted return on stocks in the highest portfolio of *BS2*. Panel C presents average coefficients for firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *PMD2*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMD2*. The 20 portfolios are created by sorting stocks into quintiles based on *BM* and four portfolios based on *BS2* each month (i.e. defender, lower analyzer, upper analyzer, and prospector). *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.18
Industry Analyses on the Innovation Factor (*FINV*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *FINV*

	Manufacturing		Services		Other	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
Intercept	0.9235	2.82***	0.9518	1.48	1.2813	3.78***
BETA	0.0425	0.34	1.1851	1.09	0.0664	0.54
SIZE	-0.0526	-1.19	-0.4080	-0.93	-0.1199	-2.54**
BM	0.3927	3.96***	-0.0827	-0.23	0.1455	1.07
FINV	0.1082	2.73***	-0.1573	-0.97	0.0259	0.51
R^2	0.0509		0.1031		0.0571	

Panel B: Time-series *FINV* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

	Portfolio number	Intercept (α)	*t*-stat	R_M-R_F	*t*-stat	*SMB*	*t*-stat	*HML*	*t*-stat	R^2
Manufacturing	**1**	-0.0920	-0.95	1.0650	48.50***	0.5081	16.15***	0.5381	16.21***	0.8674
	2	-0.0714	-0.84	1.0673	55.58***	0.4267	15.51***	0.5264	18.13***	0.8913
	3	0.0566	0.65	1.0421	52.84***	0.4317	15.27***	0.4517	15.12***	0.8834
	4	0.1798	2.34**	1.0230	58.81***	0.4809	19.30***	0.1343	5.11***	0.9121
	5	0.3126	2.84***	1.0868	43.54***	0.5499	15.38***	-0.2191	-5.81***	0.8703
	Hedge (5-1)	0.4046	2.82***	0.0218	0.67	0.0418	0.90	-0.7572	-15.41***	0.3787
	GRS *F*-statistic	2.44								
	GRS-*P* value	0.0452								

	Portfolio number	Intercept (α)	*t*-stat	R_M-R_F	*t*-stat	*SMB*	*t*-stat	*HML*	*t*-stat	R^2
Services	**1**	-0.1159	-0.47	1.0812	19.72***	0.7203	9.07***	0.5561	6.70***	0.5545
	2	0.1673	1.11	1.0095	29.66***	0.7878	16.12***	0.3214	6.23***	0.759
	3	-0.0169	-0.09	1.1108	24.80***	0.8899	13.85***	0.3454	5.08***	0.6933
	4	0.1001	0.54	1.0593	25.41***	0.7858	13.14***	-0.0003	0.00	0.7111
	5	0.0836	0.37	1.1154	21.77***	0.7390	10.03***	-0.2243	-2.88***	0.6552
	Hedge (5-1)	0.1995	0.40	0.0342	0.66	0.0187	0.59	-0.7804	-6.74***	0.1134
	GRS *F*-statistic	0.78								
	GRS-*P* value	0.5366								

Table 8.18 (Continued)

	Portfolio number	Intercept (α)	*t*-stat	R_M-R_F	*t*-stat	*SMB*	*t*-stat	*HML*	*t*-stat	R^2
Other	**1**	-0.1297	-0.71	0.9806	23.80***	0.2819	4.77***	0.3752	6.00***	0.5938
	2	-0.0685	-0.56	1.0456	37.60***	0.5253	13.21***	0.4725	11.24***	0.7997
	3	-0.1445	-1.18	1.1310	40.64***	0.4433	11.12***	0.4634	11.01***	0.8153
	4	-0.1014	-1.01	1.0721	47.07***	0.4970	15.23***	0.4349	12.63***	0.861
	5	-0.1928	-0.94	1.0466	22.47***	0.6204	9.28***	0.1215	1.72*	0.6239
	Hedge (5-1)	-0.0631	-0.29	0.0661	1.67*	0.3385	3.95***	-0.2537	-2.50**	0.0801
	GRS *F*-statistic	0.86								
	GRS-*P* value	0.4845								

Panel C: Average Returns and *FINV* Factor Loadings

	Manufacturing		Services		Other	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
Intercept	0.0992	1.86*	0.2108	1.70*	0.0083	0.11
R_M-R_F	1.0047	50.71***	0.9761	28.73***	0.9686	43.53***
SMB	0.8624	33.00***	0.8099	16.82***	0.7846	21.87***
HML	0.2718	10.55***	0.1313	2.25**	0.3645	10.42***
HLFINV	0.0819	3.17***	0.1870	5.38***	0.0793	3.27***
R^2	0.2574		0.2597		0.2415	

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *FINV*

	Manufacturing		Services		Other	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
Intercept	0.1197	4.13***	0.1156	0.82	-0.0896	-1.75*
R_M-R_F	1.0569	116.45***	0.9821	15.75***	1.0524	83.46***
SMB	0.5585	9.70***	0.7807	16.36***	0.5558	8.26***
HML	0.2999	5.38***	0.1799	2.67**	0.4199	6.31***
HLFINV	-0.0529	-0.76	-0.0277	-0.49	0.0257	0.36
R^2	0.7958		0.3687		0.5612	

Table 8.18 (Continued)

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Manufacturing		**Services**		**Other**	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
Intercept	2.9620	1.47	-0.2150	-0.14	0.6193	0.42
$\beta_{RM\text{-}RF}$	-2.4595	-1.27	1.3603	0.71	-0.0690	-0.05
β_{SMB}	0.6350	2.17**	-0.6199	-0.54	-0.4589	-0.87
β_{HML}	0.2680	0.84	1.1343	1.04	0.8864	1.82*
β_{HLFINV}	-0.1485	-0.42	0.6483	0.76	0.3027	0.86
R^2	0.3710		0.2620		0.3310	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 on the innovation factor (*FINV*) of a modified measure of business strategy (i.e. excluding historical growth or investment opportunities (*REV5*)) identified by the principal component analyses, for three broad industries: Manufacturing (two-digit SIC 20-39), Services (two-digit SIC 70-89) and Other. *FINV* is the sum of quintile ranks of research intensity (*RDS5*) and marketing and advertising efforts (*SGA5*), and thus it is a score ranging from 2 to 10. Firm-year observations from Manufacturing, Services and Other industries represent 60.80%, 12.16% and 27.04% of the full sample, respectively.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *FINV*. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *FINV* measure each April. Parameter estimates are time-series averages of the parameters from the monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *FINV* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, all firm-years in the sample are sorted into quintiles based on *FINV*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts are jointly equal to zero. The row "Hedge 5-1" presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *FINV* and sells portfolio 1 of *FINV*.

Panels C to E present firm-specific *FINV* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-FINV* portfolios. For each month, a *FINV* factor mimicking portfolio (*High minus Low FINV* denoted as *HLFINV*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *FINV* from the value-weighted return on stocks in the highest portfolio of *FINV*. Panel C presents average coefficients across firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLFINV*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLFINV*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *FINV* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates. Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Table 8.19
Industry Analyses on the Efficiency Factor (*FEFF*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *FEFF*

	Manufacturing		Services		Other	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
Intercept	1.9426	3.21***	1.3741	2.57**	1.3578	3.73***
BETA	-0.1228	-0.48	0.8851	0.83	0.0456	0.37
SIZE	-0.1599	-1.78*	-0.4340	-0.99	-0.1088	-2.33**
BM	0.0025	0.01	0.2245	1.21	0.2114	2.05**
FEFF	0.0195	0.30	0.0182	0.31	0.0011	0.03
R^2	0.0490		0.1008		0.0549	

Panel B: Time-series *FEFF* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

	Portfolio number	Intercept (α)	*t*-stat	R_M-R_F	*t*-stat	*SMB*	*t*-stat	*HML*	*t*-stat	R^2
Manufacturing	**1**	0.1537	1.88*	1.0094	54.34***	0.3795	14.26***	0.3832	13.65***	0.8869
	2	0.0933	1.20	1.0317	58.56***	0.4421	17.51***	0.2994	11.24***	0.9054
	3	0.0840	1.17	1.0473	64.27***	0.4654	19.91***	0.2080	8.43***	0.9230
	4	0.0543	0.71	1.0733	62.19***	0.5457	22.07***	0.2639	10.12***	0.9201
	5	-0.1185	-1.21	1.1155	50.08***	0.5280	16.55***	0.3590	10.66***	0.8775
	Hedge (5-1)	-0.2722	-2.74***	0.1061	4.72***	0.1485	4.61***	-0.0242	-0.71	0.1260
	GRS *F*-statistic	1.75								
	GRS-*P* value	0.1359								

	Portfolio number	Intercept (α)	*t*-stat	R_M-R_F	*t*-stat	*SMB*	*t*-stat	*HML*	*t*-stat	R^2
Services	**1**	0.2374	1.05	0.9137	17.93***	0.9772	13.36***	0.2028	2.63***	0.5923
	2	-0.0215	-0.11	1.0430	23.42***	0.6498	10.17***	0.0889	1.32	0.6552
	3	0.1285	0.77	1.0610	28.04***	0.7353	13.54***	0.0170	0.30	0.7423
	4	-0.0570	-0.30	1.1329	26.24***	0.6723	10.84***	0.3102	4.74***	0.6865
	5	0.0020	0.01	1.0417	26.78***	0.7929	14.20***	0.3110	5.28***	0.7177
	Hedge (5-1)	-0.2354	-0.91	0.1280	2.19**	-0.1843	-2.19**	0.1082	1.22	0.0188
	GRS *F*-statistic	0.42								
	GRS-*P* value	0.7943								

Table 8.19 (Continued)

	Portfolio number	Intercept (α)	*t*-stat	R_M-R_F	*t*-stat	*SMB*	*t*-stat	*HML*	*t*-stat	R^2
Other	1	0.0379	0.25	0.9579	28.22***	0.5515	11.34***	0.5069	9.88***	0.7024
	2	-0.0782	-0.61	0.9807	33.65***	0.3931	9.41***	0.3258	7.37***	0.7589
	3	-0.0803	-0.65	1.1049	39.35***	0.5142	12.80***	0.4754	11.20***	0.8107
	4	-0.1146	-0.98	1.0991	41.43***	0.5171	13.60***	0.4277	10.66***	0.8285
	5	-0.1917	-1.61	1.1182	41.46***	0.4468	11.56***	0.4124	10.12***	0.8229
	Hedge (5-1)	-0.2296	-1.61	0.1603	4.97***	-0.1048	-2.27**	-0.0945	-1.94*	0.0720
	GRS *F*-statistic	1.03								
	GRS-*P* value	0.3926								

Panel C: Average Returns and *FEFF* Factor Loadings

	Manufacturing		Services		Other	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Intercept	0.1375	1.32	0.1906	1.68*	-0.0299	-0.42
R_M-R_F	1.0301	20.79***	1.0298	31.39***	1.0121	43.95***
SMB	0.8228	17.99***	0.8518	18.21***	0.8086	25.74***
HML	0.2124	7.49***	0.0909	1.63	0.3600	10.83***
HLFEFF	0.1530	4.12***	-0.2290	-7.15***	-0.1375	-3.56***
R^2	0.2544		0.2598		0.2461	

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *FEFF*

	Manufacturing		Services		Other	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Intercept	0.0928	3.45***	0.0783	0.80	-0.0595	-1.51
R_M-R_F	1.0399	109.66***	1.0238	42.66***	1.0680	72.91***
SMB	0.5058	10.10***	0.7917	15.92***	0.5294	9.02***
HML	0.3674	6.11***	0.2521	3.80***	0.4659	7.20***
HLFEFF	0.1379	2.17**	-0.0524	-0.74	-0.1038	-1.42
R^2	0.7977		0.3653		0.5982	

Table 8.19 (Continued)

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Manufacturing		Services		Other	
	Coefficient	***t*-stat**	**Coefficient**	***t*-stat**	**Coefficient**	***t*-stat**
Intercept	0.9985	1.45	0.7153	0.39	0.7965	1.11
β_{RM-RF}	-0.6118	-0.86	-0.7640	-0.52	-0.3690	-0.51
β_{SMB}	0.8026	2.57**	1.0974	1.27	-0.1539	-0.28
β_{HML}	0.2168	0.89	0.1160	0.24	0.8729	1.90*
β_{HLFEFF}	-0.1204	-0.92	0.2304	0.53	-0.1354	-0.84
R^2	0.3181		0.2430		0.2747	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 on the efficiency factor (*FEFF*) of a modified measure of business strategy (i.e. excluding historical growth or investment opportunities (*REV5*)) identified by the principal component analyses, for three broad industries: Manufacturing (two-digit SIC 20-39), Services (two-digit SIC 70-89) and Other. *FEFF* is the sum of quintile ranks of operational efficiency (*EMPS5*), capital intensity technological efficiency (*CAP5*) and organizational stability (*TEMP5*), and thus it is a score ranging from 3 to 15. Firm-year observations from Manufacturing, Services and Other industries represent 60.80%, 12.16% and 27.04% of the full sample, respectively.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *FEFF*. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *FEFF* measure each April. Parameter estimates are time-series averages of the parameters from the monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *FEFF* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, all firm-years in the sample are sorted into quintiles based on *FEFF*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts are jointly equal to zero. The row "Hedge 5-1" presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *FEFF* and sells portfolio 1 of *FEFF*.

Panels C to E present firm-specific *FEFF* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-FEFF* portfolios. For each month, a *FEFF* factor mimicking portfolio (*High minus Low FEFF* denoted as *HLFEFF*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *FEFF* from the value-weighted return on stocks in the highest portfolio of *FEFF*. Panel C presents average coefficients across firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLFEFF*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLFEFF*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *FEFF* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Appendix 7.1

Time-series Business Strategy Portfolio Regressions of 12 Month Buy-and-hold Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	1 (Defender)	2 (Lower Analyzer)	3 (Upper Analyzer)	4 (Prospector)	Hedge (4-1)
Model 7.1.1					
Intercept (α)	0.0159	0.0271	0.0421	0.0142	-0.0017
t-stat	(0.04)	(0.08)	(0.12)	(0.03)	(-0.01)
Model 7.1.2					
Intercept (α)	-0.5191	-0.4572	-0.5512	-0.6781	-0.1590
t-stat	(-1.74)*	(-1.72)*	(-2.00)**	(-2.07)**	(-0.68)
R_M-R_F	0.9558	0.9606	1.0600	1.2368	0.2810
t-stat	(15.14)***	(17.19)***	(18.21)***	(17.87)***	(5.71)***
Model 7.1.3					
Intercept (α)	-0.6584	-0.5999	-0.5503	-0.5289	0.1294
t-stat	(-2.21)**	(-2.27)**	(-2.01)**	(-1.64)	(0.58)
R_M-R_F	0.9156	0.9311	0.9636	1.0771	0.1615
t-stat	(13.68)***	(15.69)***	(15.69)***	(14.93)***	(3.24)***
SMB	0.4157	0.3647	0.3816	0.3611	-0.0547
t-stat	(4.23)***	(4.24)***	(4.23)***	(3.41)***	(-0.75)
HML	0.1469	0.1652	-0.1457	-0.4611	-0.6080
t-stat	(1.44)	(1.83)*	(-1.56)	(-4.20)***	(-8.03)***
R^2	0.3621	0.4160	0.4506	0.4554	0.1842
GRS *F*-statistic	1.79				
GRS-*P* value	0.1273				

This table presents results for time-series business strategy portfolio regressions of 12 month buy-and-hold monthly excess returns on the Fama-French three factors. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into four portfolios based on their business strategy scores (*BS*): defender (6-12); lower analyzer (13-17); upper analyzer (18-23); prospector (24-30). See Table 6.2 for a description of how *BS* is computed. Model 7.1.1 reports the parameter estimates from a regression of the 12 month buy-and-hold monthly portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the 12 month buy-and-hold monthly portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the 12 month buy-and-hold monthly portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. Portfolio excess returns equal to the value-weighted return on the portfolio less the risk-free rate. R_M-R_F is the market risk premium calculated as the value-weighted market return less the risk-free rate. *SML* is the value-weighted size-mimicking portfolio return. *HML* is the value-weighted *BM*-mimicking portfolio return. R_M, R_F, *SMB* and *HML* are obtained from Kenneth R. French's website through WRDS. Monthly returns are measured in percentages. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS* (i.e. prospector) and sells portfolio 1 of *BS* (i.e. defender). ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Appendix 7.2

Controlling for the Carhart's (1997) Momentum Factor

Panel A: Time-series Business Strategy Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors and the Carhart's (1997) Momentum Factor

Portfolio number	1 (Defender)	2 (Lower Analyzer)	3 (Upper Analyzer)	4 (Prospector)	Hedge (4-1)
Model 7.1.3					
Intercept (α)	0.0927	0.1438	0.1410	0.2136	0.1209
t-stat	(0.73)	(1.67)*	(2.41)**	(2.21)**	(0.80)
R_M-R_F	0.9897	0.9972	1.0372	1.1014	0.1116
t-stat	(34.66)***	(51.41)***	(79.02)***	(50.76)***	(3.29)***
SMB	0.5526	0.4310	0.5198	0.5214	-0.0312
t-stat	(13.70)***	(15.77)***	(28.03)***	(17.01)***	(-0.65)
HML	0.4991	0.4275	0.2089	-0.1065	-0.6056
t-stat	(11.47)***	(14.52)***	(10.44)***	(-3.22)***	(-11.69)***
UMD	-0.1304	-0.1136	-0.1616	-0.1967	-0.0663
t-stat	(-4.75)***	(-6.10)***	(-12.79)***	(-9.42)***	(-2.03)**
R^2	0.7977	0.8885	0.9546	0.9050	0.3029
GRS *F*-statistic	2.27				
GRS-*P* value	0.0591				

Panel B: Average Firm-Specific Factor Loadings

	Intercept	R_M-R_F	*SMB*	*HML*	*UMD*	*PMD*	R^2
Coefficient	0.1310	0.9641	0.8432	0.1810	-0.1400	0.0016	0.2754
t-stat	(3.40)***	(76.13)***	(43.98)***	(8.47)***	(-8.80)***	(0.10)	

Panel C: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BS*

	Intercept	R_M-R_F	*SMB*	*HML*	*UMD*	*PMD*	R^2
Coefficient	0.1756	1.0383	0.5699	0.2585	-0.1679	-0.1136	0.7939
t-stat	(5.16)***	(120.76)***	(9.64)***	(4.11)***	(-8.22)***	(-1.40)***	

Panel D: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	β_{UMD}	β_{PMD}	R^2
Coefficient	1.5567	-0.9830	0.2951	0.5658	0.0761	-0.0015	0.4840
t-stat	(1.38)	(-0.86)	(0.80)	(2.01)**	(0.10)	(-0.01)	

This table present sensitivity results controlling for the Carhart's (1997) momentum factor (i.e. buying stocks with higher past returns and selling stocks with lower past returns). Panel A reports results for time-series business strategy portfolio regressions of monthly excess returns on the Fama-French three factors and the Carhart's (1997) momentum factor. For each month, from 1 January 1972 to 31 December 2010, all firm-years in the sample are sorted into four portfolios based on their business strategy scores (*BS*): defender (6-12); lower analyzer (13-17); upper analyzer (18-23); prospector (24-30). See Table 6.2 for a description of how *BS* is computed. Portfolio excess returns equal to the value-weighted return on the portfolio less the risk-free rate. R_M-R_F is the market risk premium calculated as the value-weighted market return less the risk-free rate. *SML* is the value-weighted size-mimicking portfolio return. *HML* is the value-weighted *BM*-mimicking portfolio return. *UMD* is the value-weighted momentum-mimicking portfolio return. R_M, R_F, *SMB*, *HML* and *UMD* are obtained from Kenneth R. French's website through WRDS. Monthly returns are measured in percentages. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS* (i.e. prospector) and sells portfolio 1 of *BS* (i.e. defender).

Panels B to D present firm-specific business strategy factor loadings and regression results of the two-stage cross-sectional regression based on 20 *BM-BS* portfolios. For each month, from 1 January 1972 to 31 December 2010, a business strategy factor mimicking portfolio (*Prospector minus Defender* denoted as *PMD*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS* (i.e. defender) from the value-weighted return on stocks in the highest portfolio of *BS* (i.e. prospector). Panel B presents average coefficients across 5,238 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors, the Carhart's (1997) momentum factor, and *PMD*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel C presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors, the Carhart's (1997) momentum factor, and *PMD*. The 20 portfolios are created by sorting stocks in to quintiles based on *BM* and four portfolios of *BS* (i.e. defender, lower analyzer, upper analyzer, and prospector) each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel C). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Appendix 7.3
Average Excess Returns for 20 *Book-to-Market* and *Business Strategy* Portfolios

	1 (Defender)	2 (Lower Analyzer)	3 (Upper Analyzer)	4 (Prospector)
Low *BM*	-0.0609	0.4374	0.2376	0.3051
2	1.6515	0.7364	0.7156	0.8741
3	1.0504	1.0092	0.7808	1.4182
4	0.4879	1.0020	0.7834	0.5931
High *BM*	0.7448	1.2031	1.0079	0.8314

This appendix presents average excess returns for the 20 *BM-BS* portfolios over the sample period. See Tables 6.2, 7.1 and 7.2 for variable definitions.

Appendix 7.4

Two-stage Cross-sectional Regression using 40 *BM-BS-SIZE* Portfolios

Panel A: Average Factor Loadings across 40 Portfolios Sorted on *BM, BS* and *SIZE*

	Intercept	R_M-R_F	***SMB***	***HML***	***PMD***	R^2
Coefficient	-0.8234	1.1640	0.5062	-0.1755	-0.1275	0.5030
t-stat	(-1.51)	(5.92)***	(2.22)**	(-0.79)	(-1.51)	

Panel B: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	β_{PMD}	R^2
Coefficient	-0.3472	0.3282	0.4972	1.3075	-0.9290	0.3120
t-stat	(-0.36)	(0.42)	(0.62)	(3.59)***	(-1.19)	

This table presents the two-stage cross-sectional regression results based on 40 *BM-BS-SIZE* portfolios. For each month, from 1 January 1972 to 31 December 2010, a business strategy factor mimicking portfolio (*Prospector minus Defender* denoted as *PMD*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS* (i.e. defender) from the value-weighted return on stocks in the highest portfolio of *BS* (i.e. prospector). See Tables 6.2 and 7.1 for a description of how *BS* and stock returns are measured and definitions of the Fama-French three factors. Panel B presents average coefficients across 40 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMD*. The 40 portfolios are created by sorting stocks in five *BM* portfolios (based on quintile), four portfolios of *BS* (i.e. defender, lower analyzer, upper analyzer, and prospector) and two size portfolios (based on median) each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel C presents average coefficients from 468 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel B). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Appendix 7.5

Bear versus Bull Period Analyses on Business Strategy Measure (*BS*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *BS*

	Bear						Bull					
	Intercept	***BETA***	***SIZE***	***BM***	***BS***	R^2	**Intercept**	***BETA***	***SIZE***	***BM***	***BS***	R^2
Coefficient	-0.5546	-0.8421	0.0098	0.5026	-0.0112	0.0661	1.7765	0.2422	-0.1243	0.1859	0.0193	0.0352
t-stat	(-0.71)	(-2.38)**	(0.10)	(2.27)**	(-0.35)		(5.74)***	(2.14)**	(-2.85)***	(2.42)**	(1.72)*	

Panel B: Time-series *BS* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

	Bear					Bull				
Portfolio number	**1 (Defender)**	**2 (Lower Analyzer)**	**3 (Upper Analyzer)**	**4 (Prospector)**	**Hedge (4-1)**	**1 (Defender)**	**2 (Lower Analyzer)**	**3 (Upper Analyzer)**	**4 (Prospector)**	**Hedge (4-1)**
Model 7.1.1										
Intercept (α)	-1.2163	-1.6067	-1.8396	-2.2557	-1.0393	1.4155	1.5195	1.5100	1.5829	0.1674
t-stat	(-1.80)*	(-2.71)***	(-2.83)***	(-2.97)***	(-2.25)**	(5.03)***	(5.98)***	(5.62)***	(5.21)***	(0.95)
Model 7.1.2										
Intercept (α)	1.0995	0.6934	0.7844	0.7591	-0.3404	0.1330	0.2408	0.1269	0.0501	-0.0829
t-stat	(2.44)**	(1.99)**	(3.04)***	(2.30)**	(-0.72)	(0.77)	(1.96)*	(1.12)	(0.36)	(-0.46)
R_M-R_F	1.0633	1.0404	1.2048	1.3843	0.3210	1.0102	1.0016	1.0893	1.2073	0.1971
t-stat	(13.11)***	(16.33)***	(25.90)***	(23.26)***	(3.76)***	(26.26)***	(36.46)***	(43.09)***	(38.57)***	(4.95)***
Model 7.1.3										
Intercept (α)	0.1202	-0.0225	0.2095	0.4673	0.3471	-0.1026	0.0480	-0.0168	0.0018	0.1044
t-stat	(0.34)	(-0.08)	(1.11)	(1.59)	(0.77)	(-0.75)	(0.55)	(-0.23)	(0.02)	(0.67)
R_M-R_F	0.8971	0.9687	1.0788	1.1911	0.2939	1.0416	1.0243	1.0619	1.1248	0.0832
t-stat	(12.64)***	(16.96)***	(28.55)***	(20.18)***	(3.24)***	(32.78)***	(50.23)***	(63.31)***	(43.07)***	(2.30)***

Appendix 7.5 (Continued)

Portfolio number	Bear: 1 (Defender)	Bear: 2 (Lower Analyzer)	Bear: 3 (Upper Analyzer)	Bear: 4 (Prospector)	Bear: Hedge (4-1)	Bull: 1 (Defender)	Bull: 2 (Lower Analyzer)	Bull: 3 (Upper Analyzer)	Bull: 4 (Prospector)	Bull: Hedge (4-1)
SMB	0.9125	0.6122	0.5931	0.5623	-0.3502	0.4672	0.3866	0.4998	0.5050	0.0378
t-stat	(8.35)***	(7.12)***	(10.20)***	(6.19)***	(-2.51)**	(10.98)***	(14.14)***	(22.26)***	(14.44)***	(0.78)
HML	0.3905	0.4260	0.1794	-0.1353	-0.5257	0.5912	0.4763	0.2940	-0.0062	-0.5974
t-stat	(4.23)***	(5.76)***	(3.65)***	(-1.76)*	(-4.46)***	(12.26)***	(15.43)***	(11.55)***	(-0.16)	(-10.87)***
R^2	0.7971	0.8362	0.9381	0.8891	0.2966	0.7901	0.8939	0.9358	0.8783	0.3072
GRS *F*-statistic	0.68					0.57				
GRS-*P* value	0.6075					0.6812				

Panel C: Average Returns and *BS* Factor Loadings

Bear

	Intercept	R_M-R_F	*SMB*	*HML*	*PMD*	R^2
Coefficient	0.2705	0.9694	0.7919	0.3166	0.0831	0.3398
t-stat	(4.26)***	(60.43)***	(32.29)***	(14.08)***	(3.76)***	

Bull

	Intercept	R_M-R_F	*SMB*	*HML*	*PMD*	R^2
Coefficient	0.1653	0.9890	0.8047	0.3219	-0.0221	0.2516
t-stat	(4.53)***	(74.79)***	(46.54)***	(15.89)***	(-1.36)	

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BS*

Bear

	Intercept	R_M-R_F	*SMB*	*HML*	*PMD*	R^2
Coefficient	0.2829	1.0356	0.7239	0.2586	-0.0416	0.7833
t-stat	(3.12)***	(54.60)***	(7.77)***	(3.88)***	(-0.46)	

Bull

	Intercept	R_M-R_F	*SMB*	*HML*	*PMD*	R^2
Coefficient	-0.0255	1.0728	0.5325	0.3549	-0.0973	0.7778
t-stat	(-0.65)	(105.61)***	(9.45)***	(4.86)***	(-1.19)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Bear: Intercept	Bear: β_{RM-RF}	Bear: β_{SMB}	Bear: β_{HML}	Bear: β_{PMD}	Bear: R^2	Bull: Intercept	Bull: β_{RM-RF}	Bull: β_{SMB}	Bull: β_{HML}	Bull: β_{PMD}	Bull: R^2
Coefficient	0.4504	-2.3674	0.6315	0.0285	-0.9598	0.4354	1.1028	0.1596	0.1813	0.4573	0.1910	0.3992
t-stat	(0.39)	(-2.12)**	(1.26)	(0.05)	(-1.73)*		(1.15)	(0.16)	(0.50)	(1.57)	(1.04)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 for the bear versus bull periods. Bear and bull periods are determined based on Bätje and Menkhoff (2013). The following periods are deemed bearish (high volatility and falling price index): December 1972 to September 1974, December 1976 to February 1978, May 1981 to July 1982, June 1983 to May 1984, August 1987 to November 1987, May 1990 to October 1990, August 2000 to September 2002, and October 2007 to February 2009. Periods falling outside of these ranges are deemed bullish (low volatility and rising price index). Doing this results in a sample period from 1 January 1972 to 31 December 2010 with 109 bearish months and 359 bullish months.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *BS*. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *BS* measure each April. Parameter estimates are time-series averages of the parameters from the monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *BS* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, all firm-years in the sample are sorted into four portfolios based on *BS*: defender (6-12); lower analyzer (13-17); upper analyzer (18-23); prospector (24-30). Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only. Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS* (i.e. prospector) and sells portfolio 1 of *BS* (i.e. defender).

Panels C to E present firm-specific *BS* factor loadings and regression results of the two-stage cross-sectional regressions based on 20 *BM-BS* portfolios. For each month, a *BS* factor mimicking portfolio (*Prospector minus Defender* denoted as *PMD*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS* from the value-weighted return on stocks in the highest portfolio of *BS*. Panel C presents average coefficients for firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *PMD*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMD*. The 20 portfolios are created by sorting stocks into quintiles based on *BM* and four portfolios based on *BS* each month (i.e. defender, lower analyzer, upper analyzer, and prospector). *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Appendix 7.6

Bear versus Bull Period Analyses on Modified Business Strategy Measure Exclusive of Historical Growth or Investment Opportunities (*BS2*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *BS2*

	Bear						Bull					
	Intercept	***BETA***	***SIZE***	***BM***	***BS2***	R^2	**Intercept**	***BETA***	***SIZE***	***BM***	***BS2***	R^2
Coefficient	-0.1300	-0.6578	-0.0164	0.3511	-0.0514	0.0466	1.4015	0.2349	-0.0964	0.2416	0.0394	0.0391
t-stat	(-0.20)	(-2.33)**	(-0.18)	(2.48)**	(-2.26)**		(3.97)***	(1.97)*	(-2.15)**	(2.96)***	(2.54)**	

Panel B: Time-series *BS2* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

	Bear					Bull				
Portfolio number	**1 (Defender)**	**2 (Lower Analyzer)**	**3 (Upper Analyzer)**	**4 (Prospector)**	**Hedge (4-1)**	**1 (Defender)**	**2 (Lower Analyzer)**	**3 (Upper Analyzer)**	**4 (Prospector)**	**Hedge (4-1)**
Model 7.1.1										
Intercept (α)	-1.3955	-1.5462	-1.9669	-2.4751	-1.0795	1.3996	1.4356	1.5975	1.6173	0.2177
t-stat	(-2.40)**	(-2.68)***	(-3.10)***	(-3.59)***	(-3.08)***	(5.22)***	(5.31)***	(5.90)***	(5.40)***	(1.32)
Model 7.1.2										
Intercept (α)	0.8852	0.8382	0.7475	0.4421	-0.4431	0.1261	0.1134	0.2188	0.1124	-0.0137
t-stat	(2.68)***	(3.06)***	(2.97)***	(1.51)	(-1.25)	(0.83)	(0.76)	(1.76)*	(0.78)	(-0.09)
R_M-R_F	1.0316	1.0785	1.2277	1.3194	0.2879	1.0129	1.0467	1.0967	1.1945	0.1816
t-stat	(17.09)***	(21.54)***	(26.72)***	(24.64)***	(4.46)***	(29.47)***	(31.29)***	(39.15)***	(36.77)***	(4.90)***
Model 7.1.3										
Intercept (α)	0.2523	0.1780	0.2446	0.2459	-0.0064	-0.0754	-0.0746	0.1031	0.0493	0.1247
t-stat	(0.92)	(0.97)	(1.48)	(0.94)	(-0.02)	(-0.63)	(-0.66)	(1.17)	(0.45)	(0.84)
R_M-R_F	0.9471	1.0039	1.0777	1.1488	0.2017	0.4228	0.4596	0.5201	0.5713	0.1485
t-stat	(16.95)***	(26.69)***	(31.82)***	(21.37)***	(2.95)***	(11.31)***	(12.96)***	(18.79)***	(16.48)***	(3.20)***

Appendix 7.6 (Continued)

Portfolio number	Bear 1 (Defender)	Bear 2 (Lower Analyzer)	Bear 3 (Upper Analyzer)	Bear 4 (Prospector)	Bear Hedge (4-1)	Bull 1 (Defender)	Bull 2 (Lower Analyzer)	Bull 3 (Upper Analyzer)	Bull 4 (Prospector)	Bull Hedge (4-1)
SMB	0.5869	0.5831	0.6455	0.4940	-0.0930	0.5471	0.5212	0.2693	0.1004	-0.4467
t-stat	(6.97)***	(10.30)***	(12.66)***	(6.10)***	(-0.90)	(12.97)***	(12.99)***	(8.62)***	(2.57)**	(-8.53)***
HML	0.3448	0.3800	0.1494	-0.1102	-0.4550	1.0407	1.0603	1.0602	1.1203	0.0796
t-stat	(4.76)***	(7.80)***	(3.41)***	(-1.58)	(-5.14)	(37.23)***	(39.91)***	(51.22)***	(43.21)***	(2.29)**
R^2	0.8364	0.9247	0.9496	0.8925	0.3277	0.8223	0.8428	0.9045	0.8772	0.2581
GRS *F*-statistic	0.66					0.62				
GRS-*P* value	0.6207					0.6482				

Panel C: Average Returns and *BS2* Factor Loadings

	Bear Intercept	Bear R_M-R_F	Bear *SMB*	Bear *HML*	Bear *PMD2*	Bear R^2	Bull Intercept	Bull R_M-R_F	Bull *SMB*	Bull *HML*	Bull *PMD2*	Bull R^2
Coefficient	0.2862	0.9470	0.8493	0.3339	0.1821	0.3493	0.1801	0.9884	0.8309	0.3584	0.0806	0.2502
t-stat	(4.77)***	(60.97)***	(35.49)***	(16.05)***	(7.20)***		(5.04)***	(80.15)***	(47.70)***	(17.65)***	(4.28)***	

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BS2*

	Bear Intercept	Bear R_M-R_F	Bear *SMB*	Bear *HML*	Bear *PMD2*	Bear R^2	Bull Intercept	Bull R_M-R_F	Bull *SMB*	Bull *HML*	Bull *PMD2*	Bull R^2
Coefficient	0.2489	1.0398	0.6339	0.2528	-0.0088	0.8385	0.0087	1.0649	0.5504	0.4025	-0.0252	0.8008
t-stat	(3.28)***	(74.11)***	(10.43)***	(4.18)***	(-0.10)		(0.34)	(120.53)***	(8.85)***	(5.36)***	(-0.29)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Bear Intercept	Bear β_{RM-RF}	Bear β_{SMB}	Bear β_{HML}	Bear β_{PMD2}	Bear R^2	Bull Intercept	Bull β_{RM-RF}	Bull β_{SMB}	Bull β_{HML}	Bull β_{PMD2}	Bull R^2
Coefficient	0.5110	-2.5446	0.2988	0.8189	-0.8402	0.4311	-0.3995	1.5482	0.6743	-0.1432	0.3387	0.4484
t-stat	(0.31)	(-1.59)	(0.58)	(1.50)	(-2.29)**		(-0.38)	(1.46)	(1.67)*	(-0.35)	(1.84)*	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 for the bear versus bull periods using a modified business strategy measure exclusive of historical growth or investment opportunities (*BS2*). Bear and bull periods are determined based on Bätje and Menkhoff (2013). The following periods are deemed bearish (high volatility and falling price index): December 1972 to September 1974, December 1976 to February 1978, May 1981 to July 1982, June 1983 to May 1984, August 1987 to November 1987, May 1990 to October 1990, August 2000 to September 2002, and October 2007 to February 2009. Periods falling outside of these ranges are deemed bullish (low volatility and rising price index). Doing this results in a sample period from 1 January 1972 to 31 December 2010 with 109 bearish months and 359 bullish months.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *BS2*. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *BS2* measure each April. Parameter estimates are time-series averages of the parameters from the monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *BS2* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, all firm-years in the sample are sorted into four portfolios based on *BS2*: defender (5-10); lower analyzer (11-15); upper analyzer (16-19); prospector (20-25). Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only. Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS2* (i.e. prospector) and sells portfolio 1 of *BS2* (i.e. defender).

Panels C to E present firm-specific *BS2* factor loadings and regression results of the two-stage cross-sectional regressions based on 20 *BM-BS2* portfolios. For each month, a *BS2* factor mimicking portfolio (*Prospector minus Defender* denoted as *PMD2*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS2* from the value-weighted return on stocks in the highest portfolio of *BS2*. Panel C presents average coefficients for firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *PMD2*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMD2*. The 20 portfolios are created by sorting stocks into quintiles based on *BM* and four portfolios based on *BS2* each month (i.e. defender, lower analyzer, upper analyzer, and prospector). *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Appendix 7.7

Bear versus Bull Period Analyses on the Innovation Factor (*FINV*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *FINV*

	Bear						Bull					
	Intercept	***BETA***	***SIZE***	***BM***	***FINV***	R^2	**Intercept**	***BETA***	***SIZE***	***BM***	***FINV***	R^2
Coefficient	-0.6095	-0.6741	-0.0279	0.3472	-0.0758	0.0455	1.5113	0.2342	-0.0785	0.3044	0.1373	0.0404
t-stat	(-0.85)	(-2.38)**	(-0.32)	(2.49)**	(-1.39)		(4.40)***	(2.00)**	(-1.73)*	(3.13)***	(3.27)***	

Panel B: Time-series *FINV* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	Bear						Bull					
	1	**2**	**3**	**4**	**5**	**Hedge (5-1)**	**1**	**2**	**3**	**4**	**5**	**Hedge (5-1)**
Model 7.1.1												
Intercept (α)	-1.5653	-1.5459	-1.7616	-1.9101	-2.3805	-0.8151	1.3610	1.4084	1.5032	1.5634	1.7453	0.3844
t-stat	(-2.59)**	(-2.59)**	(-2.95)***	(-3.12)***	(-3.40)***	(-2.30)**	(5.14)***	(5.10)***	(5.64)***	(5.98)***	(5.67)***	(2.05)**
Model 7.1.2												
Intercept (α)	0.8595	0.9086	0.7250	0.7188	0.5472	-0.3123	0.0610	0.0689	0.1722	0.2241	0.2347	0.1737
t-stat	(2.67)***	(3.13)***	(2.62)**	(3.05)***	(1.74)*	(-0.84)	(0.44)	(0.45)	(1.31)	(1.91)*	(1.46)	(0.91)
R_M-R_F	1.0967	1.1102	1.1247	1.1891	1.3242	0.2275	1.0340	1.0604	1.0565	1.0653	1.1991	0.1651
t-stat	(18.63)***	(20.93)***	(22.22)***	(27.59)***	(23.07)***	(3.36)***	(33.08)***	(30.45)***	(35.76)***	(40.39)***	(33.13)***	(3.85)***
Model 7.1.3												
Intercept (α)	0.1336	0.1925	0.0945	0.2967	0.4487	0.3152	-0.1440	-0.1292	-0.0157	0.1101	0.2629	0.4069
t-stat	(0.58)	(1.03)	(0.49)	(1.71)*	(1.58)	(0.98)	(-1.48)	(-1.10)	(-0.17)	(1.35)	(2.20)**	(2.69)***
R_M-R_F	0.9903	1.0243	1.0244	1.0554	1.1357	0.1454	1.0599	1.0761	1.0767	1.0327	1.0708	0.0108
t-stat	(21.16)***	(26.87)***	(26.16)***	(29.69)***	(19.55)***	(2.21)**	(46.29)***	(39.11)***	(49.05)***	(53.97)***	(38.29)***	(0.31)

Appendix 7.7 (Continued)

Portfolio number	Bear 1	Bear 2	Bear 3	Bear 4	Bear 5	Bear Hedge (5-1)	Bull 1	Bull 2	Bull 3	Bull 4	Bull 5	Bull Hedge (5-1)
SMB	0.6938	0.6431	0.6196	0.5584	0.4701	-0.2237	0.4424	0.4772	0.4239	0.4953	0.5997	0.1573
t-stat	(9.84)***	(11.20)***	(10.51)***	(10.43)***	(5.37)***	(-2.26)**	(14.45)***	(12.99)***	(14.44)***	(19.35)***	(16.04)***	(3.32)***
HML	0.3811	0.4046	0.3191	0.1137	-0.2099	-0.5910	0.5548	0.5505	0.5047	0.2684	-0.1828	-0.7376
t-stat	(6.29)***	(8.20)***	(6.29)***	(2.47)**	(-2.79)***	(-6.94)***	(16.06)***	(13.25)***	(15.24)***	(9.30)***	(-4.33)***	(-13.79)***
R^2	0.8939	0.9278	0.9241	0.9403	0.8779	0.3923	0.878	0.8382	0.8888	0.9125	0.8649	0.407
GRS *F*-statistic	0.57						2.29					
GRS-*P* value	0.6867						0.0578					

Panel C: Average Returns and *FINV* Factor Loadings

	Bear Intercept	R_M-R_F	*SMB*	*HML*	*HLFINV*	R^2	Bull Intercept	R_M-R_F	*SMB*	*HML*	*HLFINV*	R^2
Coefficient	0.3859	0.9614	0.8372	0.2683	0.0845	0.3458	0.1200	0.9971	0.8301	0.3820	0.0740	0.2518
t-stat	(6.27)***	(62.44)***	(34.18)***	(12.40)***	(3.36)***		(3.09)***	(70.32)***	(45.87)***	(18.21)***	(3.49)***	

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *FINV*

	Bear Intercept	R_M-R_F	*SMB*	*HML*	*HLFINV*	R^2	Bull Intercept	R_M-R_F	*SMB*	*HML*	*HLFINV*	R^2
Coefficient	0.2088	1.0470	0.6597	0.2359	-0.0436	0.8505	0.0606	1.0629	0.5586	0.3592	-0.0557	0.8196
t-stat	(4.35)***	(79.45)***	(11.91)***	(4.24)***	(-0.61)		(3.03)***	(116.81)***	(9.65)***	(5.37)***	(-0.79)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Bear Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	β_{HLFINV}	R^2	Bull Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	β_{HLFINV}	R^2
Coefficient	-0.6448	-1.3372	0.0032	0.9682	-0.7723	0.3747	1.6510	-0.3508	0.3181	0.3175	0.4252	0.4057
t-stat	(-0.73)	(-1.50)	(0.01)	(2.04)**	(-2.10)**		(1.08)	(-0.24)	(0.86)	(1.06)	(2.22)**	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 for the bear versus bull periods using the innovation factor (*FINV*) of a modified measure of business strategy (i.e. excluding historical growth or investment opportunities (*REV5*)) identified by the principal component analyses. *FINV* is the sum of quintile ranks of research intensity (*RDS5*) and marketing and advertising efforts (*SGA5*), and thus it is a score ranging from 2 to 10. Bear and bull periods are determined based on Bätje and Menkhoff (2013). The following periods are deemed bearish (high volatility and falling price index): December 1972 to September 1974, December 1976 to February 1978, May 1981 to July 1982, June 1983 to May 1984, August 1987 to November 1987, May 1990 to October 1990, August 2000 to September 2002, and October 2007 to February 2009. Periods falling outside of these ranges are deemed bullish (low volatility and rising price index). Doing this results in a sample period from 1 January 1972 to 31 December 2010 with 109 bearish months and 359 bullish months.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *FINV*. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *FINV* measure each April. Parameter estimates are time-series averages of the parameters from the monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *FINV* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, all firm-years in the sample are sorted into quintiles based on *FINV*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only. Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *FINV* and sells portfolio 1 of *FINV*.

Panels C to E present firm-specific *FINV* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-FINV* portfolios. For each month, a *FINV* factor mimicking portfolio (*High minus Low FINV* denoted as *HLFINV*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *FINV* from the value-weighted return on stocks in the highest portfolio of *FINV*. Panel C presents average coefficients across firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLFINV*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLFINV*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *FINV* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Appendix 7.8

Bear versus Bull Period Analyses on the Efficiency Factor (*FEFF*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *FEFF*

	Bear						Bull					
	Intercept	***BETA***	***SIZE***	***BM***	***FEFF***	R^2	**Intercept**	***BETA***	***SIZE***	***BM***	***FEFF***	R^2
Coefficient	-0.5609	-0.6690	-0.0124	0.3861	-0.1146	0.0460	2.1570	0.1989	-0.1378	0.0729	0.0461	0.0379
t-stat	(-0.81)	(-2.30)**	(-0.14)	(2.58)**	(-2.40)**		(5.77)***	(1.29)	(-2.63)***	(0.55)	(0.87)	

Panel B: Time-series *FEFF* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	Bear						Bull					
	1	**2**	**3**	**4**	**5**	**Hedge (5-1)**	**1**	**2**	**3**	**4**	**5**	**Hedge (5-1)**
Model 7.1.1												
Intercept (α)	-1.4229	-1.7569	-1.8241	-1.8789	-2.0900	-0.6671	1.4929	1.4496	1.5375	1.4684	1.4446	-0.0482
t-stat	(-2.55)***	(-3.08)***	(-2.99)***	(-2.96)***	(-3.22)***	(-3.22)***	(5.96)***	(5.70)***	(5.91)***	(5.02)***	(5.22)***	(-0.53)
Model 7.1.2												
Intercept (α)	0.8588	0.6764	0.7910	0.8017	0.6298	-0.2290	0.2438	0.1408	0.1943	0.0290	0.0543	-0.1895
t-stat	(3.12)***	(2.95)***	(3.36)***	(2.94)***	(2.19)**	(-1.14)	(1.96)*	(1.26)	(1.75)*	(0.18)	(0.41)	(-2.00)**
R_M-R_F	1.0320	1.1006	1.1828	1.2124	1.2302	0.1982	0.9936	1.0411	1.0662	1.1395	1.1036	0.1101
t-stat	(20.51)***	(26.27)***	(27.50)***	(24.38)***	(23.41)***	(5.38)***	(35.51)***	(41.54)***	(42.79)***	(32.07)***	(36.74)***	(5.21)***
Model 7.1.3												
Intercept (α)	0.3030	0.1993	0.3124	0.2219	0.0532	-0.2497	0.0840	0.0162	0.0751	-0.1204	-0.1097	-0.1937
t-stat	(1.39)	(1.19)	(1.90)*	(1.22)	(0.25)	(-1.20)	(0.91)	(0.20)	(1.01)	(-0.97)	(-1.14)	(-2.04)**
R_M-R_F	0.9549	1.0043	1.0614	1.0718	1.1055	0.1506	1.0002	1.0264	1.0359	1.1135	1.0984	0.0981
t-stat	(21.32)***	(29.28)***	(31.56)***	(28.84)***	(25.13)***	(3.52)***	(46.19)***	(54.36)***	(59.34)***	(37.98)***	(48.65)***	(4.45)***

Appendix 7.8 (Continued)

Portfolio number	Bear 1	Bear 2	Bear 3	Bear 4	Bear 5	Bear Hedge (5-1)	Bull 1	Bull 2	Bull 3	Bull 4	Bull 5	Bull Hedge (5-1)
SMB	0.5217	0.5128	0.5680	0.6742	0.6378	0.1161	0.4165	0.4300	0.4801	0.5518	0.4912	0.0747
t-stat	(7.74)***	(9.93)***	(11.21)***	(12.05)***	(9.63)***	(1.80)*	(14.38)***	(17.03)***	(20.53)***	(14.10)***	(16.27)***	(2.53)**
HML	0.2985	0.2109	0.1743	0.2209	0.2424	-0.0560	0.4207	0.3112	0.2678	0.3800	0.4210	0.0003
t-stat	(5.15)***	(4.75)***	(4.00)***	(4.59)***	(4.26)***	(-1.01)	(12.88)***	(10.92)***	(10.15)***	(8.59)***	(12.36)***	(0.01)
R^2	0.8856	0.9359	0.9460	0.9394	0.9185	0.2456	0.8778	0.9099	0.9262	0.8363	0.8909	0.0853
GRS *F*-statistic	0.81						1.73					
GRS-*P* value	0.5207						0.1401					

Panel C: Average Returns and *FEFF* Factor Loadings

	Bear Intercept	Bear R_M-R_F	Bear *SMB*	Bear *HML*	Bear *HLFEFF*	Bear R^2	Bull Intercept	Bull R_M-R_F	Bull *SMB*	Bull *HML*	Bull *HLFEFF*	Bull R^2
Coefficient	0.3802	0.9529	0.8178	0.2076	0.2413	0.3438	0.2247	0.9957	0.8529	0.3100	-0.0158	0.2486
t-stat	(6.17)***	(61.12)***	(35.39)***	(10.01)***	(6.68)***		(6.29)***	(77.94)***	(48.67)***	(15.28)***	(-0.55)	

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *FEFF*

	Bear Intercept	Bear R_M-R_F	Bear *SMB*	Bear *HML*	Bear *HLFEFF*	Bear R^2	Bull Intercept	Bull R_M-R_F	Bull *SMB*	Bull *HML*	Bull *HLFEFF*	Bull R^2
Coefficient	0.2108	1.0257	0.6362	0.2879	0.0278	0.8583	0.0383	1.0417	0.5104	0.4117	0.0767	0.8176
t-stat	(3.94)***	(81.83)***	(11.75)***	(5.38)***	(0.40)		(1.44)	(142.57)***	(9.99)***	(6.21)***	(1.20)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Bear Intercept	Bear β_{RM-RF}	Bear β_{SMB}	Bear β_{HML}	Bear β_{HLFEFF}	Bear R^2	Bull Intercept	Bull β_{RM-RF}	Bull β_{SMB}	Bull β_{HML}	Bull β_{HLFEFF}	Bull R^2
Coefficient	-0.0126	-1.9750	0.2698	0.5871	-0.5006	0.4044	-2.2109	3.3518	0.7582	-0.3440	-0.0332	0.3478
t-stat	(-0.01)	(-2.02)**	(0.41)	(0.99)	(-2.32)**		(-1.90)*	(2.76)***	(2.02)**	(-1.06)	(-0.34)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 for the bear versus bull periods using the efficiency factor (*FEFF*) of a modified measure of business strategy (i.e. excluding historical growth or investment opportunities (*REV5*)) identified by the principal component analyses. *FEFF* is the sum of quintile ranks of operational efficiency (*EMPS5*), capital intensity technological efficiency (*CAP5*) and organizational stability (*TEMP5*), and thus it is a score ranging from 3 to 15. Bear and bull periods are determined based on Bätje and Menkhoff (2013). The following periods are deemed bearish (high volatility and falling price index): December 1972 to September 1974, December 1976 to February 1978, May 1981 to July 1982, June 1983 to May 1984, August 1987 to November 1987, May 1990 to October 1990, August 2000 to September 2002, and October 2007 to February 2009. Periods falling outside of these ranges are deemed bullish (low volatility and rising price index). Doing this results in a sample period from 1 January 1972 to 31 December 2010 with 109 bearish months and 359 bullish months.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *FEFF*. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *FEFF* measure each April. Parameter estimates are time-series averages of the parameters from the monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *FEFF* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, all firm-years in the sample are sorted into quintiles based on *FEFF*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only. Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *FEFF* and sells portfolio 1 of *FEFF*.

Panels C to E present firm-specific *FEFF* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-FEFF* portfolios. For each month, a *FEFF* factor mimicking portfolio (*High minus Low FEFF* denoted as *HLFEFF*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *FEFF* from the value-weighted return on stocks in the highest portfolio of *FEFF*. Panel C presents average coefficients across firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLFEFF*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLFEFF*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *FEFF* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Appendix 8.1
Simultaneous Inclusion of All Individual or Component Business Strategy Measures

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and Individual Measures of Business Strategy (*BS*)

	Intercept	***BETA***	***SIZE***	***BM***	***RDS5***	***SGA5***	***REV5***	***EMPS5***	***CAP5***	***TEMP5***	R^2
Coefficient	0.8271	0.1456	-0.0660	0.4410	0.0927	0.0449	-0.0181	-0.0743	-0.0295	0.0607	0.0551
t-stat	(1.24)	(0.82)	(-0.79)	(2.06)**	(2.34)**	(1.65)*	(-0.82)	(-2.60)***	(-1.25)	(1.68)*	

Panel B: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and the Three Factors of Business Strategy Measure (*BS*) Identified through the Principal Component Analysis (*F1* Representing *RDS5* and *SGA5*; *F2* Representing *EMPS5* and *TEMP5*; *F3* Representing *REV5* and *CAP5*)

	Intercept	***BETA***	***SIZE***	***BM***	***F1***	***F2***	***F3***	R^2
Coefficient	1.8891	-0.2267	-0.1992	0.1059	0.1508	0.0513	-0.0369	0.0469
t-stat	(3.38)***	(-0.86)	(-1.70)*	(0.64)	(2.01)**	(0.54)	(-1.50)	

Panel C: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and Individual Measures of Modified Business Strategy (i.e. *BS2*, Exclusive of *REV5*)

	Intercept	***BETA***	***SIZE***	***BM***	***RDS5***	***SGA5***	***EMPS5***	***CAP5***	***TEMP5***	R^2
Coefficient	0.9984	0.0373	-0.0777	0.4074	0.0824	0.0417	-0.0842	-0.0175	0.0731	0.0497
t-stat	(2.20)**	(0.35)	(-1.07)	(2.23)**	(2.42)**	(1.78)*	(-4.59)***	(-0.92)	(2.23)**	

Panel D: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and the Two Factors of Modified Business Strategy Measure (*BS2*) Identified through the Principal Component Analysis (*FINV* Representing *RDS5* and *SGA5*; *FEFF* Representing *EMPS5*, *CAP5* and *TEMP5*)

	Intercept	***BETA***	***SIZE***	***BM***	***FINV***	***FEFF***	R^2
Coefficient	1.1044	0.0421	-0.0648	0.3103	0.0950	-0.0362	0.0439
t-stat	(3.62)***	(0.38)	(-1.59)	(3.83)***	(2.72)***	(-1.86)*	

This table presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and all individual or components of business strategy measures from 1 January 1972 to 31 December 2010. Panel A includes simultaneously all individual measures of business strategy (*BS*). Panel B includes simultaneously the three factors of business strategy measure (*BS*) identified through the principal component analysis (*F1* Representing *RDS5* and *SGA5*; *F2* Representing *EMPS5* and *TEMP5*; *F3* Representing *REV5* and *CAP5*). Panel C includes simultaneously all individual measures of modified business strategy (i.e. *BS2*, exclusive of *REV5*). Panel D includes simultaneously the two factors of modified business strategy measure (*BS2*) identified through the principal component analysis (*FINV* Representing *RDS5* and *SGA5*; *FEFF* Representing *EMPS5*, *CAP5* and *TEMP5*). Refer to Table 6.2 for variable definitions. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and the aforementioned individual or component business strategy measures each April. Parameter estimates are time-series averages of the parameters from the 468 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Appendix 8.2

Analyses on Business Strategy Measure Computed Using a Rolling Three-Year Window (*BSRW3*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *BSRW3*

	Intercept	*BETA*	*SIZE*	*BM*	*BSRW3*	R^2
Coefficient	1.3999	-0.0440	-0.1046	0.2564	0.0072	0.0416
t-stat	(4.83)***	(-0.41)	(-2.47)**	(3.72)***	(0.75)	

Panel B: Time-series *BSRW3* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	1 (Defender)	2 (Lower Analyzer)	3 (Upper Analyzer)	4 (Prospector)	Hedge (4-1)
Model 7.1.1					
Intercept (α)	0.7781	0.7400	0.7252	0.6085	-0.1696
t-stat	(3.22)***	(3.11)***	(2.80)***	(2.05)**	(-1.02)
Model 7.1.2					
Intercept (α)	0.3501	0.2845	0.2218	0.0447	-0.3054
t-stat	(2.64)***	(2.75)***	(2.16)**	(0.34)	(-2.04)**
R_M-R_F	0.9769	1.0376	1.1517	1.2899	0.3130
t-stat	(34.69)***	(47.13)***	(52.79)***	(46.21)***	(9.95)***
Model 7.1.3					
Intercept (α)	0.0969	0.0564	0.0813	0.0405	-0.0565
t-stat	(0.93)	(0.83)	(1.24)	(0.39)	(-0.41)
R_M-R_F	0.9724	1.0239	1.0766	1.1498	0.1775
t-stat	(40.90)***	(66.31)***	(71.88)***	(48.97)***	(5.99)***
SMB	0.5055	0.4988	0.5881	0.6012	0.0956
t-stat	(14.83)***	(22.53)***	(27.38)***	(17.85)***	(2.25)**
HML	0.4768	0.4257	0.2171	-0.0841	-0.5609
t-stat	(13.20)***	(18.15)***	(9.54)***	(-2.36)**	(-12.47)***
R^2	0.8209	0.9222	0.9383	0.8846	0.3753
GRS *F*-statistic	0.36				
GRS-*P* value	0.8380				

Panel C: Average Returns and *BSRW3* Factor Loadings

	Intercept	R_M-R_F	*SMB*	*HML*	*PMDRW3*	R^2
Coefficient	0.0625	0.9825	0.9044	0.2705	0.1058	0.2430
t-stat	(1.92)**	(90.18)***	(58.61)***	(15.29)***	(6.96)***	

Appendix 8.2 (Continued)

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BSRW3*

	Intercept	R_M-R_F	*SMB*	*HML*	*PMDRW3*	R^2
Coefficient	0.0572	1.0591	0.6157	0.3422	-0.0060	0.8045
t-stat	(1.60)	(144.86)***	(11.16)***	(4.45)***	(-0.07)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	β_{PMDRW3}	R^2
Coefficient	1.6701	-1.2819	0.4835	0.4837	-0.1204	0.4521
t-stat	(1.54)	(-1.21)	(1.15)	(1.68)*	(-0.69)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 with business strategy measure computed using a rolling three-year window (*BSRW3*).

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *BSRW3* from 1 January 1969 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *BSRW3* measure each April. Parameter estimates are time-series averages of the parameters from the 492 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *BSRW3* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1969 to 31 December 2010, all firm-years in the sample are sorted into four portfolios based on *BSRW3*: defender (6-12); lower analyzer (13-17); upper analyzer (18-23); prospector (24-30). Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BSRW3* (i.e. prospector) and sells portfolio 1 of *BSRW3* (i.e. defender).

Panels C to E present firm-specific *BSRW3* factor loadings and regression results of the two-stage cross-sectional regressions based on 20 *BM-BSRW3* portfolios. For each month, from 1 January 1969 to 31 December 2010, a *BSRW3* factor mimicking portfolio (*Prospector minus Defender* denoted as *PMDRW3*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BSRW3* from the value-weighted return on stocks in the highest portfolio of *BSRW3*. Panel C presents average coefficients across 6,897 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *PMDRW3*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMDRW3*. The 20 portfolios are created by sorting stocks into quintiles based on *BM* and four portfolios based on *BSRW3* each month (i.e. defender, lower analyzer, upper analyzer, and prospector). *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 492 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Appendix 8.3

Analyses on Modified Measure of Business Strategy Exclusive of Historical Growth or Investment Opportunities Computed Using a Rolling Three-Year Window (*BS2RW3*)

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *BS2RW3*

	Intercept	*BETA*	*SIZE*	*BM*	*BS2RW3*	R^2
Coefficient	1.2270	0.0196	-0.0923	0.2830	0.0087	0.0412
t-stat	(4.48)***	(0.17)	(-2.31)**	(4.29)***	(0.84)	

Panel B: Time-series *BS2RW3* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	1 (Defender)	2 (Lower Analyzer)	3 (Upper Analyzer)	4 (Prospector)	Hedge (4-1)
Model 7.1.1					
Intercept (α)	0.7348	0.7230	0.6892	0.6079	-0.1269
t-stat	(3.04)***	(3.07)***	(2.69)***	(2.10)**	(-0.78)
Model 7.1.2					
Intercept (α)	0.2979	0.2483	0.1847	0.0553	-0.2426
t-stat	(2.37)**	(2.49)**	(1.81)*	(0.42)	(-1.60)
R_M-R_F	1.0121	1.0502	1.1577	1.2683	0.2562
t-stat	(37.72)***	(49.34)***	(53.18)***	(44.74)***	(8.44)***
Model 7.1.3					
Intercept (α)	0.0325	0.0108	0.0426	0.0196	-0.0129
t-stat	(0.33)	(0.16)	(0.67)	(0.19)	(-0.04)
R_M-R_F	1.0148	1.0312	1.0722	1.1250	0.1103
t-stat	(45.41	(69.10)***	(73.78)***	(48.53)***	(3.90)***
SMB	0.4809	0.4948	0.6077	0.6530	0.1720
t-stat	(15.00)***	(23.19)***	(29.26)***	(19.71)***	(4.42)***
HML	0.4895	0.4085	0.1924	-0.0417	-0.5312
t-stat	(14.41)***	(17.98)***	(8.71)***	(-1.18)	(-12.26)***
R^2	0.8433	0.9268	0.9414	0.8832	0.3571
GRS *F*-statistic	0.35				
GRS-*P* value	0.8411				

Panel C: Average Returns and *BS2RW3* Factor Loadings

	Intercept	R_M-R_F	*SMB*	*HML*	*PMD2RW3*	R^2
Coefficient	0.0776	0.9877	0.9093	0.3323	0.1879	0.2424
t-stat	(2.35)**	(95.03)***	(60.79)***	(18.46)***	(10.44)***	

Appendix 8.3 (Continued)

Panel D: Average Factor Loadings across 20 Portfolios Sorted on *BM* and *BS2RW3*

	Intercept	R_M-R_F	*SMB*	*HML*	*PMD2RW3*	R^2
Coefficient	0.0648	1.0547	0.6205	0.3485	0.0259	0.8389
t-stat	(1.87)*	(161.88)***	(11.19)***	(4.67)***	(0.30)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	$\beta_{PMD2RW3}$	R^2
Coefficient	0.0758	0.3025	0.1265	0.7671	-0.0232	0.4771
t-stat	(0.08)	(0.31)	(0.38)	(3.13) ***	(-0.15)	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of a modified measure of business strategy exclusive of historical growth or investment opportunities computed using a rolling three-year window period (*BS2RW3*), which is a score ranging from 5 to 25.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *BS2RW3* from 1 January 1969 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *BS2RW3* measure each April. Parameter estimates are time-series averages of the parameters from the 492 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *BS2RW3* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1969 to 31 December 2010, all firm-years in the sample are sorted into four portfolios based on *BS2RW3*: defender (5-10); lower analyzer (11-15); upper analyzer (16-19); prospector (20-25). Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB,* and *HML).* The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 4 of *BS2RW3* (i.e. prospector) and sells portfolio 1 of *BS2RW3* (i.e. defender).

Panels C to E present firm-specific *BS2RW3* factor loadings and regression results of the two-stage cross-sectional regressions based on 20 *BM-BS2RW3* portfolios. For each month, from 1 January 1969 to 31 December 2010, a *BS2RW3* factor mimicking portfolio (*Prospector minus Defender* denoted as *PMD2RW3*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *BS2RW3* from the value-weighted return on stocks in the highest portfolio of *BS2RW3*. Panel C presents average coefficients across 7,177 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *PMD2RW3*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 20 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *PMD2RW3*. The 20 portfolios are created by sorting stocks into quintiles based on *BM* and four portfolios based on *BS2RW3* (i.e. defender, lower analyzer, upper analyzer, and prospector) each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 492 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Appendix 8.4

Analyses of Innovation Factor of a Modified Measure of Business Strategy Computed Using a Rolling Three-Year Window (*FINVRW3*): Research Intensity and Marketing and Advertising Efforts

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *FINVRW3*

	Intercept	***BETA***	***SIZE***	***BM***	***FINVRW3***	R^2
Coefficient	1.1591	0.0137	-0.0881	0.2964	0.0660	0.0419
t-stat	(3.98)***	(0.12)	(-2.27)**	(4.93)***	(2.08)**	

Panel B: Time-series *FINVRW3* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	**1**	**2**	**3**	**4**	**5**	**Hedge (5-1)**
<u>Model 7.1.1</u>						
Intercept (α)	0.6718	0.7013	0.7028	0.6931	0.7366	0.0648
t-stat	(2.68)***	(2.90)***	(2.87)***	(2.74)***	(2.52)***	(0.61)
<u>Model 7.1.2</u>						
Intercept (α)	0.2058	0.2380	0.2100	0.1787	0.1935	-0.0123
t-stat	(1.67)*	(2.19)**	(2.02)**	(1.76)*	(1.36)	(-0.12)
R_M-R_F	1.0687	1.0632	1.0903	1.1379	1.2566	0.1879
t-stat	(40.83)***	(45.80)***	(49.30)***	(52.66)***	(41.34)***	(5.47)***
<u>Model 7.1.3</u>						
Intercept (α)	-0.0637	-0.0197	-0.0148	0.0353	0.2740	0.3377
t-stat	(-0.74)	(-0.28)	(-0.21)	(0.51)	(2.65)***	(2.88)***
R_M-R_F	1.0595	1.0464	1.0606	1.0598	1.0635	0.0040
t-stat	(53.55)***	(64.44)***	(65.26)***	(67.14)***	(44.83)***	(0.15)
SMB	0.5487	0.5340	0.5155	0.5664	0.6620	0.1133
t-stat	(19.32)***	(23.01)***	(22.19)***	(25.10)***	(19.45)***	(2.71)***
HML	0.5011	0.4510	0.3775	0.1952	-0.2760	-0.7770
t-stat	(16.62)***	(18.27)***	(15.25)***	(8.12)***	(-7.65)***	(-17.53)***
R^2	0.8855	0.9177	0.9195	0.9287	0.8798	0.4277
GRS *F*-statistic	2.13					
GRS-*P* value	0.742					

Panel C: Average Returns and *FINVRW3* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***HLFINVRW3***	R^2
Coefficient	-0.0103	0.9947	0.9206	0.3511	0.1641	0.2432
t-stat	(-0.30)	(94.82)***	(60.88)***	(18.88)***	(8.81)***	

Appendix 8.4 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *FINVRW3*

	Intercept	R_M-R_F	*SMB*	*HML*	*HLFINVRW3*	R^2
Coefficient	0.0935	1.0597	0.6376	0.2971	-0.0321	0.8553
t-stat	(4.34)***	(172.43)***	(12.47)***	(4.34)	(-0.45)	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	β_{RM-RF}	β_{SMB}	β_{HML}	$\beta_{HLFINVRW3}$	R^2
Coefficient	1.1912	-0.6670	0.1061	0.6818	0.1289	0.4289
t-stat	(1.43)	(-0.79)	(0.23)	(2.08)**	(0.70)	45.54

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of the innovation factor of a modified measure of business strategy (i.e. excluding historical growth or investment opportunities) computed using a three-year rolling period (*FINVRW3*). *FINVRW3* is the sum of quintile ranks of research intensity and marketing and advertising efforts, and thus it is a score ranging from 2 to 10.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *FINVRW3* from 1 January 1969 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *FINVRW3* measure each April. Parameter estimates are time-series averages of the parameters from the 492 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *FINVRW3* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1969 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *FINVRW3*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB*, and *HML)*. The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *FINVRW3* and sells portfolio 1 of *FINVRW3*.

Panels C to E present firm-specific *FINVRW3* factor loadings and regression results of the two-stage cross-sectional regressions based on 25 *BM-FINVRW3* portfolios. For each month, from 1 January 1969 to 31 December 2010, a *FINVRW3* factor mimicking portfolio (*High minus Low FINVRW3* denoted as *HLFINVRW3*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *FINVRW3* from the value-weighted return on stocks in the highest portfolio of *FINVRW3*. Panel C presents average coefficients across 7,177 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLFINVRW3*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLFINVRW3*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *FINVRW3* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 492 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.

Appendix 8.5

Analyses of Efficiency Factor of a Modified Measure of Business Strategy Computed Using a Rolling Three-Year Window (*FEFFRW3*): Operational Efficiency, Capital Intensity or Technological Efficiency, and Organizational Stability

Panel A: Cross-sectional Regression of Monthly Excess Returns on the Fama-French Three Factors and *FEFFRW3*

	Intercept	***BETA***	***SIZE***	***BM***	***FEFFRW3***	R^2
Coefficient	1.4602	0.0174	-0.0889	0.3029	-0.0318	0.0409
t-stat	(5.01)***	(0.15)	(-2.21)**	(4.21)***	(-1.78)*	

Panel B: Time-series *FEFFRW3* Portfolio Regressions of Monthly Excess Returns on the Fama-French Three Factors

Portfolio number	**1**	**2**	**3**	**4**	**5**	**Hedge (5-1)**
<u>Model 7.1.1</u>						
Intercept (α)	0.7900	0.7340	0.7447	0.6788	0.5613	-0.2287
t-stat	(3.43)***	(3.04)***	(3.01)***	(2.66)***	(2.11)**	(-2.80)***
<u>Model 7.1.2</u>						
Intercept (α)	0.3316	0.2606	0.2436	0.1772	0.0494	-0.2823
t-stat	(3.20)***	(2.78)***	(2.39)**	(1.71)*	(0.42)	(-3.97)***
R_M-R_F	1.0140	1.0953	1.1086	1.1512	1.1748	0.1609
t-stat	(45.94)***	(54.80)***	(51.15)***	(52.02)***	(46.56)***	(9.99)***
<u>Model 7.1.3</u>						
Intercept (α)	0.1215	0.1109	0.0787	0.0139	-0.1661	-0.2876
t-stat	(1.58)	(1.69)*	(1.28)	(0.20)	(-2.00)**	(-4.12)***
R_M-R_F	0.9888	1.0437	1.0287	1.0831	1.1221	0.1333
t-stat	(56.20)***	(69.28)***	(73.32)***	(67.71)***	(58.92)***	(7.73)***
SMB	0.4715	0.4944	0.6119	0.5742	0.6057	0.1343
t-stat	(18.74)***	(22.87)***	(30.51)***	(25.12)***	(22.25)***	(5.39)***
HML	0.3550	0.2408	0.2321	0.2433	0.3485	-0.0065
t-stat	(13.25)***	(10.51)***	(10.87)***	(10.01)***	(12.04)***	(-0.33)
R^2	0.8937	0.9290	0.9412	0.9287	0.9067	0.2060
GRS *F*-statistic	5.33					
GRS-*P* value	0.0003					

Panel C: Average Returns and *FEFFRW3* Factor Loadings

	Intercept	R_M-R_F	***SMB***	***HML***	***HLFEFFRW3***	R^2
Coefficient	0.1435	1.0087	0.9408	0.1906	0.0418	0.2392
t-stat	(4.28)***	(93.03)***	(61.79)***	(11.37)***	(1.57)	

Appendix 8.5 (Continued)

Panel D: Average Factor Loadings across 25 Portfolios Sorted on *BM* and *FEFFRW3*

	Intercept	R_M-R_F	*SMB*	*HML*	*HLFEFFRW3*	R^2
Coefficient	0.1041	1.0324	0.5806	0.3478	0.1477	0.8549
t-stat	(3.69)***	(228.01)***	(12.86)***	(5.34)***	(2.30)**	

Panel E: Monthly Cross-sectional Regressions of Portfolio Returns on Factor Loadings

	Intercept	$\beta_{RM\text{-}RF}$	β_{SMB}	β_{HML}	$\beta_{HLFEFFRW3}$	R^2
Coefficient	-3.6870	3.7622	0.7823	0.4577	-0.2249	0.3975
t-stat	(-1.01)	(1.10)	(1.89)*	(2.08)**	(-2.70)***	

This table replicates analyses in Tables 6.3, 7.1, and 7.2 by investigating the effect of the efficiency factor of a modified measure of business strategy (i.e. excluding historical growth or investment opportunities) computed using a three-year rolling period (*FEFFRW3*). *FEFFRW3* is the sum of quintile ranks of operational efficiency, capital intensity technological efficiency and organizational stability, and thus it is a score ranging from 3 to 15.

Panel A presents the cross-sectional regression results of monthly excess returns on the Fama-French three factors and *FEFFRW3* from 1 January 1969 to 31 December 2010. All variables for a given fiscal year become available for the monthly regressions four months after the fiscal year-end. For instance, a December year-end firm gets a new *BETA*, *SIZE*, *BM*, and *FEFFRW3* measure each April. Parameter estimates are time-series averages of the parameters from the 492 monthly cross-sectional regressions. *t*-statistics are estimated from the standard errors of these monthly averages based on the Fama-Macbeth (1973) approach.

Panel B presents results for time-series *FEFFRW3* portfolio regressions of monthly excess returns on the Fama-French three factors. For each month, from 1 January 1969 to 31 December 2010, all firm-years in the sample are sorted into quintiles based on *FEFFRW3*. Model 7.1.1 reports the parameter estimates from a regression of the portfolio excess returns on an intercept only (i.e. the average excess returns for each portfolio over the sample period). Model 7.1.2 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the market risk premium (R_M-R_F). Model 7.1.3 reports the parameter estimates from a regression of the portfolio excess returns on an intercept and the Fama-French three factors (R_M-R_F, *SMB,* and *HML*). The GRS test (see Gibbons et al., 1989) is a test of whether all intercepts in Model 7.1.3 are jointly equal to zero. The last column presents parameter estimates and *t*-statistics on a hedge portfolio that buys portfolio 5 of *FEFFRW3* and sells portfolio 1 of *FEFFRW3*.

Panels C to E present firm-specific *FEFFRW3* factor loadings and regression results of the two-stage cross-sectional regression based on 25 *BM-FEFFRW3* portfolios. For each month, from 1 January 1969 to 31 December 2010, a *FEFFRW3* factor mimicking portfolio (*High minus Low FEFFRW3* denoted as *HLFEFFRW3*) is constructed by subtracting the value-weighted return of stocks in the lowest portfolio of *FEFFRW3* from the value-weighted return on stocks in the highest portfolio of *FEFFRW3*. Panel C presents average coefficients across 7,177 firm-specific, time-series regressions of excess monthly returns on the Fama-French three factors plus *HLFEFFRW3*. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel D presents average coefficients across 25 portfolio-specific, time-series regressions of excess value-weighted monthly returns on the Fama-French three factors plus *HLFEFFRW3*. The 25 portfolios are created by sorting stocks in to quintiles based on *BM* and *FEFFRW3* each month. *t*-statistics are estimated from the standard errors of the average parameter estimates. Panel E presents average coefficients from 492 monthly cross-sectional regressions of excess value-weighted portfolio returns on portfolio factor loadings (i.e. the slope coefficients from the regressions in Panel D). *t*-statistics are estimated from the standard errors of the average monthly parameter estimates.

Refer to Tables 6.2 and 7.1 for variable definitions. ***, **, and * indicate the level of significance at the 1%, 5% and 10% (two-tailed), respectively.