ESSAYS ON ECONOMIC DEVELOPMENT AND INEQUALITY

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This thesis is dedicated to my family
for their endless love, support and encouragement

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Abstract

This thesis explores the role of government policy in enhancing economic development and addressing income equality. It includes three self-contained chapters, examining three different forms of government policy, namely policies to increase education attainment, to improve physical infrastructure and to boost the higher-value domestic production respectively.

Chapter 2 provides an empirical examination of the impact of education expansion on income inequality through three channels: level effects, dispersion effects and interaction between technological progress and tertiary education. Probably the first in literature to do so, the chapter allows for intergenerational education inequality in the estimation of the educational inequality and shows that the augmented method is a more reliable compared to the conventional one. It finds a structural shift in the association between educational inequality and income inequality around WWII, switching from positive before WWII to negative thereafter. It also shows that the interaction between tertiary education and technological progress has advanced income inequality since WWII.

Chapter 3 focuses on the relationship between mobile money (MM) service and local economic activity. Using night-time light intensity as a proxy for economic activity and mobile phone coverage as a proxy for access to MM service, this chapter provides an empirical evidence of a robust, positive and significant impact of MM on local economic activity. It confirms that the positive, partial equilibrium effects of MM found in previous literature also hold in the aggregate and are also generalizable over a broader set of countries.

Chapter 4 studies industrial policy (IP) in a contemporary setting. Specifically, it investigates the impact on industrial development of ongoing IP to promote Supporting Industries – an emerging sector that is crucial for higher-value domestic production. The chapter highlights the importance of IP in improving industrial development outcomes of firms subject to the policies. However, it finds weak evidence that the policy significantly increased investment-related outcomes.

Declaration

This thesis is an original work of my research and contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

Signature

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Date: 8th December 2020

Thesis including published works declaration

I hereby declare that this thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

This thesis includes zero original papers published in a peer reviewed journal and one submitted publications. The core theme of the thesis is "Economic Development and Inequality". The ideas, development and writing up of all the papers in the thesis were the principal responsibility of myself, the student, working within the Department of Economics under the supervision of Professor Jakob Madsen, Associate Professor Paul Raschky and Associate Professor Nathaniel Lane.

The inclusion of co-authors reflects the fact that the work came from active collaboration between researchers and acknowledges input into team-based research.

In the case of Chapter 2, my contribution to the work involved the following:

Thesis Chapter	**Publication Title**	**Status** *(published, in press, accepted or returned for revision, submitted)*	**Nature and % of student contribution**	**Co-author name(s) Nature and % of Co-author's contribution***	**Co-author(s), Monash student Y/N***
Chapter 2	Is Income Inequality Driven by Biased Technological Progress, Education and Educational Inequality? International Evidence, 1870-2016".	Submitted	50 %- Data processing, programming and write-up	Jakob Madsen 50% - Idea of paper, input into data compiling, writing and concept	No

I have renumbered sections of published paper in order to generate a consistent presentation within the thesis.

Student name: Thi Phuong Dung Le

Student signature: **Date:** 8th December 2020

I hereby certify that the above declaration correctly reflects the nature and extent of the student's and co-authors' contributions to this work. In instances where I am not the responsible author I have consulted with the responsible author to agree on the respective contributions of the authors.

Main Supervisor name: Paul Raschky

Main Supervisor signature: **Date:** 8th December 2020

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Chapter 1

Introduction

Economic development and income inequality are among the core problems that economists try to address. While economic development refers to the study of measures to raise a nation's gross domestic product and total welfare, income inequality is concerned with how to distribute income and wealth within society. There is consensus that economic development is centrally important as raising the quality of life is of mutual interest not only to economists, socialists and politicians but also to everyday citizens. Of equal importance is the topic of income inequality: recently, this topic has emerged in the centre of discussions because inequality has increased in almost all countries in the world over the period 1980-2016 (Alvaredo, Piketty, Saez, Chancel & Zucman, 2018). Moreover, income inequality is anticipated to be more severe in the future as the rate of growth tends to deteriorate relative to the returns to capital (Piketty, 2014).

One strategy on how countries have tried to improve economic development and reduce income inequality is through some form of government policy. The rationale for government intervention in the economy is explained clearly in any microeconomics textbook (e.g., see Gans, King, Byford & Mankiw, 2018). Basically, whenever there is market failure or the presence of externalities, the role of government intervention is emphasised to enhance economic development and equality.

It is without question that education is crucial for economic growth. The level of educational achievement is often used as a proxy for human capital, a key factor in any economic growth model (see Barro, 1995; Mankiw, Romer & Weil, 1992; Romer, 1989). For this reason, governments across the world have invested significant portions of their budgets on increasing the educational attainments of members of their population (Mandl, Dierx, & Ilzkovitz, 2008).

Another area of government activity is the provision of infrastructure, which is also considered to have in general, positive effects on economic development (Aschauer, 1989; Duffy-Deno & Eberts, 1991; Eisner, 1991; Munnell, 1990; Ratner, 1983). This is achieved through two mechanisms: First, infrastructure acts as an intermediate input to production, and advancement in these inputs would crowd in additional resources. Second, better infrastructure can boost the productivity of other factors of production (such as labour and other capital), thereby raising output, income and employment (Ghosh & De, 1998).

Another area of government intervention frequently used is industrial policy (IP), broadly defined as intentional state action meant to allocate economy activity to key sectors (Lane, 2020). Popular examples of IP include tariffs, subsidies, and tax breaks. The primary purpose of IP is to speed up the industrialisation process and boost the manufacturing sector, widely regarded as the key driver of productivity growth, technological innovation and economic capabilities upgrade (Altenburg, 2015). For this reason, according to Altenburg (2015), ‘IP has become a synonym for policies seeking to influence the direction, structure and pace of economic growth and development’.

There is a large theoretical literature supporting the use of IP (Baldwin, 1969; Harrison & Rodríguez-Clare, 2010; Krueger, 1990; Stiglitz, Lin & Monga, 2013). Accordingly, export subsidies are justified by arguing that policies such as tax breaks for FDI result in ‘learning externalities’, or knowledge spillovers from multinational corporations (MNCs). That is, production externalities in high-skilled sectors could explain company and infant-industry protection. Additionally, generating fiscal revenue, improving terms of trade and rent-seeking are also plausible reasons for IP (Harrison & Rodríguez-Clare, 2010). The justification for IP is a consensus, as stated by Rodrik (2009): ‘IP: don’t ask why, ask how’.

This thesis contains three self-contained papers that are concerned with the above aspects of government policy. The first paper (chapter 2) looks into the impacts of education expansion on income inequality. The second paper (chapter 3) aims to causally estimate the effects of government-initiated infrastructure improvement on local economic activity. In particular, the chapter looks into the aggregate impact on local economic activity of mobile money service developed using a mobile phone platform that arose thanks to the miracle growth of mobile phone coverage. The third paper (chapter 4), examines the effect of IP in promoting the industrialization process and transition into hi-tech manufacturing.

In what follows, I present a brief summary of important related literature underpinning each chapter, outline the limitations of this literature, discuss the contribution of my thesis to the literature and outline specific details of each chapter.

In Chapter 2, the simultaneous expansion of tertiary education and increasing income inequality since the 1980s has motivated us to address the question: Does education expansion contribute to higher income inequality? Intuitively, we would expect a positive relationship between education inequality and income inequality because income derives from human capital, towards which education plays an important role (Todaro, 2009). However, empirical evidence on this relationship remains mixed. Some authors find a significant positive relationship (Becker & Chiswick, 1966; Winegarden, 1979) or a marginally significant positive relationship (Lee & Lee, 2018; Lin, 2007). Some authors do not find any significant correlation between education and income inequality (Carnoy, 2011; Földvári & van Leeuwen, 2011; Teulings & Rens, 2008). Castelló-Climent and Doménech (2012) report a significant negative relationship between income and education inequality.

Additionally, Bourguignon, Ferreira, and Lustig (2005) find the relationship between education inequality and income inequality to be an inverted U-shaped relationship.

We argue that education inequality calculated in previous literature lacks an important component: intergenerational (inter-age) educational inequality. We observe that the empirical specifications of most previous studies do not include variables that are determinants of earnings in standard earnings functions: particularly variables such as technological progress, the level of education, trade openness, and labour market institutions, which are shown to be important (Caselli & Ciccone, 2019; Madsen, Islam & Doucouliagos, 2018). This could make the coefficients of educational inequality more prone to bias. Additionally, previous studies employ cross-country or cross-state data, which may be potential sources for several problems. First, this type of data may fail to take into account unobserved cross-country heterogeneity caused by factors that simultaneously affect educational and income inequality. Second, results from studies focusing on a group of countries may not be generalisable because the parameter estimates are sensitive to country sample. Third, developing countries face a serious problem of poor quality data for income inequality and educational attainment (Földvári & van Leeuwen, 2011), making it problematic to draw inferences from.

To address the above limitations of previous studies, we introduce an augmented method to estimate the educational Gini, considering intergenerational educational inequality. Conventionally, education inequality is estimated as the dispersion between educational levels (e.g., no education, primary or secondary) for the entire adult population. We augment this method by estimating the education inequality as the dispersion between educational levels of age cohorts in the 23–65 age bracket (working-age population). As we illustrate in our paper, the education Gini that allows for intergenerational effects is a significantly more reliable measure of education inequality than the conventional education Gini. We overcome the problem of using cross-country or cross-state data in previous studies by employing a unique long time-series data set for 21 OECD countries for the periods 1870–2016 (regression analysis) and 1818–2016 (data required to estimate educational inequality starting from 1870)[1]. We are also the first at the macro level to empirically control for direct effects of technological progress (proxied by patent intensity, estimated as the ratio of patent applications of residents to employment) and the interaction between technological progress and tertiary educational attainment on income inequality.

In the chapter, we first summarize the theoretical results in the literature to build the base for the empirical model specification. We carry out our empirical analysis for 21 OECD countries in three periods 1870–2016, 1870–1940 and 1940–2016. We split the regressions into two periods with a

[1] Only OECD countries have long time series data set, allowing us to improve the shortcomings of previous studies' data.

breaking point in 1940 because of a significant shift in the structural relationship between income inequality and education. We also run another estimation over the period 1960–2010 for 61 countries, categorized into three approximately equally sized income groups: high-income countries, middle-income countries and low-income countries to corroborate our results from the OECD dataset. We conduct a simulation analysis to see how much the evolution of each explanatory variable has contributed to the income inequality path. We find that the association between educational inequality and income inequality has switched from positive before WWII to negative after that and that the interaction between tertiary education and technological progress has contributed to rising income inequality since WWII.

Chapter 3 presents our empirical analysis of the local economic impacts of mobile money service in Africa. The reason we have implemented our research of mobile money impacts in Africa is Africa has two distinct characteristics, namely low financial inclusion and high growth rate of mobile phones, which have made the region the enduring epicenter of mobile money. Thirteen countries in the world that have the highest rate of MM penetration are all in Sub-Saharan Africa. In five of these thirteen countries—Côte d'Ivoire, Somalia, Tanzania, Uganda, and Zimbabwe – more adults reported having a MM account than an account at a financial institution (Demirguc-Kunt et al. , 2015).

Even though the MM industry is just over a decade old, the astonishing achievements of MM have made it a fruitful source for attention from economists. There is a large body of literature documenting the success of MM at the microeconomic level. For example, MM is found to increase household consumption (Munyegera & Matsumoto, 2016), smooth household consumption during major shocks (Jack & Suri, 2014) and increase savings rates (Morawczynski & Pickens, 2009). MM helps users move out of extreme poverty, increase household consumption and savings rates and empower women to have a significant change in occupational choices (Suri & Jack, 2016). MM increases household agricultural commercialisation (Kirui, Okello, Nyikal & Njiraini, 2013) and improves companies access to supplier credit (Beck, Pamuk, Ramrattan & Uras, 2018). The presence of MM is associated with an increase in firm investment in fixed assets (Islam, Muzi & Rodriguez Meza, 2018).

We argue that prior studies share a common problem, in that their analysis tends to focus on a single economic indicator (such as consumption or investment) and utilise data from a single area or country, making their results represent only a partial equilibrium. Our paper builds a complement to these microeconomic studies by analysing the aggregate impact of MM on local economic activity. The contribution of our paper to the literature also lies in our dataset, which includes data for seven countries, hence providing general equilibrium and more generalisable results.

We follow Doll, Muller, and Morley (2006), Elvidge et al. (2009), Henderson, Storeygard, and Weil (2012) and Hodler and Raschky (2014) to use night-time light as a proxy for economic development, and we use access to mobile phone coverage as a proxy for access to MM services. We first develop granular mobile phone coverage boundaries in seven African countries by incorporating the coordinates of mobile phone towers and the surrounding topography in a viewshed model. We then use these coverage boundaries in a spatial discontinuity approach to assign grids into control and treatment cells. We estimated the effect of the introduction of MM on the treated cells using the standard difference-in-differences (DID) method. Our empirical analysis is carried out on a balanced panel dataset of around 1.9 million grid cells for the period 2000–2012. We checked the robustness of the results in our study by incorporating different bandwidths, as well as both sharp discontinuity and fuzzy discontinuity. Our main finding is a robust, significant impact of MM on local economic activity.

In Chapter 4, the primary motivation for our paper is the success story of Vietnam as a modern, globalised economy, brought by two ongoing efforts from the Vietnam Government: active trade liberalisation and substantial use of IP aiming to promote the transition into high-tech manufacturing. Supporting industries (SI), which basically include all industries that manufacture production inputs for finished industries, is one of the sectors that has received dramatic support from the Vietnamese Government. Since 2007, SI policy has aimed to promote the production of high-quality domestic inputs to be used in downstream production.

Our study provides an empirical examination of the deployment of SI incentives and their corresponding impact on firms' industrial development. We do so by comparing the evolution of firms producing SI products (treated) to other industrial firms (controls), before and after its introduction in 2007, using a DID methodology.

Our paper makes three main contributions to the literature. First, while most previous studies examine historical IP (for a comprehensive review, see Harrison & Rodríguez-Clare, 2010 and Lane, 2020), we study IP that is in progress. Second, our paper complements the large literature on the impacts of trade liberalisation on fostering economic growth. It does so by arguing that trade liberalisation is just part of the story, and the impacts of IP should not be ignored. For example, see Amiti and Konings (2007), Billmeier and Nannicini (2009), Goldberg and Pavcnik (2003), McMillan and Rodrik (2011) and Melitz (2003) for remarkable studies on this general topic. Papers specifically on Vietnam trade liberalisation effects include Athukorala (2006), McCaig (2011), McCaig and Pavcnik (2013) and Minot and Goletti (1998). Third, we contribute to the 'middle-income trap' literature (see Bulman, Eden & Nguyen, 2017; Eichengreen, Park & Shin, 2014; Hausmann, Pritchett & Rodrik, 2005; Paus, 2012; Pritchett & Summers, 2014 for some remarkable studies). The 'middle income trap' is the term describing the phenomenon that even though many middle income countries strive to transform from commodity production to industrialised and hi-tech economies, the transformation is unsuccessful and these countries stagnate at middle-income status. Existing literature focuses on three areas: 1. They build theoretical frameworks explaining why middle-income countries may have difficulties in maintaining high growth rates. 2. They predict some income thresholds at which growth slows. 3. They recommend measures to overcome the dilemma. Our study adds to this strand of literature by showing that by setting SI policy, Vietnam is on its way to avoid stagnation.

We find that treated firms have significant improvements across industrial development outcomes, including total revenue, employment, factor productivity and wages. However, there is weak evidence that SI policy significantly increased investment-related outcomes.

Chapter 5 provides a summary of my thesis, concluding remarks and discussion about potential areas for future research.

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Chapter 2

Is Income Inequality Driven by Biased Technological Progress, Education and Educational Inequality? International Evidence, 1870-2016[2]

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Abstract

The simultaneous expansion of tertiary education and increasing income inequality since the 1980s has raised the question of 1) the role of education for educational and income inequality; and 2) the influence of educational inequality on income inequality. To address these issue we construct annual data for 21 OECD countries over two centuries to examine the impact of the almost uninterrupted expansion in education on inequality through three channels: level effects, dispersion effects, and interaction between technological progress and tertiary education. As probably the first paper to do so, we allow for intergenerational education inequality in our estimates of the educational inequality. We find that the association between educational inequality and income inequality has switched from positive before WWII to negative thereafter and that the interaction between tertiary education and technological progress has advanced income inequality since WWII.

Keywords: Education inequality; income inequality; technological progress; educational attainment

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2.1 Introduction

Following the seminal paper of Becker and Chiswick (1966), education has been emphasized as one of the most important factors explaining the income inequality path and, particularly the skill premium (Acemoglu, 2002). Intuitively, since income derives from human capital for which education plays a fundamental role, increasing educational inequality will automatically translate into increasing income inequality. This raises the possibility that the expansion of tertiary education since the 1980s has contributed to the increasing income inequality in the OECD countries between the younger and more educated cohorts and less educated older cohorts in the labor force.

Empirically, however, it has been difficult to find a robust positive relationship between educational inequality and income inequality. Becker and Chiswick (1966) and Winegarden (1979) find a significant positive relationship between income inequality and education inequality. De Gregorio and Lee (2002), Lin (2007) and Lee and Lee (2018), find a marginally significantly positive relationship between educational and income inequalities. Ram (1984, 1989), De Ferranti et al. (2004), Teulings and van Rens (2008), Carnoy (2011), and Földvári and Leeuwen (2011) do not obtain any statistical significant correlation between education and income inequalities. Castelló-Climent and Doménech (2014) identify a significantly negative relationship between income and education inequalities. Finally, Bourguignon et al. (2005) find a non-linear inverted U-shaped relationship: as education inequality falls, income inequality rises initially and then starts declining.

Why are these results so conflicting when the literature consistently finds a positive skill premium and positive private returns to investment in education (see, e.g., Acemoglu, 2002; Caselli and Ciccone, 2019)? First, intergenerational (interage) educational inequality has, thus far, not been accounted for in the literature, hence, the education inequality between young and old workers has been excluded. Conventionally, education inequality is estimated as the dispersion between educational levels (no education, primary, secondary, etc.) for the entire adult population. Therefore, even if the educational Gini coefficient, based on the conventional estimation method, is constant, then an educational expansion will drive the education inequality of the labor force up to a level that will peak shortly after the expansion levels off, and the education inequality will return to its steady state approximately half a century later when the lower educated age cohort has exited the labor force.

Second, the coefficients of educational inequality are likely to be biased in most studies due to the omission of variables that are determinants of earnings in standard earnings functions; particularly variables such as technological progress, the level of education, trade openness, and labor market institutions. As shown by Caselli and Ciccone (2019), the skill premium varies across countries and over time because of the influence of labor market institutions and innovations in the demand for and the supply of skilled labor. More importantly, in addition to educational inequality, the income inequality, derived from a standard earnings function, is a function of the levels of education and returns to education, where the returns are a function of skill biased technological progress.

Third, the early studies use cross-country or cross-state data and, as such, cannot control for unobserved cross-country heterogeneity caused by factors that simultaneously affect educational and income inequalities. This may explain why the contributions of Becker and Chiswick (1966) and Winegarden (1979), both of which use cross-sectional data, are the only significant studies that find a positive relationship between income and educational inequalities. Furthermore, using panel data for the world, we show that it is generally difficult to find a robust relationship between income and educational inequality, partly because the parameter estimates are sensitive to country sample. A more serious problem relates to the extraordinarily poor quality of the data for income inequality and educational attainment for developing countries, which makes it problematic to draw inferences from regressions based on these data (see, for discussion of the quality of the income inequality data for developing countries and references, Moll, 1992).

This paper goes a step further than the previous literature on the nexus between education and income inequalities by investigating the effects of education on income inequality through three principal channels: dispersion effects, level effects, and the interaction between higher education and technological progress. More specifically, the paper makes the following contributions to the literature. First, we augment the educational Gini with educational attainment dispersion across age cohorts at all levels of education. While the conventional education inequality measures only account for education inequalities between all adults, the augmented measure allows for education inequality at all levels of education between all age cohorts in the 23-65 age bracket (working age population)[5]. Though highly data and computationally intensive, this extension is important since there are large generational educational inequalities that, as shown below, have had significant effects on overall educational inequality. As shown in Section 2.5.2, the education Gini that allows for intergenerational effects is a significantly more reliable measure of education inequality than the conventional education Gini.

Second, we employ unique long time series data set for 21 OECD countries for the periods 1870-2016 (regression analysis) and 1818-2016 (data required to estimate educational inequality starting

[5] The working age population is between 23-65 age brackets because following most of the literature, we consider four levels of education: No education; primary education (age 6-12); secondary education (age 13-17); and tertiary education (age 18-22). To calculate the augmented education Gini, we need to utilize the education attainment of the age cohorts that complete tertiary education (ie: must be at least 23 years old) and not older than 65 years old to remain in the working age range.

from 1870). Thus, the estimates in this paper go well beyond the conventional estimates that typically cover a cross-section of countries or a few observations per country (typically 3-5). The benefits from long data are that they: 1) are much less influenced by the medium-term movements than data covering a few decades and, as such, better capture the structural relationships between variables; 2) enable us to identify a structural change around WWII that gives insight into the factors affecting income inequality; and 3) make it possible to identify a Kuznets (1955) curve for educational attainment.

Third, this paper is probably the first empirical attempt at the macro level to allow for the direct effects of technological progress and the interaction between technological progress and tertiary educational attainment on income inequality. As a measure of technological progress, we use patent intensity, estimated as the ratio of patent applications of residents to employment. The interaction term allows us to check whether the income inequality effects of technological progress are reinforced by tertiary education and vice versa.

In Section 2.2 we motivate the empirical model specification by summarizing the theoretical results in the literature. The estimation model is outlined in Section 2.3, and Section 2.4 presents and discusses the data. Empirical estimates for the OECD countries and for the world are shown in Sections 2.5 and 2.6. Counterfactual simulations, in which the income inequality effects of education, educational inequality, technological progress, etc., are carried out in Section 2.7, and Section 2.8 concludes.

2.2 Education, technology and income inequality

In this section, we show that a bivariate model in which income inequality is regressed on educational inequality is prone to give biased estimates because income and educational inequalities are influenced by common factors; primarily technology. To this end we focus on the effects of education on income inequality through three principal channels: 1) its first moment (level of education); 2) its second moment (education inequality); and 3) its interaction with technological progress.

Consider the first moment. Formally, the relationship between the level of education and income inequality has been shown by Robinson (1976) to evolve in a non-linear fashion (see for survey of the literature on the nexus between the level of education and income inequality, Abdullah et al., 2015). Defining the weighted log of the mean income of the skilled and unskilled workers, YT, as:

$$Y_T = \phi_U Y_U + \phi_S Y_S, \tag{1}$$

where Y_U and Y_S are the log of average income of unskilled and skilled workers, and ϕ_U and ϕ_S are the share of unskilled and skilled workers in the total labor force, $\phi_S + \phi_U = 1$.

The variance is given by:

$$\sigma_Y^2 = \phi_S\sigma_S^2 + \phi_U\sigma_U^2 + \phi_S(\bar{Y}_S - \bar{Y}_T)^2 + \phi_U(\bar{Y}_U - \bar{Y}_T)^2, \tag{2}$$

where σ_S^2 and σ_U^2 are the variances of income of skilled and unskilled labor; and σ_Y^2 is the variance of total income, i.e. the income inequality.

Differentiating Eq. (2) w.r.t. the share of the skilled labor force yields:

$$\frac{\partial\sigma^2}{\partial\phi_S} = (\sigma_S^2 - \sigma_U^2) + (1 - 2\phi_S)(\bar{Y}_S - \bar{Y}_U)^2 + 2\phi_S(1 - \phi_S)(\bar{Y}_S - \bar{Y}_U)\left(\frac{\partial\bar{Y}_S}{\partial\phi_S} - \frac{\partial\bar{Y}_U}{\partial\phi_S}\right). \tag{3}$$

To obtain the Kuznets curve, assume that $\partial\bar{Y}_S/\partial\phi_S = \partial\bar{Y}_U/\partial\phi_S = 0$. Then income inequality peaks when the share of skilled workers in the total labor force is given by:

$$\phi_S^* = \frac{\sigma_S^2 - \sigma_U^2}{2(\bar{Y}_S - \bar{Y}_U)^2} + \frac{1}{2}, \qquad 0 \leq \phi_S^* \leq 0. \tag{4}$$

Since $(\bar{Y}_S - \bar{Y}_U) > 0$ and earnings in the skilled group tend to have a higher variance than the unskilled group (Acemoglu, 2002), $\sigma_S^2 > \sigma_U^2$, it follows that income inequality reaches a peak after more than one-half of the labor force has become skilled; e.g., $\phi_S^* > 1/2$. Beyond this point, income inequality is decreasing. Eq. (4) substantiates Kuznets' (1955) hypothesis that the reallocation of workers from low to high wage sectors initially raises inequality as more individuals acquire high income, however, as fewer and fewer workers remain in the low-income sector, income inequality eventually starts decreasing. This is referred to as the *compositional* effect.

If we relax the assumption that $\partial\bar{Y}_S/\partial\phi_S = \partial\bar{Y}_U/\partial\phi_S = 0$, then we may end up with a time-profile of income inequality that is quite different from the one predicted by Kuznets (1955). Knight and Sabot (1983), for example, argue that the last term in Eq. (3) is negative because $\partial\bar{Y}_S/\partial\phi_S < 0$ and $\partial\bar{Y}_U/\partial\phi_S > 0$. An increase in the share of skilled workers tends to reduce the skill premium through an excess supply of skilled workers (compression effect). Accordingly, for a sufficiently large compression effect, income inequality will decrease in response to an increase in ϕ_S.

However, we may get the result that $\partial\bar{Y}_S/\partial\phi_S > 0$ if the compression effect is outweighed by an endogenous technology response. Teulings and van Rens (2008) and Acemoglu (2002), for example, argue that a larger supply of educated workers induces investment in new skill-biased technology because these technologies are more profitable when educated workers are more abundant. However, as the unskilled labor is becoming scarcer, the skill premium is compressed through the term, $\partial\bar{Y}_U/\partial\phi_S$; thus, rendering the sign of the last term in Eq. (3) ambiguous.

Turning to the effects of the second moment of education on income inequality, consider the simple Mincerian model in which the returns to one additional year of education for an individual are independent of the number of years of education:

$$Y_E = Y_0 e^{rE} u, \tag{5}$$

where Y_E is the expected income with E years of education, r is the real returns to education and u is an error term that captures earnings that are unrelated to education. Eq. (5) yields the following variance-covariance decomposition:

$$\sigma^2_{\ln Y_E} = r^2\sigma^2_E + E^2\sigma^2_r + 2rE \cdot \sigma(r, E) + \sigma^2_u. \tag{6}$$

This equation shows that income inequality, $\sigma^2_{Y_E}$, is positively related to educational inequality, σ^2_S, the variance in returns across levels of education, σ^2_r, and unobserved factors affecting earnings inequality, σ^2_u, such as years of experience, cognitive ability, specialized skills, and luck, etc. If $\sigma(r, E) \geq 0$, then income inequality is unambiguously a positive function of the average years of education, E. Ultimately, however, $\sigma(r, E)$ depends on time-varying factors such as compression effects, compositional effects, skill-induced technological progress, and, not least, the supply of and demand for educated workers.

Study of Becker and Chiswick (1966) was the first study that indicates a positive relationship between income and education inequalities. This study was based on cross-section data and used the variance of years of schooling as a measure of educational inequality. The prediction of a positive relationship between income and education inequalities in the Becker-Chiswick (1966) model, however, is inconsistent with what we have observed in the post-WWII period. Over the period 1965-1980, for example, income inequality decreased despite increasing educational inequality. Furthermore, income inequality has increased while educational inequality has decreased since 1990 as shown below (based on our augmented educational inequality measure). One compelling reason for this is that the demand for skilled labor is neglected in the models above and yet there is considerable evidence of strong interaction effects between (biased) technological progress and education. The information, communication and technology revolution, for example, has been associated with an excess demand for skilled labor despite increasing education attainment, suggesting that the demand for skills has outpaced the supply of skilled labor (Acemoglu, 2002). This result is consistent with the finding of Caselli and Ciccone (2019). Caselli and Ciccone (2019) employ a labor-input aggregator of the CES form and with only two types of labor:

$$H^c = [(h_1^c L_1^c)^{\varepsilon-1/\varepsilon} + (h_2^c L_2^c)^{\varepsilon-1/\varepsilon}]^{\varepsilon/\varepsilon-1}$$

where c denotes a country index, ε is an elasticity of substitution, H^c is labor-input per worker; L_1^c and L_2^c are the proportion of the labor force with educational attainment below and above some level; and h_1^c and h_2^c are coefficients that convert bodies into productive services, or the efficiency units delivered by workers of the two types. They show that skill premia are not only resulted in by the differences in human capital but also shaped by institutions, technology, organizational structures, infrastructure, the structural composition of the economy, openness to trade, social norms, and other attributes of the environment. When technology and institutions are allowed for, educational attainment becomes insignificant in explaining cross-country income inequality. More specifically, their result indicates that human capital could not account for any differences in income across countries for values of ε around 1.5.

Additionally, Teulings (2005) has shown that a decrease in educational inequality tends to increase the returns to human capital and, therefore, income inequality. He derives this finding by applying the principle of comparative advantage to a theory of factor substitutability in a model with a continuum of worker and job types. He shows that highly skilled workers have a comparative advantage in complex job and analyzes changes in relative wages due to human capital accumulation.

Another possible reason for the divergence in educational and income inequalities since 1990 is that residual inequality has increased, as is reflected in an increase in the σ_u^2-term. A problematic assumption underlying the Becker-Chiswick model and Eq. (6) is that of perfect substitutability between different types of human capital within the same educational group. This assumption is at odds with the extensive literature that documents large, systematic time-varying movements in relative wages within education groups, measured by type of degree or length of education, in the United States (Acemoglu, 2002; Teulings and van Rens, 2008; Caselli and Ciccone, 2019). It is well known that the returns to skills vary across the same education groups – the so-called residual inequality in which inequality cannot be explained by between group characteristics (Acemoglu, 2002; Caselli and Ciccone, 2019). Residual inequality in the US, which was stable during the 1960s, began to increase rapidly during the early 1970s, indicating a discontinuity in labor market prices and, most likely, in the rate of increase of the demand for skills (Acemoglu, 2002). If we allow for a time-varying skill-premium that depends on skill-biased technological progress and other factors, the $2rE \cdot \sigma(r, E)$-term in Eq. (6) may overrule the effects on income inequality from the other terms in the equation and blur the correlation between income and education inequalities. If the residual inequality and educational inequality are sufficiently negatively correlated, then we may get into a situation in which increasing educational inequality is associated with declining income inequality.

Finally, the interaction between technological progress and education is reflected in the $2rE \cdot \sigma(r,E)$ and $r^2\sigma_E^2$-terms in Eq. (6). Skill-biased technological progress increases the returns to education, *r*; thus, increasing income inequality if $\sigma(r,E)$ is positive. Furthermore, at a given level of educational inequality, skill-biased technological progress unambiguously increases income inequality in the short run. With a fixed supply of educated workers, an increase in innovative activity will affect income inequality positively because the supply of skilled workers is fixed in a period the length of which depends on the time it takes to complete a degree and to learn the industry skills. Therefore, skill-biased technological epochs are likely to have prolonged positive effects on income inequality. However, technological progress may create new tasks in which unskilled labor has a comparative advantage; thus counterbalancing the displacement effects of technological progress (Acemoglu and Restrepo, 2019). Such new tasks generate a redeployment of unskilled labor into a broader range of tasks, change the task content of production and may work in favor of unskilled labor. In the case of a fixed level of technology, an expansion of the share of the skilled labor force will increase income inequality through the compositional and compression effects, as discussed above.

2.3 Model specification

Following the discussion in the previous section, we estimate the following income inequality model for 21 OECD countries over the period 1870-2016:

$$\begin{aligned} \ln Top_{it}^{10} &= \beta_0 + \beta_1 \ln Gini_{it}^{EZ} + \beta_2 \ln S_{it} + \beta_3 \ln S_{it}^2 + \beta_4 (Pat/L)_{it} \\ &+ \beta_5 (Pat/L)_{it}\sqrt{S_{it}^T} + \beta_6\sqrt{S_{it}^T} + Z_{it}\zeta' + CD_i + TD_t + \varepsilon_{it}. \end{aligned} \tag{7}$$

where Top^{10} is the top 10% income shares; $Gini^{XZ}$ is the educational Gini coefficient $X \in (C, A)$, where $Gini^{EC}$ is the conventional educational Gini (excluding interage effects) and $Gini^{EA}$ is the augmented educational Gini; *S* is education attainment (years of schooling) of the working age population; S^T is tertiary educational attainment of the working age population; *Pat*/*L* is patent intensity, where *Pat* is the number of patent applications of residents and *L* is total employment; *Z* is a vector of control variables; *CD* is country-dummies, *TD* is time-dummies; and ε is a stochastic error term.

The innovative activity is measured by patent intensity since patents are the only good technology indicators that are available far back in time, and patents have been shown to be excellent indicators of technological progress (Madsen, 2008). Patents are divided by employment to allow for product proliferation following the second-generation Schumpeterian growth models in which horizontal innovations are proportional to the size of the population in steady state (Peretto, 1998; Howitt, 1999; Peretto and Smulders, 2002; Madsen et al., 2020).

Here, S and S^2, are both included in the model to allow for the Kuznets effect, viz., that the income inequality is positively related to level of education until the share of skilled labor in the labor force is so large that a further increase in its share reduces income inequality (compositional effect). The interaction between patent intensity and the square root of S^T captures the income inequality effects of tertiary education conditional on patent intensity and vice versa. We take the square root of S^T in the interaction term under the assumption that a lower fraction of the working age population with a tertiary education is involved in innovative activity the larger is S^T. If we do not take the square root of S^T, then the coefficient of the interaction term becomes sensitive to estimation period.

Following the discussion in the previous section, the coefficient of educational inequality can take positive or negative values. The coefficient of educational inequality is predicted to be positive in the Becker-Chiswick (1966) model. However, it will be negative in Teulings' (2005) model if the residual inequality and education inequality are negatively correlated, or if $\sigma(r, S)$ affects income and educational inequalities with opposite signs, for example, if an expansion in tertiary education simultaneously reduces the skill premium and enhances the educational inequality.

The income inequality effects of patent intensity may be positive or negative. Addressing income inequality in a two-sector Schumpeterian model of inequality, Madsen et al. (2020) show that income inequality is positively related to the innovative activity (patent intensity) because the rent derived from the innovations accrues to capital owners, but negatively related to the income growth induced by innovations, which suggests that the effects of patent intensity on income inequality are ambiguous. Furthermore, the income inequality effects of innovations are influenced by the direction of technological progress (skill or unskilled biased). Most technological progress and technological epochs are likely to have been skill-biased. Investment-specific technological progress, for example, which accounts for a large share of technological progress (Gort et al., 1999), tends to increase the skill premium because these advances, which are implemented through investment, are complementary to skilled workers (Krusell et al., 2000). It is well known that skill-biased technological progress tends to increase income inequality and that it has been a prime suspect in the post-1980 increase in income inequality (Acemoglu, 2002). Furthermore, there is evidence that skilled workers gain from industrial revolutions that tend to be skill-biased. During a period with surging innovative activity, the demand for skills increases and, at least during the recent ICT revolution, the demand for skilled workers outpaced the supply of skilled workers. Increasing education during skill-biased technological revolutions, therefore, alleviates the increasing income inequality (the so-called wage compression effect). Finally, Acemoglu and Restrepo (2019) show that automation increases the number of new tasks, which may counter the displacement effects of professions that have been made redundant by new technologies.

The interaction between patent intensity and the square root of tertiary education captures how innovations may amplify income inequality by increasing the returns to tertiary education as suggested in the previous section. An expansion of the share of the labor force with a tertiary degree tends to increase income inequality because workers with a tertiary education are complementary to new technology; thus, leading to a positive compositional effect and an ambiguous compression effect. Conversely, an expansion in the innovative activity when the skilled fraction of the labor force is fixed increases the marginal productivity of skilled workers. Following the literature, we measure skilled workers by the average years of tertiary education of the working age population. While most people with a tertiary education are not directly involved in the innovative process, they are indirectly involved in innovations through administrative support, management decisions on new technology investment, and the implementation and use of complex new technologies.

As control variables, we include the import tariff rate, *Tar*, and Unionization, *Union*. The tariff rate, *Tar*, which is calculated as the ratio of tariff revenue and imports of goods, is expected to negatively relate to income inequality because it deters imports of products produced with a large component of unskilled labor. A large body of literature argues that imports of unskilled labor-intensive goods since the 1980s have reduced the demand for unskilled labor in the advanced countries (Acemoglu, 2002). Unionization is measured as the union membership per employed workers. Several studies have established that unions can have a profound influence on income distribution between workers and among workers and capitalists for the following reasons (Blanchard and Giavazzi, 2003; Checchi and García-Peñalosa, 2010; Madsen et al., 2018). First, unions tend to compress income inequalities by increasing the pay of the unskilled relative to the skilled and are often instrumental in increasing the minimum wage (Checchi and García-Peñalosa, 2010). Second, unions usually support social democratic governments, which tend to implement income inequality reducing policies. Third, unions seek to extract a share of the firm’s rents (Blanchard and Giavazzi, 2003).

2.3.1 Endogeneity issues

Even though we have included relevant control variables, which are potentially correlated with educational inequality to minimize endogeneity, we cannot rule out the possibility that the coefficients of education inequality are biased because of feedback effects from income inequality to educational inequality because the past gross enrolment rates are correlated with the error term. Like the existing literature, we do not use instruments for educational inequality for two reasons. First, simultaneity is likely to bias the coefficient of educational inequality in the opposite direction of our main findings: A high dispersion in income is likely to result in a high dispersion in gross enrollment rates because unprivileged parents tend to have high fertility rates and invest little in education (De La Croix and Doepke, 2003). A mean-preserving increase in income inequality, consequently leads to a larger spread in the educational inequality; thus, establishing a positive relationship between the two inequality variables. Second, since the level education is a predetermined variable, it follows that i) any instrument for contemporaneous education inequality is invalid; and that ii) endogeneity is only an issue if the residuals in the structural equation (Eq. (7)) are determined by events up to 60 years earlier and, at the same time, are correlated with the contemporary income inequality. The relevant endogenous variables are gross enrollment rates (GER's) and not education attainment because education attainment is determined by events that determined GERs at the time adults did their education. To take an extreme example, the 65-year age cohort started their education 58 or 59 year earlier. Thus, any contemporaneous instrument for the education attainment of this cohort is deemed to be invalid. Furthermore, the stationarity tests of Islam and Madsen (2015) show that income inequality is trend-stationary, suggesting low persistence in inequality and, therefore, that potential feedback effects from the dependent variable tend to be low.

2.4 Data, computations, reliability tests, and graphical analysis

In this section, we focus on the construction, time-profile, and reliability of the intergenerational measure of educational inequality in comparison with the conventional Gini coefficient. We use data over the period 1811-2016 for the following 21 OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, New Zealand, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK, and the US. The data stretches back to 1811 to allow for the education gap between the oldest and the youngest working age cohort starting from 1870. The data sources are relegated to the Data Appendix.

2.4.1 Estimation of the level and the distribution of education attainment

We construct two sets of estimates of the education Gini: The conventional in which intergenerational inequality is not accounted for (the conventional education Gini) and our augmented education Gini in which intergenerational educational inequality is accounted for (the augmented education Gini). The conventional education Gini is measured as:

$$G^{HC} = \frac{1}{2S}\sum_{i=0}^{M_i}\sum_{j=0}^{M_j}\left|S_i - S_j\right| p_i p_j, \tag{8}$$

where G^{HC} is the educational Gini coefficient, conventionally measured; S is the average years of education of the population of working age; M_i and Mj are the years of education at levels i and j; S_i

and S_j are the average years of education at levels i and j; and p_i and p_j are the shares of the working age population with levels i and j of education.

We estimate the augmented education Gini coefficient, in which interage inequality is accounted for, as follows:

$$G^{HA} = \frac{1}{2S}\sum_{i=0}^{Mi}\sum_{j=0}^{Mj}\sum_{\tau=23}^{65}\left|S_{\tau i} - S_{\tau j}\right| p_{\tau i}p_{\tau j}, \tag{9}$$

where G^{HA} is the augmented education Gini coefficient; τ is age cohort $\tau\epsilon(23{,}65)$; and $p_{\tau i}(p_{\tau j})$ is the population in age cohort τ with an $i(j)$ level education as the share of the total working age population.

Following most of the literature, we consider four levels of education: No education; primary education (age 6-12); secondary education (age 13-17); and tertiary education (age 18-22)[6]. For tertiary education, we include students with degrees from universities, technical high schools such as civil engineering schools, pharmaceutical schools, veterinarian and medical schools, and schools of agricultural science. A decomposition of education into finer grades is not feasible because these data are mostly not available and, when they are, the finer data are often defined differently across countries and over time.

Education attainment for *each age cohort* is computed as:

$$S_{\pi tj}^{P} = \sum_{i=6}^{12} GER_{n,t+i-\pi}^{P},$$
$$S_{\pi tj}^{S} = \sum_{i=13}^{17} GER_{n,t+i-\pi}^{S},$$
$$S_{\pi tj}^{T} = \sum_{i=18}^{22} GER_{n,t+i-\pi}^{T},$$

where $S_{\pi tj}^{P}$, $S_{\pi tj}^{S}$ and $S_{\pi tj}^{T}$ are education attainment at the primary, secondary and tertiary levels for each age cohort, $\pi \in (23, 65)$, at year t and for country j; $GER_{t+i-\pi}^{P}$ is the share of the population at the age of π that was enrolled in primary education $i - \pi$ years earlier, $i \in (6, 12)$; $GER_{t+i-\pi}^{S}$ is the share of the population at the age of π that was enrolled in second education $i - \pi$ years earlier, $i \in (13, 17)$; $GER_{t+i-\pi}^{T}$ is the share of the population at the age of π that was enrolled in tertiary education $i - \pi$ years earlier, $i \in (18, 22)$. For example, the education attainment at the primary level for the 65 years age cohort in 1870, $S_{65,1870}^{P}$, is the sum of gross enrollment rates for primary education, GER^P, over the years 1811-1817.

[6] In this research, we assume the maximum duration of Primary, Secondary, Tertiary education are 7 years, 5 years, 5 years respectively in all 21 countries.

The educational attainment at the primary level for the *entire working age population* is computed using the following equation derived by Madsen (2014):

$$S_{t,j}^{P} = \frac{\sum_{i=0}^{49}\left[Pop_{j,23+i}\sum_{\mu=0}^{8} GER_{j,t-i-\mu}^{P}\right]}{\sum_{i=0}^{49} Pop_{j,23+i}}, \tag{10}$$

where Pop_{23+i} is the size of the population aged 23+i; and GER^{P} is gross enrollment rates at the primary level (fraction of population of the relevant schooling age that is enrolled in primary education). Education attainment at secondary and tertiary levels are computed using the same principle (see, for details, Madsen, 2014). The educational data are compiled by Madsen (2014).

2.4.2 Estimation of income inequality

We measure income inequality as the top 10% income share because it is available on an annual basis and covers the income of all taxpayers (see Atkinson et al., 2011, for discussion of the merits of different inequality measures). Additionally, we use the 10% income share because it is the income inequality measure with broadest coverage of the standard inequality measures such as the Gini coefficient, top 1% etc. The Gini coefficient for example is mostly only available in 10-year intervals before WWII and is not going further back for several countries in our sample. However, since various income inequality measures are highly correlated (Leigh, 2007), the choice of income inequality measure is probably not essential for the results achieved here. The time span covered by the top 10% income share data, which is derived from tax returns, is limited by the time that direct income taxes have been in place – typically since the late 19th or early 20th century in our sample countries. We, therefore, retropolated the 10% income share data using income Gini coefficients that are available further back in time.

2.4.3 Reliability tests

We carry out reliability tests to check the quality and the reliability of the conventional and the augmented educational Gini's as measures of education inequality. Such checks will reveal whether the augmented Gini coefficient is measured with an error that is significantly different from that of the conventional Gini and, consequently, the extent to which the coefficients of the two inequality measures in the income inequality regressions are subject to errors-in-variable bias.

The reliability tests, which are adopted by Krueger and Lindahl (2001), involve simple bivariate OLS regressions. Consider the variable x in which the signal x^{*} reflects the true information about the variable and a noise term embodying the measurement error, *e*. The two different measures of educational inequality, x_A and x_C with different measurement errors, e_A and e_C, are given by:

$$x_A = x^* + e_A, \tag{11}$$
$$x_C = x^* + e_C, \tag{12}$$

where the subscripts 'A' and 'C' stand for augmented and conventional educational Gini coefficients.

Assuming that x^* is uncorrelated with e_A and e_C, the reliability ratios of x_A and x_C can be estimated from the bivariate regressions as follows:

$$R_A = \frac{cov(x_A,x_C)}{var(x_A)}, \qquad R_C = \frac{cov(x_C,x_A)}{var(x_C)},$$

where R_A is the reliability ratio of the augmented Gini and R_C is the reliability ratio of the conventional Gini. The corresponding probability limits of the two estimates are given by:

$$p\text{lim } R_A = \frac{var(x^*)}{var(x^*)+var(e_A)}, \; p\text{lim } R_C = \frac{var(x^*)}{var(x^*)+var(e_C)}.$$

These equations show that the lower is the variance of the measurement error of the augmented (conventional) educational Gini, the closer R_A (R_C) is to one and, consequently, the more reliable is the augmented (conventional) Gini.

Table 2.1. Reliability of the augmented and conventional educational Gini's.

Levels/Differences	***R_A***	***R_C***	***Obs.***
Levels	0.954 (2.46)**	0.810 (15.0)***	3087
Differences	1.030 (0.20)	0.616 (4.62)***	3087

Notes: The numbers in parentheses are *t*-tests of the null hypothesis of unity of the reliability ratio. R_A and R_C are the estimated coefficients of x_A and x_C obtained by regressing the conventional Gini on the augmented Gini on country and time dummies over the period 1870-2016. Educational inequality is measured in logs. *, **, *** = significant at 10, 5 and 1% levels.

The reliability ratios and robust *t*-tests of the null hypothesis of unity of the reliability ratios are presented in Table 2.1. The reliability coefficients of the augmented education Gini, which are presented in column (1), are both close to one, and the null hypothesis of a coefficient of one cannot be rejected in the first difference regression, but is rejected at the 5% level in the level estimates. Conversely, for the conventional Gini, the null hypothesis of a unity reliability ratio is strongly rejected for both estimates (column (2)). From these results, it can be concluded that the augmented Gini is prone to give significantly more unbiased parameter estimates than the conventional Gini.

2.4.4 Graphical analysis

Figure 2.1 illustrates the conventional and the augmented educational Ginis and Figure 2.2 displays the education attainment; both of which are averaged between the 21 OECD countries in our sample. Although the estimation period starts first in 1870 because the income inequality data are scant before 1870, the graphs cover the period 1522-2016 to get a long perspective on the data, where the long data are constructed by Madsen (2020). Regardless of whether the conventional or augmented education Gini is used, education inequality has trended downwards throughout the period 1522-2016. Education attainment, at the same time, has increased throughout the whole period (Figure 2.2).

Figures 2.1 and 2.2 give the following insights. First, the educational level and educational inequality are almost mirror images of each other up until 1950: In absolute terms, they both have moderate slopes before the mid-19$^{\text{th}}$ century and steep slopes in the approximate period 1850-1950. Thereafter, the negative association appears to somewhat disappear; at least as far as the conventional education Gini is concerned. The negative relationship between education attainment and the educational Gini up to circa 1950 is consistent with the evidence of Castelló-Climent and Doménech (2014) who find that education inequality has been reduced by increasing literacy rates in the developing countries over the period 1950 to 2010. Essentially, the narrowing gap between the literate elite and the illiterate broad cross-section of the population was the force behind the declining educational Gini, an effect that gained momentum during the expansion of mass education from the mid-19th century. Second, after WWII the evolution of secondary and tertiary education have been the main determinants of education inequality. The expansion of post-WWII secondary education increased both measures of the education inequality over the approximate period 1965-1990, after which time, inequality started to decline when a sufficiently large fraction of the working-age population had a secondary education.

Third, the *growth* in the conventional and augmented educational Ginis coincide up until circa 1800 as a reflection of a steady state situation in which the intergenerational educational inequality was probably almost non-existent (Figure 2.3). Thereafter, the two measures tend to follow distinctive paths, particularly after circa 1830 along with the expansion of mass education. While the growth in the conventional educational Gini declines immediately after each growth spurt in education, the growth in the augmented education Gini first increases and then declines with a time-lag of approximately 20 years after the conventional Gini has started to decline. These time-profiles can be traced in the curves following the expansion in primary education in the mid-19th century and the expansion in secondary education in the last decades of the 20th century. The expansion in tertiary education, by contrast, has not produced the same growth profiles as the expansion in primary and secondary education; mainly because of counterbalancing effects from secondary education. The expansion of secondary education during the second half on the 20th century has reduced the education inequality as the new graduates replace the retiring workers with a modest secondary education.

Figure 2.1. Education Gini, OECD

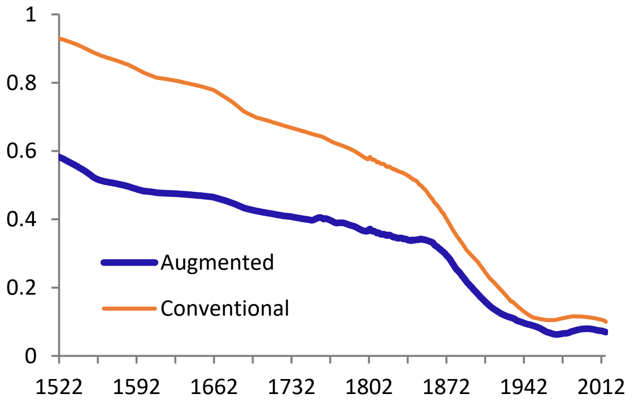


Figure 2.2. Education attainment, OECD

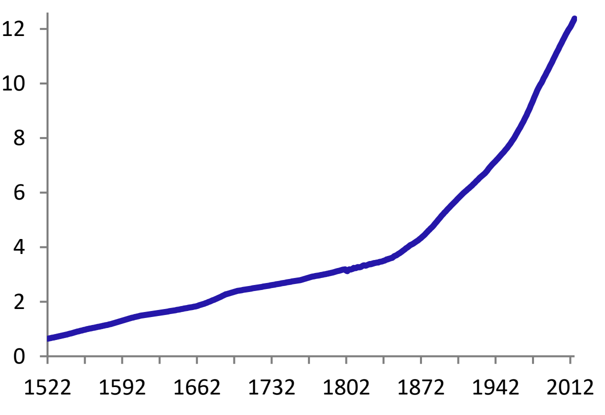


Figure 2.3. Growth in education Gini coefficient, OECD

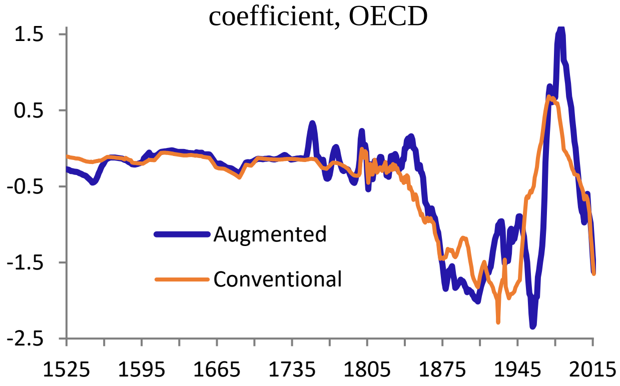
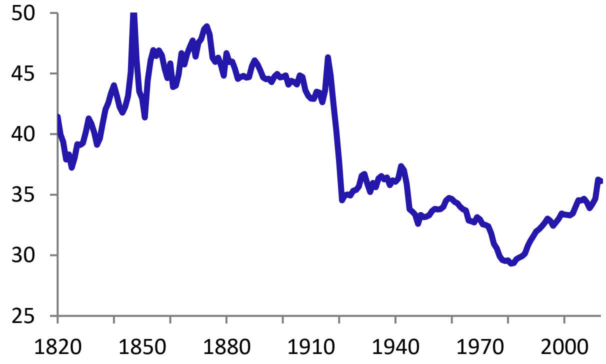


Figure 2.4. Top 10% Share, OECD



Notes: A 5-year centered moving average are taken of the educational Gini coefficients in Figure 2.3. *, **, *** = significant at 10, 5 and 5% levels.

Displayed in Figure 2.4, the top 10% income shares in the OECD countries have, on average, declined substantially over the period 1870-1982 and since increased. Piketty (2014) and Roine et al. (2009) attribute the declining income inequality up to 1982 to increasing top marginal income tax rates, post WWII nationalization, inflation and the syndicalist uprising immediately following WWI. Considering the long trends, income and education inequality are both declining significantly up to the 1940s and, since then, mostly moved in opposite directions. Thus, depending on the extent to which these trends carry through across countries, it is possible that the relationship between income inequality and education inequality has changed over the course of the last 156 years.

2.5 Estimation results

We estimate Eq. (7) over the three periods 1870-2016, 1870-1940 and 1940-2016. We split the regressions up in two periods with a breaking point in 1940 because of a significant shift in the structural relationship between income inequality and education.

2.5.1 Period 1870-2016

The results of estimating Eq. (7) are shown in Table 2.2. In this section, we will focus on the educational Gini and the interaction between technology and higher education and relegate the discussion of the level of education to the next subsections because of the structural shift in their coefficients. The augmented educational Gini, $Gini^{EA}$, is included in the regressions in the first five columns, while the conventional education Gini, $Gini^{EC}$, is included in the estimates in columns (6)-(8), and $Gini^{EA}$ and $Gini^{EC}$ are both included in the regression in the last column.

The coefficients of $Gini^{EA}$ are significantly negative in the regressions in the first three columns; however, they become insignificant when the tariff rate, *Tar*, and unionization, *Union*, are included as control variables. We get almost the same results when educational inequality is measured by $Gini^{EC}$: The magnitude of the coefficient of $Gini^{EC}$ in the bivariate regression reduces to a quarter when we include all the regressors. The key to this reduction in the absolute magnitudes of the coefficients of $Gini^{EA}$ and $Gini^{EC}$ is the inclusion of unionization, as can be seen by comparing columns (4) and (7) against (5) and (8). From this result, we can conclude that the coefficient of educational inequality may be subject to a significant endogeneity bias when unionization is omitted from the regressions. The importance of the unionization rate is, furthermore, supported by its high statistical significance (its economic significance is discussed below). Unionization is likely to have been a main factor behind the sharp reductions in income inequality immediately after the world wars. A dissatisfaction with the increasing income inequality driven by a combination of staggering wage contracts and high inflation during the two world wars, fueled by the successful communist revolutions in several countries around the end of the world wars, mobilized workers to claim compensation for the lost real income during the world wars (Madsen et al., 2018).

Table 2.2. Determinants of top 10% income shares, 1870-2016

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
$\ln Gini^{EC}$						-0.071***	-0.016***	-0.062***	-0.058***
						(11.1)	(2.77)	(10.5)	(6.36)
$\ln Gini^{EA}$	-0.051***	-0.042***	-0.041***	0.003	-0.035***				0.055***
	(6.94)	(8.81)	(6.21)	(0.50)	(5.03)				(5.66)
$\ln S$		0.103***	0.158***	0.065**	0.139***		0.087***	0.177***	0.090***
		(7.92)	(5.05)	(2.24)	(4.59)		(2.91)	(5.67)	(3.03)
$(\ln S)^2$		-0.034**	-0.023	0.022*	-0.02		-0.086	-0.040***	-0.011
		(2.32)	(1.62)	(1.78)	(1.22)		(0.67)	(2.70)	(0.82)
(Pat/L)			-0.199***	-0.055*	-0.178***		-0.067**	-0.174***	-0.052*
			(5.48)	(1.79)	(4.88)		(2.17)	(4.91)	(1.68)
$\sqrt{S^T}(Pat/L)$			0.338***	0.224***	0.327***		0.230***	0.315***	0.216***
			(7.50)	(5.29)	(7.21)		(5.48)	(7.24)	(5.33)
$\sqrt{S^T}$			-0.285***	-0.167***	-0.292***		-0.178***	-0.279***	-0.152***
			(5.00)	(3.41)	(5.12)		(3.67)	(5.16)	(3.19)
Tar				-0.002***	-0.002***		-0.002***	-0.002***	-0.003***
				(5.97)	(4.46)		(5.71)	(5.02)	(7.17)
$Union$				-0.494***			-0.463***		-0.446***
				(22.4)			(19.9)		(18.8)
Obs.	3087	3087	3087	3087	3087	3087	3087	3087	3087
Est. Period	1870-2016	1870-2016	1870-2016	1870-2016	1870-2016	1870-2016	1870-2016	1870-2016	1870-2016

Notes: The numbers in parenthesis are absolute *t*-values based on heteroscedasticity and serial correlated consistent standard errors. The dependent variable is $\ln Top_{it}^{10}$. Time- and country dummies and constant terms are included in all regressions. $Gini^{EC}$ = conventional Gini coefficient; $Gini^{EA}$ = augmented Gini coefficient; *S* = educational attainment (years of education) of the working age population; S^T = tertiary educational attainment of the working age population; *Tar* = macro tariff rate; *Inst* = institutions; *Union* = unionization rate. Heteroscedasticity and serial correlated consistent standard errors are used. *, **, *** = significant at 10, 5 and 1% levels.

When $Gini^{EC}$ and $Gini^{EA}$ are included simultaneously in the regression (last column), the coefficient of $Gini^{EC}$ is significantly negative, while the coefficient of $Gini^{EA}$ is significantly positive. This result suggests that intergenerational education inequality, on average, increases income inequality, while education inequality between different levels of education reduces income inequality.

Turing to innovations, the coefficients of patent intensity are significantly negative while the coefficients of the interaction between patent intensity and tertiary education are significantly positive regardless of how the educational inequality is measured ((3)-(5) and (7)-(9)). These findings imply that tertiary education needs to exceed a minimum level before innovations influence income inequality positively. Based on the estimations in column (4), for example, the coefficient of patent intensity is -0.05 and the coefficient of the interaction between patent intensity and the square root of tertiary education is approximately 0.22. This suggests that patent intensity has positive effects on income inequality when the condition $(\beta_4/\beta_5)^2 = (0.05/0.22)^2 = 0.05 < S^T$ is met. Thus, innovations have positive effects on income inequality if the average person of working age has at least 0.05 years of tertiary education. This condition was first met after 1908 for the average OECD country. We find almost the same benchmark levels for the pre and post-1940 estimates below. The implication of this is that technological progress did not promote income inequality in the 19th century because the fraction of the working age population with a tertiary education was far too small to affect the income distribution even if the technological progress were skill-biased. Furthermore, if secondary education is included in the skilled category in the pre-1940 estimates, we find that the benchmark level at which educational attainment at the secondary plus tertiary levels increases income inequality is passed in 1880 for the average OECD country (the results are not shown). From these results, we can infer that technological progress during most of the 19th century did not particularly favor skilled labor because the new tasks created by the technological progress enhanced the demand for unskilled labor, a possibility that gains support from the discussion in Acemoglu (2002) and Galor (2005).

2.5.2 Estimation periods 1870-1940 and 1940-2016

The graphs presented in the previous section show a tendency for educational and income inequality to move in tandem before WWII and in opposite directions thereafter. To investigate whether a structural break occurred in 1940, we estimate Eq. (7) over the periods 1870-1940 and 1940-2016 (using 1950 as the structural break year give us the same principal results and various structural break tests indicate that the structural break occurs during the 1940s).

The estimates, which are presented in Table 2.3[7], show a change in the sign of the coefficients of educational inequality over the two periods. Consistent with the graphical evidence, the coefficient of

[7] In both Table 2.2 and Table 2.3, we have conducted the experiment to include the square root of education attainment in a separate specification where all the variables could be included as first order moment, and the results did not change.

augmented educational inequality is significantly positive before 1940, but significantly negative thereafter. Varying the estimation periods within the pre- and post-WWII estimates hardly changes the coefficients of $Gini^{EA}$ (the results are not shown), suggesting that there was a marked structural shift in the data generating process around WWII. A potential reason for this was that complexity of tasks accelerated in the post-1940 period along with the increase in technical advances after WWII.

Given the lack of historical data, we do not know the historical evolution of the complexity of tasks. However, we can infer a plausible path from economic growth theory. Theory and evidence suggest that the sophistication and complexity of tasks are increasing in product variety (Hu et al., 2008). Coupled with the insight from standard endogenous growth models in which growth is driven by product variety or product quality (see, for overview, Barro and Sala-i-Martin, 2004, Aghion and Howitt, 2008), it follows that the complexity of tasks are proportional to the productivity trend. Greasley et al. (2013) show that the main structural break in labor productivity in today's advanced countries occurred immediately after WWII. Thus, these countries transited from a low-growth regime to a high growth regime that is likely to have been associated with an increase in the complexity and the sophistication of work tasks which, consequently, gave rise to residual inequality. As documented by Acemoglu (2002), residual inequality started to increase from 1970 in the US; a trajectory that may well have started much earlier along with the transition to a new growth regime, but we don't have the data to check this possibility. If the residual inequality is negatively correlated with educational inequality, as argued by Teulings (2005), the decrease in educational inequality increased the returns to human capital and, consequently, income inequality.

Table 2.3. Determinants of the top 10% income shares, 1870-1940 and 1940-2016

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln Gini^{EC}$			-0.021			-0.045***
			(1.58)			(7.19)
$\ln Gini^{EA}$	0.066***	0.052***		-0.083***	-0.062***	
	(7.62)	(6.20)		(11.0)	(8.58)	
$\ln S$		0.051**	0.100***		0.962***	1.012***
		(2.22)	(3.70)		(4.73)	(4.93)
$(\ln S)^2$		0.036***	0.023*		-0.246***	-0.252***
		(3.58)	(1.94)		(4.17)	(4.22)
(Pat/L)		-0.240***	-0.290***		-0.035***	-0.036
		(6.82)	(5.51)		(4.17)	(1.65)
$\sqrt{S^T}(Pat/L)$		0.972***	0.389***		0.131***	0.133***
		(8.33)	(7.33)		(4.79)	(5.12)
$\sqrt{S^T}$		-0.006	-0.086**		0.073	0.069
		(0.05)	(2.27)		(1.45)	(1.33)
Tar		0.001***	0.000		-0.001	-0.001*
		(3.04)	(0.92)		(0.91)	(1.68)
$Union$		-0.121**	-0.100*		-0.413***	-0.376***
		(2.31)	(1.76)		(14.2)	(12.6)
Obs.	1491	1491	1491	1617	1617	1617
Est. Period	1870-1940	1870-1940	1870-1940	1940-2016	1940-2016	1940-2016

Notes: The numbers in parenthesis are absolute *t*-values based on heteroscedasticity and serial correlated consistent standard errors. The dependent variable is $\ln Top^{10}_{it}$. Time- and country dummies and constant terms are included in all regressions. Heteroscedasticity and serial correlated consistent standard errors are used. *, **, *** = significant at 10, 5 and 1% levels.

In the pre-1940 estimates, the coefficients of $Gini^{AC}$ are significantly positive while the coefficient of $Gini^{EC}$ is insignificant (columns (1)-(3)), suggesting that educational inequality affected income inequality through intergenerational educational inequality as opposed to between-levels of educational inequality. In the post-1940 period, by contrast, the coefficients of both $Gini^{AC}$ and $Gini^{EC}$ are significantly negative. However, the coefficient of $Gini^{AC}$ is 38% more negative than that of $Gini^{EC}$ (column (5) vs. (6)), suggesting that educational inequality across generations as well as across educational levels have contributed to the post-1940 income inequality path.

Why did the coefficient of augmented educational inequality switch from positive to negative around 1940? The main structural break in the growth regime immediately after WWII in the OECD, as argued above, has likely increased the complexity and the sophistication of work tasks. This, in turn, has signaled a departure from a simple positive relationship between educational and income inequalities and the emergence of residual inequality, as documented in several studies (see, e.g., Acemoglu, 2002). Provided that residual inequality is negatively correlated with educational inequality, as argued by Teulings (2005), the decrease in educational inequality increased the returns to human capital and, consequently, income inequality. Alternatively, the negative coefficient of

$Gini^{EA}$ in the post-1940 regressions suggests that the compositional effect of education inequality on income inequality is less important than the compression effect that derives from low substitutability between different types of labor.

In terms of the theoretical framework in Section 2.2, the coefficient reversal can be explained by reference to Eq. (4), in which income inequality reaches a peak after more than one-half of the labor force has become skilled provided that the compression effect is absent or not too large: The increasing number of individuals with tertiary and even secondary education before WWII promoted income inequality because their share of the work force was below the peak of the Kuznets curve. Furthermore, since most wage earners had only a basic education or less before WWII and their income was kept down through a high fertility the compression effect from higher educated workers was deemed to be low.

Turning to educational attainment, the coefficients of S are positive in both periods, whereas the coefficients of S^2 are positive in the pre-1940 period but significantly negative in the post-1940 estimates. Based on the post-1940 regression in column (5), the years of education of the labor force at which education reduces income inequality is $S > \exp[-\beta_2/(2\beta_3)] = \exp(0.962/0.492) = 7.1$. Since the average level of educational attainment of the working age population in our sample was 7.2 years in 1940, the post-1940 educational expansion contributed to a reduction in income inequality throughout the whole period. This suggests that the educational Kuznets curve peaked around WWII. This corroborates with the marked expansion in the secondary and tertiary education after WWII, which has had two effects on inequality. First the compositional effect in which the share of high-income wage earners has gone beyond the peak in the Kuznets curve. Second, it is highly likely that the share of educated high-income workers' share of total wage earners increased along with the increasing sophistication of manufacturing and the increase in the service sector. Unfortunately, we cannot substantiate the last conjecture because wage inequality statistics are not available until well after WWII in most countries, partly reflecting the lack of data on skilled wages.

The income inequality effects of patent intensity are conditional on the level of tertiary education in both periods because the coefficients of patent intensity are negative, whereas the coefficients of the interaction between patent intensity and tertiary education are significantly positive. The benchmark levels of S^T at which patent intensity starts increasing income inequality, $(-\beta_4/\beta_5)^2$, is 0.07 in both estimation periods (based on regressions in columns (2) and (6)). Since S^T, for the average OECD country, crossed the 0.07 boundary in 1927 and increased thereafter, the patent-intensity switched from being income inequality reducing to being income inequality augmenting around 1927, depending on the country in question. This result is consistent the increasing investment in intellectual property products (mostly R&D) during the interwar period and its acceleration after WWII (Madsen et al., 2020). It is reasonable to assume that increasing investment in intellectual property products increases the fraction of complex tasks because of the related auxiliary tasks required to assist the R&D efforts and the highly skilled workers that are required to implement the innovations.

A channel through which the *level* of patent intensity influences income inequality is through tertiary education, S^T. Since the coefficients of $\sqrt{S^T}$ are insignificant in three of the four cases, the income inequality effects of increasing tertiary education, ceteris paribus, derives from the positive effects of the interaction between $\sqrt{S^T}$ and patent intensity. Although the coefficient of the interaction term is substantially larger in the pre-1940 regression than the post-1940 regression, the income inequality elasticities of mean in the pre- and post-1940 estimates, are quite close because we need to multiply the coefficient of the interaction terms by the average of $\sqrt{S^T}$ over the considered estimation period. Finally, the coefficients of tariff rates are mixed, while the coefficients of unionization are significantly negative, particularly after 1940. Based on the baseline regression in column (4) in Table 2.3, the 18 percentage point increase in unionization from 1945 to its peak in 1980, resulted in a 7.4% or a 2.5 percentage point reduction in the top 10% income share, noting that the top 10% income share decreased 4.3 percentage point over the period 1945-1980.

2.6 Evidence for the world, 1960-2010

Our finding that educational inequality is robustly negatively associated with income inequality in the post-WWII period; a period that is covered in the existing studies, begs the question of why our results differ from a large strand of the literature. To investigate this issue we regress income inequality, measured by the net income Gini coefficient, on educational inequality and the level of educational attainment at quinquennial frequencies over the period 1960-2010 for 61 countries, where the net income Gini is measured as the post-tax and post-transfer income inequality. We estimate the conventional educational Gini coefficient based on the share of the adult population with 1) no education; 2) primary education; 3) secondary education; and 4) tertiary education. We do not compute the augmented educational Gini because the long annual data on gross enrollment rates that are required in the estimates are not available. As detailed in the online Appendix, the country sample is constrained to countries for which at least three observations of income inequality, which are five years apart, are available (the educational data are available for all the countries that satisfy this criteria). We split the estimates into three approximately equally sized income groups, classified by the size of the average per capita income over the period 1990-2017): High-income countries, middle-income countries and low-income countries. We have refrained from using the World Banks' country classification because only six of the countries in our sample belong to the low-income group as classified by the World Bank. Details of the country sample, data sources, and country classification are relegated to the Data Appendix.

The estimation results are reported in Table 2.4 with country and time fixed-effects (top panel) and with time fixed-effects only (bottom panel). The principal results are similar if the variables are measured in logs as shown in the online Appendix. The most important aspects of the results are that they are 1) sensitive to inclusion of country fixed effects; and 2) that income inequality tends to be negatively related to educational inequality and the level of education. When country fixed effects are included in the regressions, income inequality is negatively associated with educational inequality for the high-income countries; a result that corroborates with the results for the OECD countries in this paper. For middle- and low-income countries, the association between income and educational inequalities is weak (columns (3)-(6), top panel). When country fixed effects are excluded (bottom panel), the relationship between income and educational inequality for the high-income countries remains negative. However, for the middle- and low-income countries, the results are largely reversed when the country fixed effects are omitted from the models. In this case, there is a significantly negative relationship between educational and income inequalities in three of the four cases. The negative relationship is particularly pronounced for the low-income countries: A one-point increase in educational inequality is associated with a 0.24-0.55 point reduction in the income inequality. Finally, the coefficients of education, *S*, are negative for high- and low-income countries, suggesting that education promoting-policies are a promising way to reduce income inequalities.

Table 2.4. The nexus between the income Gini and the educational Gini, World

	High income countries		**Middle income countries**		**Low income countries**	
	(1)	(2)	(3)	(4)	(5)	(6)
			Inclusive Country Fixed Effects			
$Gini^{EC}$	-0.101**	-0.218***	0.158***	0.0631	-0.0745	-0.127
	(2.35)	(4.20)	(2.65)	(0.77)	(0.90)	(0.64)
S		-0.0169***		-0.0192**		-0.00696
		(4.44)		(2.14)		(0.32)
			Exclusive Country Fixed Effects			
$Gini^{EC}$	0.0120	-0.152*	-0.090**	-0.046	-0.238***	-0.550***
	(0.28)	(1.66)	(2.42)	(0.82)	(6.27)	(7.02)
S		-0.0125**		0.00574		-0.0406***
		(2.4)		(0.92)		(4.54)
Obs.	205	205	221	221	162	162

Notes: The numbers in parenthesis are absolute *t*-values based on heteroscedasticity and serial correlated consistent standard errors. The regression applies to an unbalanced panel data set for 61 countries over the period 1960 to 2010 at quinquennial frequencies. All variables are measured in levels (see online Appendix for results with the variables measured in logs). Time-dummies and constant terms are included in all regressions. The dependent variable is the net income Gini coefficient. *, **, *** = significant at 10, 5 and 1% levels.

Can the results in this section shed light on the diversity of results in the literature on the nexus between income and educational inequalities? Yes and no. The results in Table 2.4 show that the results are sensitive to the inclusion of country fixed-effects, country sample and whether the level of education is included in the estimates; thus, going some way in explaining the conflicting results in the literature. A significantly positive coefficient of educational inequality when the level of education is omitted from the regression for the middle-income countries, for example, is consistent with some of the findings in the literature. However, the overwhelming finding is that income inequality is negatively affected by educational inequality - a result that is robust to estimation period, inclusion of regressions, and functional form (the results are available from the authors). Therefore, why some authors find a positive relationship between these inequalities remains a puzzle.

Finally, relating the results in Table 2.4 to those in the previous section, we could expect a positive relationship between income and educational inequality in low-income countries. Like the pre-1940 results for the OECD countries, one would expect the number of differentiated tasks to be low in low-income countries. The absence of a significantly positive coefficient of the educational Gini for the low-income group may reflect large measurement errors or that important control variables are excluded from the estimates. Like the income inequality data, the educational data for developing countries are notoriously unreliable because schools, to a varying degree, over report school enrollments to the government to gain resources, the teacher is frequently absent from the class, the facilities and learning resources are often substandard, teachers' education is often poor, and rote learning is emphasized, etc. (see, for discussion, Földvári and Leeuwen, 2011). This stands in contrast to the advanced countries in which school attendance and number of students have been checked and reported by school inspectors for centuries (see, e.g., Madsen and Murtin, 2017). For the middle-income group, the indeterminacy/insignificance of the educational inequality may reflect that, during large parts of the estimation period, 1960-2010, these countries have been in the transitional phase of development during which complex tasks have gradually increased in significance.

2.7 Counterfactuals

In this section, we ask the question of how much the evolution of educational inequality, technological progress, education, tariffs, and unionization have contributed to the income inequality path over the periods 1870-1940, 1940-2016, and 1980-2016. To achieve this, we derive the elasticities of each variable contained in Eq. (7) and multiply them by the change in the variable in question over the periods 1870-1940 and 1940-2016. Consider, again, Eq. (7):

$$\ln Top_{it}^{10} = \beta_0 + \beta_1 \ln Gini_{it}^{EZ} + \beta_2 \ln S_{it} + \beta_3 \ln S_{it}^2 + \beta_4 (Pat/L)_{it} + \beta_5 (Pat/L)_{it} \sqrt{S_{it}^T} + \beta_6 \sqrt{S_{it}^T} + Z_{it}\zeta' + CD_i + TD_t + \varepsilon_{it}. \quad (7)$$

The impact of the variables on income inequality follows directly from the coefficient estimates except the variables included in the interaction terms. The income inequality effects of tertiary education and research intensity are derived from Eq. (7):

$$d \ln Top^{10} = \left[\ln\left(\frac{Pat}{L}\right)_t - \ln\left(\frac{Pat}{L}\right)_{t-j}\right]\left[\hat{\beta}_4 + \hat{\beta}_5 \overline{S^T}^{1/2}\right]\overline{(Pat/L)},$$

and

$$d \ln Top^{10} = \overline{S^T}\left[S_t^T - S_{t-j}^T\right]\left[\widehat{\beta_5}\overline{(Pat/L)} + \widehat{\beta_6}\right]\tfrac{1}{2}\,\overline{S^T}^{(-1/2)} = \left[S_t^T - S_{t-j}^T\right]\left[\widehat{\beta_5}\overline{(Pat/L)} + \widehat{\beta_6}\right]\tfrac{1}{2}\,\overline{S^T}^{(+1/2)},$$

where j = 70 for the calibration period 1870-1940 and j = 76 for the calibration period 1940-2016; $\overline{S^T}$ is the average number of years of tertiary education of the working age population over the period *t-j*; and $\overline{(Pat/L)}$ is the is the average of the log of patent intensity over the considered period. All variables are measured as the averages for the 21 OECD countries in our sample. The derivations of the income inequality effects of the other regressors in Eq. (7) follow the same principle.

Table 2.5. Simulated effects of regressors on top 10% income shares.

	1870-1940	**1940-2016**	**1980-2016**
		---------------- Percent --------------	
Education Inequality	-6.3	1.9	0.9
Education, total	9.4	-7.9	-5.4
Education, tertiary	0.1	4.4	1.9
Patent intensity	0.0	0.4	0.7
Tariffs	0.1	1.3	0.2
Unionization	0.0	-1.3	1.2
Total	**3.3**	**-1.2**	**-0.5**

Notes: The table shows the effects of each variable on the top 10% income shares based on coefficient estimates. The variables are unweighted averages for the 21 OECD countries in our sample. For the periods 1870-1940 and 1980-2016, the coefficients in column (2) in Table 2.3 are used. For the period 1940-2016, the coefficients in column (6) in Table 2.3 are used.

The simulation results, which are presented in Table 2.5, show distinctively different effects of the explanatory variables on income inequality before and after 1940. Educational inequality contributed to a 6.3% decline in income inequality over the period 1870-1940 and a 1.9% increase over the period 1940-2016. The expansion of educational attainment contributed to a 9.4% increase in income inequality before 1940 by a 7.9% decline thereafter - due to the Kuznets compositional effect. However, through its interaction with technological progress, tertiary education has contributed significantly to the increasing income inequality in the post-WWII period, particularly since the 1990s.

As a whole, education (level, variance, and tertiary education) has contributed to a 3.2% increase in the income inequality path in the pre-1940 period, and to a further 1.6% increase thereafter.

Patent intensity did not affect income inequality before 1940 and only contributed by a modest 0.4% to income inequality thereafter. This result may look counterintuitive since biased technological progress has often been stressed as a contributor to the increase in income inequality since the early 1980s (Acemoglu, 2002). The reason for this finding is that patent intensity has not significantly increased for the average OECD country in the overall period 1940-2016. However, it has indirectly contributed to increasing income inequality through its interaction with tertiary education. Furthermore, there has been a large cross-country dispersion in the change in technology-induced income inequality after 1940. The US and Australia, for example, have experienced an approximately two-fold increase in patent intensity over the period 1940-2016, while France, the UK, and the Scandinavian countries have experienced a decline over the same period.

Finally, post-1980 simulations are presented in the last column of Table 2.5. Strikingly, education has not contributed to the increasing income inequality during this period. The expansion in secondary and tertiary education has contributed to a 5.4% decline in income inequality due to the Kuznets effect that has overridden the positive effects of tertiary education and declining educational inequality. The increasing patent intensity and the declining unionization have contributed to a 0.7% and a 1.2% increase in income inequality.

2.8 Conclusion

This paper focuses on the nexus between income inequality and education. For this purpose, we have introduced a new augmented measure of educational inequality for 21 OECD countries over the period 1870-2016 that allows for intergenerational educational inequality. Furthermore, we allow for the effects on income inequality of the interaction between technological progress and tertiary education, educational attainment and unionization. We show that the income inequality effects of educational inequality are highly complex 1) because education influences income inequality through its first and second moments and its interaction with technological progress; and 2) because the inequality effects depend on the level of economic and technological sophistication of the country.

We find that a major structural shift in the nexus between income inequality, education and technology around WWII, which we attribute to the acceleration in the complexity of new tasks and a consequent movement along the Kuznets curve. First, peaking in the 1940s for the average OECD country, educational attainment unconditionally increases income inequality in the pre-WWII period but reduces income inequality thereafter, following the predictions of the educational Kuznets curve.

Second, the inequality promoting effects of technological progress through its interaction with tertiary education first gained momentum after WWII as the share of skilled labor in the total labor force has become sufficiently large for the skill premium to impact significantly on income inequality. The share of the working age population with a tertiary education in the OECD was, on average, 0.4% in 1870, 1.4% in 1940 and 21.3% in 2016. Thus, the share of the working age population with a tertiary education was too small before WWII for skill-biased technological progress to have a significant impact on income distribution. However, the post-WWII expansion in tertiary education has increased the critical mass of the skilled labor that gains from biased technological progress sufficiently for technological progress to significantly affect income inequality.

Third, the association between income inequality and educational inequality turns from being positive before WWII, as predicated by the model of Becker and Chiswick (1966), to be negative after WWII. While the available data are unable to give the exact reason for the post-WWII results, the acceleration in per capita income, the increasing residual inequality, and the increasing investment in intellectual property products as a share in total income in the post-WWII period point towards an acceleration in the complexity of tasks that has been correlated with the returns to skills. The nexus between income and educational inequalities is further complicated by compressional and compositional effects. In sum, there is no clear relationship between income inequality and educational inequality because of the heterogeneity of skills and their complex interaction with technological progress. A policy implication from this chapter includes improvements in education equality are not a sufficient condition to reduce income inequality anymore. There are factors affecting unobserved skills and residual inequality that need further study and investigation.

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Appendix

RESULTS FOR THE WORLD

Table 2A.1. The nexus between the income Gini and the educational Gini, World (in logs)

	High income countries		Middle income countries		Low income countries	
	(1)	(2)	(3)	(4)	(5)	(6)
	With Country Fixed Effects					
$Gini^{EC}$	-0.00477	0.00146	0.0444	-0.0599	-0.0601	-0.0472
	(0.24)	(0.07)	(0.67)	(0.84)	(0.74)	(0.52)
S		0.0685		-0.240***		0.0374
		(0.80)		(3.49)		(0.55)
	Without Country Fixed Effects					
$Gini^{EC}$	0.0170	-0.0260	-0.0680**	-0.0236	-0.263***	-0.392***
	(0.70)	(0.63)	(2.12)	(0.49)	(6.57)	(5.34)
S		-0.149		0.0745		-0.130**
		(1.34)		(1.23)		(2.18)
Obs.	205	205	221	221	162	162

Notes: The numbers in parenthesis are absolute t-values based on heteroscedasticity and serial correlated consistent standard errors. The regression applies to an unbalanced panel data set for 61 countries over the period 1960 to 2010 at quinquennial frequencies. All variables are measured in logs. Time-dummies and constant terms are included in all regressions. The dependent variable is the net income Gini coefficient. ***, **, *: Significant at 1%. 5% and 10% levels.

DATA APPENDIX

OECD Countries

Gross enrollment rates

Used to estimate the level of education and educational inequality

<u>Data covering the period 1600-2016 (Figure 2.1)</u>

Madsen, J.B. (2020). The Modernization Hypothesis and the Expansion in Education Since 1600, Economics Discussion Paper, Department of Economics, University of Western Australia. Mimeo

<u>Data covering the period 1800-2016 (used in all regressions)</u>

Madsen, J. B. (2014), “Human Capital and the World Technology Frontier.” *Review of Economics and Statistics*, 96(4), 676-692. Updated using data from the UNESCO

Top 10% income shares

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Table 2A.2. List of countries by our income classification

	High income		Middle income		Low income
1	Norway	1	Malaysia	1	Guatemala
2	USA	2	Argentina	2	Philippines
3	Netherlands	3	Turkey	3	Bolivia
4	Austria	4	Chile	4	Pakistan
5	Sweden	5	Iran	5	Nicaragua
6	Denmark	6	Venezuela	6	Honduras
7	Canada	7	Uruguay	7	India
8	Belgium	8	Mexico	8	Sudan
9	Australia	9	Panama	9	Cameroon
10	Finland	10	Brazil	10	Ghana
11	Japan	11	Algeria	11	Zambia
12	UK	12	Thailand	12	Kenya
13	France	13	Costa Rica	13	Bangladesh
14	Italy	14	South Africa	14	Lesotho
15	Spain	15	Colombia	15	Senegal
16	Korea	16	Ecuador	16	Zimbabwe
17	Greece	17	Peru	17	Nepal
18	Portugal	18	Egypt	18	Sierra Leone
19	Trinidad & Tobago	19	Indonesia	19	Malawi
		20	Fiji	20	Niger
		21	China		
		22	Paraguay		

Table 2A.3. List of countries by World Bank's income classification

	High income		Middle income		Low income
1	Japan	1	Cameroon	1	Malawi
2	Korea	2	Ghana	2	Niger
3	Panama	3	Kenya	3	Senegal
4	Trinidad & Tobago	4	Lesotho	4	Sierra Leone
5	Argentina	5	Sudan	5	Zimbabwe
6	Chile	6	Zambia	6	Nepal
7	Uruguay	7	Egypt		
8	Australia	8	Indonesia		
9	Austria	9	Philippines		
10	Belgium	10	Bangladesh		
11	Canada	11	India		
12	Denmark	12	Pakistan		
13	Finland	13	Honduras		
14	France	14	Nicaragua		
15	Greece	15	Bolivia		
16	Italy	16	South Africa		
17	Netherland	17	Algeria		
18	Norway	18	Iran		
19	Portugal	19	Malaysia		
20	Spain	20	Thailand		
21	Sweden	21	Fiji		
22	UK	22	Costa Rica		
23	USA	23	Guatemala		
		24	Mexico		
		25	Brazil		
		26	Colombia		
		27	Ecuador		
		28	Paraguay		
		29	Peru		
		30	Venezuela		
		31	Turkey		
		32	China		

Data source: *World Development Indicators* https://data.worldbank.org/indicator

Chapter 3

Mobile Money and Economic Development[1]

Dung Le[2] and Paul A. Raschky[3]

Abstract

This paper provides an empirical analysis of the local economic impact of mobile money (MM) in Africa. We combine night-time light data at the 1 x 1 km grid cell level with spatial boundaries of mobile phone coverage for seven African nations that have implemented a MM system. The discontinuity at the mobile phone coverage boundary acts as a spatial discontinuity that allows us to assign grids for control and treatment groups. Our final dataset is a balanced panel of around 1.9 million grid cells for the period 2000–2012. We estimate the causal impact of the introduction of MM on economic development at the fine spatial level. We find that the introduction of MM increases the local night-time light intensity by around 3.83%. Our results are robust to various bandwidths, controlling for a fuzzy discontinuity and various sample compositions.

Keywords: economic development, mobile money, spatial discontinuity, Africa.

JEL classification: O10, O55

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It does not matter if you are poor or rich, educated or illiterate, here in Kenya, everybody has a phone, and everybody has mobile money.

Restaurant owner in Kenya.

3.1 Introduction

Mobile money (MM), financial services provided via mobile network operators, is considered a major success story for Sub-Saharan Africa. MM services are primarily e-wallets allowing mobile network customers to either deposit cash into their phones or withdraw cash that has been sent to their phones. MM has become the main gateway to financial services for the unbanked population, enabling users to store money on their MM accounts and transfer money to other MM users. In addition, some MM services offer credit and savings products.

A plethora of empirical studies have documented the success of MM at the microeconomic level. For example, MM is used to instantly and securely send remittances to distant households. As a result, it can increase household consumption in rural areas (e.g., Munyegera & Matsumoto, 2016), increase savings rates (e.g., Morawczynski & Pickens, 2009) and smoothen household consumption during major shocks (e.g., Jack & Suri, 2014; Riley, 2018). Suri and Jack (2016) show that that positive impacts of MM on its users are long lasting. MM adopters are more likely to move out of extreme poverty and have increased household consumption and savings rates. MM has also led to a significant change in occupational choices, mainly by women. Further, MM can improve the livelihood of its adopters through other channels. For example, Kirui et al. (2013) show that MM increases household agricultural commercialisation, while Beck, Pamuk, Ramrattan and Uras (2018) find that MM improves companies' access to supplier credit. Islam, Muzi and Rodriguez Meza (2018) find that the presence of MM increases firm investment in fixed assets. Taken together, these microeconomic studies show that by decreasing transaction costs and improving access to financial services, MM can systematically increase household consumption and foster investment.

The purpose of this paper is to complement these microeconomic studies and analyse the aggregate impact of MM on local economic activity. Prior studies often study out a single economic indicator (such as consumption or investment), utilise data from a single area or country and thus generate partial equilibrium. We differentiate our study by studying data from seven countries and generating general equilibrium results which are more generalisable.

In the absence of subnational gross domestic product (GDP) data for Sub-Saharan African countries, we rely on satellite data on night-time light luminosity as an empirical proxy of aggregate economic activity in a local area. We conduct our analysis using data from seven African countries that were early adopters of MM. The main empirical challenge is that mobile phone coverage, a prerequisite for MM services, is not randomly distributed in Sub-Saharan Africa and is likely affected by any given area's level of economic development. To address this potential source of endogeneity, we apply a spatial discontinuity approach that exploits the discontinuity at the mobile phone coverage boundary. Using this approach and the fine granularity of the night-time luminosity data, we conduct our analysis at the 1 x 1 km grid cell level. In particular, we compare the differential rates in economic development before and after the introduction of MM between grid cells from those just inside the reach of mobile phone coverage to those just outside of mobile phone coverage using various bandwidths. Using our preferred specification, we find that the introduction of MM increases yearly night-time light intensity on average by around 3.83%. Using a back-of-the-envelope calculation, this translates into an approximately 1% higher level of local GDP per capita. Our results are robust to the inclusion of a large set of fixed effects, different choices of cut-off bands and different specifications.

The remainder of this paper is structured as follows. Section 3.2 provides an overview of the related literature; Section 3.3 presents background information about financial inclusion, mobile phones and MM services in Africa; Section 3.4 describes how the main variables and spatial discontinuity were constructed; Section 3.5 discusses the empirical strategy; Section 3.6 presents the results; and Section 3.7 concludes the paper.

3.2 Related Literature

There are three main sets of literature related to our study. The first set investigates the effects of mobile phones on economic development, the second argues that MM spurs economic growth through financial inclusion and the third examines the micro and macro impacts of MM. These literatures are summarised below.

First, the proliferation of information and communication technologies (including mobile phones) and how they impact economic development have captured scholars' attention in the last two decades. There is evidence from prior studies that mobile phones have a positive impact on economic development (Datta & Agarwal, 2004; Waverman, Meschi & Fuss, 2005). Mobile phones could create additional employment by increasing labour demand in mobile-related sectors and facilitating risk sharing within social networks (Aker & Mbiti, 2010). Mobile phones spur rural development by reducing price dispersions (Aker, 2010; Jensen, 2007), reducing marketing costs of agricultural products and promoting market participation of farmers in remote areas (Muto & Yamano, 2009). However, some studies contend that there are econometric challenges to the identification of the linkage between infrastructure and development (Straub, 2011) or that the causal relationship between information and communication technologies and development is difficult to establish (Grace, Kenny & Qiang, 2004).

Second, the literature shows that MM plays an important role in increasing financial inclusion (Andrianaivo & Kpodar, 2011; Demirguc-Kunt, Klapper, Singer, Ansar & Hess, 2018; Donovan, 2012), which is an important factor for promoting growth. According to Demirguc-Kunt et al. (2018), MM can increase the speed of payments and reduce transaction cost. It can also enhance security of payments and lower crime by reducing the amount of cash holding, increase transparency through digital accounting and, thus, reduce corruption. More importantly, it can provide an entry point into the formal financial system and increase savings. Relatedly, there is theoretical and empirical literature that implies that the expansion of banking and financial systems could lead to economic growth and reduce poverty in developing countries (Burgess & Pande, 2005; Levine, 2005). More specifically, previous research has suggested that access to financial services increases household agricultural commercialisation (Kirui, Okello, Nyikal & Njiraini, 2013), increases economic growth (Sahay, 2015) and lowers income inequality (Park & Mercado, 2015).

Third, although MM has only recently been adopted in developing countries, there is a growing literature on MM's impacts on their economies. In general, this research could be categorised into two main strands, focusing on the micro or macro impacts of MM. Studies on MM's micro impacts seem to dominate the literature. Macro impact studies are scarce and their results regarding monetary indicators are inconclusive. Our paper closely links to these two strands of literature.

Literature on MM's micro impacts is vast, and the affected parties normally fall into one of three categories: individual and household level, firm level and government level.

Regarding MM's micro impact on the individual and household level, existing literature shows that MM has a positive effect on household consumption. Empirical studies by Jack and Suri (2014) and Riley (2018) find that MM has a sizeable impact on smoothing household consumption through a risk-sharing mechanism. Jack and Suri (2014) use panel data of randomly selected households in Kenya, while Riley (2018) uses panel data of randomly selected households in Tanzania. Jack and Suri (2014) find that while shocks reduce household consumption by 7% for MM non-users, the household consumption of MM users is unaffected.

The complementary result from Riley (2018) is a 6% household consumption reduction due to shocks for MM non-users and no effect on MM users. In another study by Munyegera and Matsumoto (2016) using panel data of rural households in Uganda, there is strong evidence that MM adoption increases real household per capita consumption. Remarkably, in all three above studies, the positive effect of MM is argued to be the result of using the remittance channel. The authors notice that when exposed to a shock, MM users, compared to non-users, are more likely to receive remittances from friends and family, receive more remittances and receive a larger value of remittances in total. In other words, risk sharing is promoted through remittance channels made more available and accessible by MM services.

Morawczynski and Pickens's (2009) 14-month qualitative study also explores MM and remittances in two Kenyan communities, Kibera and Bukura. Among other findings, they report that MM increases savings for both the banked and unbanked, probably because storing money in MM is more secure than holding cash, and the wide agent network facilitates MM users to make frequent small deposits of money into their MM account. The authors also find that MM improves women's empowerment because MM facilitates remittances. Access to MM means women are not limited to their husbands regarding the source of remittances and can solicit remittances from other contacts, thus reducing their financial dependence on their husbands.

The nexus between MM and violence has also inspired interests among researchers. Using the same dataset as Morawczynski and Pickens (2009), Morawczynski (2009) examines the transformational benefits of MM adoption. The most significant benefit is a reduction in vulnerability to consumption shocks achieved through the accumulation of financial capital and preservation of social networks. However, Morawczynski (2009) also notes that the demand for MM services increased dramatically during periods of violence, such as the 2007 post-election violence in Kenya. During times of violence, there was an important change in the pattern of transactions: urban customers withdrew cash rather than depositing into their MM accounts (probably because MM was the only means by which they could access cash). Blumenstock, Callen and Ghani (2020) found a similar pattern between MM and violence. Using a dataset comprised of monthly panel data from an experiment that incentivised MM take-up, a cross-section of financial survey data, administrative records of all violent incidents and a dataset of geo-tagged mobile phone records (allowing the authors to locate each mobile phone subscriber over a period of several years), they show that people exposed to violence are less likely to adopt and use MM, hold less funds in their MM accounts but increase cash holdings during periods of violence.

Using cross-sectional data in three provinces, Kirui et al. (2013) investigate the impact of MM on small farm households in Kenya. Using propensity score matching technique, they find that MM use increases household annual input use by $42, household agricultural commercialisation by 37%, and household annual income by $224.

Suri and Jack (2016) use the last round of their panel survey conducted in 2014 to investigate the long-term impacts of MM. They find that better access to MM (measured by increased agent access) increases household consumption and savings, allows for more efficient allocation of labour and, thus, reduces poverty rates. Increased agent access significantly reduces both extreme poverty (the share of the population living on less than US$1.25) and general poverty (less than US$2 per day). MM led to significant changes in occupational choice, mostly among women (186,000), who switched from agriculture as their main occupation to business and retail. This could be because MM allows women to directly access remittances and/or have more agency.

In terms of MM impact at the firm level, nascent literature also shows some positive results. Blumenstock, Callen, Ghani and Koepke (2015) use a randomised experiment to identify the changes caused by MM adoption among an employer and individual employees. They assign employees in a large firm into treatment and control groups, with the treatment group receiving their salary via MM and the control group receiving their salary in cash. While their findings regarding employees were ambiguous, MM use was found to result in significant cost savings for the firm in terms of managing salaries. In another study, Beck, Pamuk, Ramrattan and Uras (2018) find the presence of MM to be positively associated with access to supplier credit. Islam, Muzi and Rodriguez Meza (2018) use firm-level data representing the private sector in three East African countries—Kenya, Tanzania and Uganda—to empirically estimate the relationship between MM use and firm investment. They find that MM use is positively related to firms' purchases of fixed assets. This is achieved through the impact of MM on reducing firms' transaction costs, increasing the level of trade credit and reducing information asymmetries.

For MM impact at the government level, prior research shows that the switch from cash to digital payment using MM could reduce administration costs. Aker, Boumnijel, McClelland and Tierney (2016) use a randomised experiment to investigate the effects of using MM in delivering a cash transfer program, introduced after the 2009–2010 drought and food crisis in Niger. They find that compared to manual cash distribution, social transfers through MM reduced the variable costs of administering the benefits by 20%.

Our paper complements these studies on MM's micro impact and investigates the aggregate impact of MM on local economic activity. While prior studies present partial equilibrium when examining a single economic indicator and utilising data from a single area or country, we analyse data from seven countries and present general equilibrium results, which are more generalisable.

While the consensus is that MM's micro-level impacts are positive and significant, studies on MM's macro-level impacts are scare and their results regarding monetary indicators are mixed. The first notable macro-level study of MM is a theory paper by Jack, Suri and Townsend (2010). In their model, they find that as electronic payment (including MM) expands, financial transaction costs reduce and financial connectedness among economic agents increases. This leads to an increase in labour specialisation, consumption of goods and, ultimately, GDP.

A growing body of literature has tried to understand the linkage between MM and monetary indicators such as velocity of money or inflation but evidence from these studies is still mixed. In an African Development Bank (AfDB) economic brief, Simpasa, Gurara, Shimeles, Vencatachellum and Ncube (2012) contend that the velocity of money has increased since 2006 and substantially jumped in 2009, propagating inflation expectations in Kenya, Tanzania and Uganda, and that this increase is mainly due to financial innovations (including MM). However, the creditability of their results is questioned by Aron (2017), who points to their problematic methodology when using a highly restrictive and mis-specified empirical inflation model that excludes key variables such as rainfall and does not take into account a structural break of inflation during the study period. Contrary to the findings in that 2012 AfDB economic brief, Mbiti and Weil (2015) report no significant impact of MM on the velocity of money in Kenya. By their calculations, the transactions velocity of MM in Kenya was four transactions per month in 2008, which is not much greater than the velocity of cash.

Plyler, Haas and Ngarajan's (2010) qualitative study using data from three Kenyan districts appears to be the first to attempt to evaluate the economic effects of MM at the community level. They identify the three most important economic effects of MM as increased money circulation, business expansion and security. Specifically, they find a greater volume of money flowing into and out of communities and a faster flow of money within these communities. Additionally, MM promotes the expansion of existing small-scale firms because MM use increases money circulation and lowers transactions costs for vendors that use MM to purchase stocks. Finally, MM increases security, either in the form of physical security (reduction of robberies and thefts) or food security (increase in agricultural productivity, enabling access to a wider variety of foods and enabling better and more timely access to agricultural inputs).

Mbiti and Weil (2015) use aggregation data to estimate the impacts of MM in Kenya. They use employment, which incorporates farm labour, non-farm labour and self-employment, as a measure of economic activity. They find that MM adoption is associated with an increase in overall employment but do not find any impact on non-farm employment. This implies that the increase in overall employment is mainly driven by farm employment. The authors suggest that this pattern is likely due to increasing resources due to MM being directed towards farming, thus boosting the demand for farm labour.

The study most closely related to our paper is a theoretical and empirical study on MM's macro impact by Beck et al. (2018). The authors use data from a small and medium enterprise (SME) survey in Kenya, develop a dynamic general equilibrium model and calibrate their model to a set of moments from the SME survey. Their regression analysis shows a strong positive covariance between the use of MM as a payment method by firms when purchasing inputs from suppliers and access to supplier credit. According to their model, trade credit allows higher firm's production, which complements and raises the likelihood of MM use (when taking into account the risk of theft). As a result, access to MM can significantly improve firm performance and ultimately macroeconomic performance through trade credit. Specifically, they find that the availability of MM technology increased the macroeconomic output of the Kenyan entrepreneurial sector by 0.33–0.47%.

Our study contributes to this macro-level literature by testing the theoretical propositions on MM's impact on aggregate economic activity at the local level.

3.3 Background

3.3.1 Mobile Money Services

MM is a service that allows users to store, receive and spend money using a basic mobile phone. Initially, MM only allowed simple domestic money transfers from person to person and store electronic value on a mobile phone. MM services have since greatly evolved to include other services such as paying bills, utilities, salaries, social benefits and taxes; making transfers from a bank account to a mobile wallet; international money transfers; buying mobile phone airtime and data; and providing microfinancing, savings and insurance services (Mawejje & Lakuma, 2019).

Most MM services are provided by local mobile telecom operators who have registered a licence to operate electronic payment services. Other MM providers include banks and other companies. MM operators use a wide range of agents in close proximity to customers, including operator-owned retail locations or other operator-approved small retailers such as basic grocery stores, petrol stations, post offices or chemists.

MM is different from mobile banking even though both types of services are accessed via mobile phones. For mobile banking, customers transact using their bank accounts and the operators are banks. For MM, customers transact using their MM accounts and the operators are MM providers (mostly local mobile telecom companies). MM users are not required to own a formal bank account.

MM transactions are executed using PIN-secured SMS text messages. To send a money transfer to a person via a MM service, the only thing needed is the recipient's phone number. There is a small fee (that increases with transaction size) charged for sending and withdrawing money.

To access a MM service, users need to register for a MM account and deposit money via MM agents. The money in a MM account is called 'e-money'. Customers create e-money by trading one for one with cash (minus transactions costs) with MM agents. Thus, for MM accounts, when a customer deposits or withdraws money, they are essentially buying or selling the same value of e-money with the MM agent. Therefore, the agent must hold an inventory of e-money to trade with customers (Suri, 2017). To ensure the security of the MM business model, each MM operator needs to partner with a supervised financial institution. The role of these financial institutions is to hold escrow accounts that equal the respective agent's MM deposit balances (Mawejje & Lakuma, 2019).

3.3.2 Financial Inclusion in Africa

Financial inclusion means that adults have access to and can effectively use a range of appropriate financial products and services. Financial inclusion, at its most basic level, is having an account at a bank or other financial institution, or a MM account with a MM service provider, that can be used to make and receive payments and to store or save money (Demirguc-Kunt, Klapper & Singer, 2017). The Global Financial Inclusion (Global Findex) database, launched by the World Bank in 2011, has measured financial inclusion as having an account at a formal financial institution or a MM service provider.

Demirguc-Kunt, Klapper, Singer and van Oudheusden (2015) analyse the Global Findex database and report that in 2014, 62% of adults globally own an account at a formal financial institution or a MM service provider. In other words, in 2014, 38% of adults globally were financially excluded. If we further investigate account ownership within countries by income level, in 2014, 6% of adults in high-income countries were financially excluded (i.e., did not have an account) versus 46% of adults in developing countries.

This picture of low financial inclusion (or a high degree of financial exclusion) is most dramatically illustrated in Africa. Using data from the Global Findex database 2012, Demirguc-Kunt and Klapper (2012) document that Sub-Saharan Africa and the Middle East and North Africa, with 24% and 18% of adults with an account at a formal financial institution respectively, are the bottom two regions in the world in terms of account penetration rate.

Another distinguishable feature of the financial landscape in Africa compared to high-income economies is the dominance of informal finance. In Sub-Saharan Africa in 2011, while about 40% of adults reported having saved in the past 12 months, only 13% of adults reported having done so at a formal financial institution. While 57% of adults in Sub-Saharan Africa reported having borrowed money in the past 12 months, 40% had borrowed money from friends or family and 5% from informal lenders (Demirguc-Kunt & Klapper, 2012).

Tables 3.1 and 3.2 report the financial inclusion landscape of our sample countries, with the figures of Australia also reported as a benchmark. The four financial inclusion indicators presented in Tables 3.1 and 3.2 include the percentage of people over the age of 15 who hold an account with a financial institution, the number of commercial bank branches per 100,000 adults, ATMs per 100,000 adults and depositors with commercial banks per 100,000 adults. Clearly, Sub-Saharan African countries have very low financial inclusion compared to Australia (a developed country). Comparing the seven countries of our study, Kenya and Ghana seem to have the highest financial inclusion, while Côte d’Ivoire and Tanzania seem to have the lowest financial inclusion.

Table 3.1. Percentage of people (>15 Years Old) holding an account with a financial institution

Country	2011	2014	2017
Australia	99%	99%	100%
Kenya	42%	55%	56%
Tanzania	17%	19%	21%
Ghana	29%	35%	42%
Uganda	20%	28%	33%
Rwanda	33%	38%	37%
Zambia	21%	31%	36%
Côte d’Ivoire	–	15%	15%

Notes: Figures from Global Findex database.

Table 3.2. Formal financial institution penetration

Country	Commercial bank branches[a]	ATMs[b]	Depositors[c]
Australia	30	161.25	–
Kenya	4.88	8.44	–
Tanzania	2.06	4.55	202.96
Ghana	6.27	7.38	437.22
Uganda	2.47	3.91	212.62
Rwanda	5.3	3.64	191.75
Zambia	4.18	8.34	193.58
Côte d'Ivoire	4.13	5.82	162.83

[a] Commercial bank branches per 100,000 adults (average for 2007–2018), [b] ATMs per 100,000 adults (average for 2007–2018), [c] Depositors with commercial banks per 100,000 adults (average for 2007–2018).

Notes: Figures from Global Findex database.

3.3.3 Mobile Phone Penetration

The last two decades have seen a massive increase in mobile phone penetration worldwide, and this increase is most clearly observed in developing countries. Globally, by the end of 2018, 5.1 billion people, equivalent to 67% of the world population, were mobile phone subscribers (GSMA, 2019a). It is projected that by 2025, the total number of mobile subscribers will be 5.8 billion, indicating a mobile phone penetrate rate of 71%. In Sub-Saharan Africa, the mobile phone penetration rate was 45% in 2018, and this is projected to increase to 51% in 2025. Among the 710 million new mobile phone subscribers in 2018–2025, half will come from the Asia-Pacific region and just under one-quarter will come from Sub-Saharan Africa (GSMA, 2019a).

Mobile phones started to appear in Sub-Saharan Africa in the mid-1990s and achieved miracle growth in the period 1995–2004. This growth seems to have slowed recently, indicating markets are approaching saturation (see Table 3A.1 in Appendix). Compared to the Sub-Saharan Africa average, Ghana, Côte d'Ivoire, Kenya and Zambia have higher mobile subscription per capita and mobile phone growth rates, while Uganda has lower subscription per capita and mobile phone growth rates. In 2018, Ghana lead with a mobile phone subscription rate of 137.5%,[4] followed by Côte d'Ivoire (134.9%), Kenya (96.3%) and Zambia (89.2%).

[4] Ghana's mobile phone penetration rate of 137.5% in 2018 means that on average, a person has more than one mobile phone subscription.

3.3.4 Growth of MM Services

The MM industry is just over a decade old but has made astonishing achievements. In 2019, the number of registered MM accounts reached 1.04 billion. Total transaction values via MM services was $690 billion in 2019, implying a $2 billion transaction value processed by the industry each day. In 2019, the industry had 290 live services in 95 countries, and MM services were present in 96% of countries where less than one-third of the population has an account at a formal financial institution (GSMA, 2019b). The success of the MM model is largely due to the wide agent network, which enables the industry to better penetrate remote and rural areas compared to conventional bank branches. According to the GSMA (2019b), over the past five years, the number of MM agent outlets has nearly tripled, reaching 7.7 million in 2019. Remarkably, the reach of MM agents is seven times that of ATMs and 20 times that of bank branches (GSMA, 2019b).

Sub-Saharan Africa is the enduring epicentre of MM, consistently containing almost half of all MM registered accounts and accounting for 67% of total global MM transactions in 2018 (GSMA, 2018). In 2014, 12% of adults in Sub-Saharan Africa reported having a MM account (Demirguc-Kunt et al., 2017). Using data from the Global Findex database, Demirguc-Kunt et al. (2015) report that the thirteen countries with the highest rate of MM penetration are all in Sub-Saharan Africa. Further, in five of these countries-Côte d'Ivoire, Somalia, Tanzania, Uganda and Zimbabwe-the number of adults with a MM account exceeded the number with an account at a financial institution.

We investigate the rollout time of MM service in Africa for the period 2007–2013 (see Table 3A.2 in Appendix), with the seven earliest MM adopters-Kenya (2007), Tanzania (2008), Côte d'Ivoire (2008), Ghana (2009), Uganda (2009), Rwanda (2009) and Zambia (2009) (all in Sub-Saharan Africa)-as our countries of study. We choose 2009 as the cut-off year to allow for a sufficient number of post-intervention years in our analysis.

Table 3A.3 in Appendix shows the year MM was first introduced in our countries of study and the countries' current MM products and service providers.

Table 3.3 shows the percentage of people in our sample countries over the age of 15 with a MM account. As can be seen, MM has been most widely adopted in Kenya, with 73% of the population over 15 years of age having a MM account in 2014, followed by Uganda (51%) and Tanzania and Ghana (both with 39%). However, it is noted that MM adoption in Tanzania is quite slow compared to the other three countries, increasing from 32% in 2011 to 39% in 2014, versus, for example, Ghana increasing from 13% in 2011 to 39% in 2014. Notably, Zambia more than doubled its MM account penetration rate between 2014 and 2017, but its MM account penetration rate is the lowest of our seven sample countries.

Table 3.3 Percentage of people (>15 Years Old) holding a MM account

Country	2014	2017
Kenya	58%	73%
Uganda	35%	51%
Tanzania	32%	39%
Ghana	13%	39%
Côte d’Ivoire	24%	34%
Rwanda	18%	31%
Zambia	12%	28%

Notes: Figures from Global Findex database.

3.4 Data

Our empirical analysis uses data for the seven African countries from the year MM services were introduced to 2009. This cut-off year was chosen to ensure a sufficient number of post-intervention years in our analysis. The unit of analysis is at the 1 × 1 km pixel level. A pixel is a square polygon and reflects the size of the resolution of the night-time light satellite images. Using this level of analysis, we construct two datasets: 1) a cross-sectional dataset at the pixel level for around 1.9 million pixels and 2) a balanced panel dataset with yearly observation for each of the 1.9 million pixels over the period 2000-2012. The following sections describe our outcome variable, night-time light intensity at the pixel level and the construction of the spatial discontinuity boundaries using mobile phone coverage.

3.4.1 Dependent Variable: Night-time Lights at the Pixel Level

For our analysis, we use night-time light to proxy for economic activity, which follows a large and growing literature in using night-time light intensity to proxy for economic development at the subnational level (see discussion below). These data are based on daily measures from the Operational Linescan System of the US Defense Meteorological Satellite Program and provided by the National Oceanic and Atmospheric Administration (NOAA). The NOAA uses evening observations during the dark half of the lunar cycle in seasons when the sun sets early, but removes observations likely to be affected by fires, cloud coverage, or northern or southern lights, with the objective to report man-made night-time light intensity. The NOAA provides annual data for the period 1992–2013 for output pixels that correspond to less than one square kilometre. The data come on a scale from 0–63, with higher values implying more intense night-time light. Night-time light is a good proxy for economic activity as most forms of consumption and production in the evening require light, and public infrastructure is often lit at night. Using night-time light as a proxy for economic development has been widely used in the literature (see Doll, Muller & Morley, 2006; Elvidge et al., 2009; Henderson, Storeygard & Weil, 2012; Hodler & Raschky, 2014). Night-time light, objectively measured has been found to be highly correlated with GDP (both level and growth rates) and is available for all world land areas except for high latitudes (Chen & Nordhaus, 2011). Henderson et al. (2012) and Hodler and Raschky (2014) find a high correlation between changes in night-time light intensity and GDP at the level of countries and provinces, respectively. In addition, Bruederle and Hodler (2018) document a positive association between night-time light intensity and broader measures of human development at the local level.

As an outcome variable, we use the natural logarithm of the average night-time light pixel value in a given district and year. To avoid losing observations with a reported night-time light intensity of zero, we follow the literature in adding 0.01 before taking logs (e.g., Michalopoulos & Papaioannou, 2013; Hodler & Raschky, 2014; Amarasinghe, Hodler, Raschky & Zenou, 2020).

3.4.2 Constructing Spatial Discontinuities from Mobile Phone Coverage

To construct the boundaries for the spatial discontinuity analysis, we exploit the sharp limits of mobile phone coverage due to topographic features. This section explains the process of constructing the coverage boundaries (see Figure 3.1) and then defining the inner and outer buffers (see Figure 3.2). As the first step, we collected the exact point location of every mobile phone tower in our seven African sample countries (yellow dots in Figure 3.1). We also accessed raster data (GeoTIFFs) of the digital elevation model for the seven countries. The data is provided in tiles with a resolution of 0.005 degree (grey topography in Figure 3.1). Cross-section data on cell towers is obtained from the OpenCelliD[5], which is the largest open database on the location of cell towers around the world. Data for the digital elevation model (DEM) stems from the Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global, which was accessed through the USGS EROS Archive[6]. We then assumed an average height of the mobile phone towers of 15 meters and a maximum signal reach of 35 km[7]. Applying a standard viewshed analysis tool-that takes into account the height of the tower, signal strength and topographic

[5] https://www.opencellid.org

[6] Shuttle Radar Topography Mission 1 Arc-Second Global (Digital Object Identifier (DOI) number: /10.5066/F7PR7TFT

[7] This is typical characteristics of a mobile phone tower.

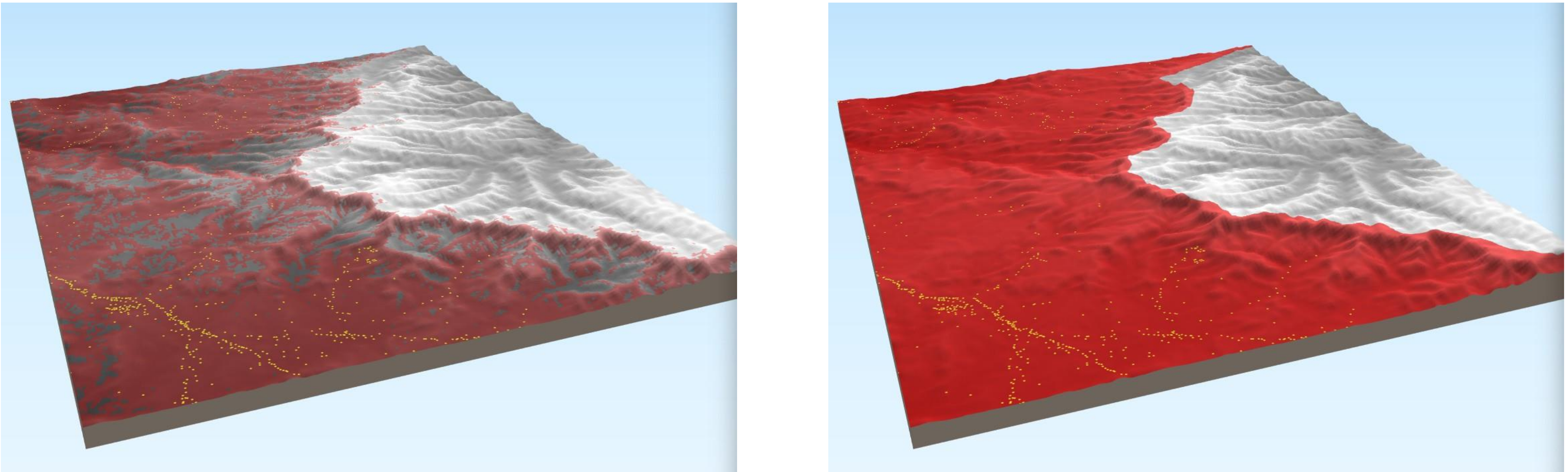
features-results in the first viewshed model (dark red area in Figure 3.1A). We then smoothen the coverage wherever there are small gaps in the coverage area to construct the mobile phone coverage area (light red area in Figure 3.1B). We then build a polyline at the boundary between the mobile phone coverage area (light red area in Figure 3.1B) and the area without mobile phone reception (light grey area in Figure 3.1B), which is our spatial discontinuity.

In the next step, we use this discontinuity to define our treatment (areas with mobile phone coverage) and control areas (areas without mobile phone coverage). This is depicted in Figure 3.2. Figure 3.2A shows an area in Ghana with continuous mobile phone coverage. At the boundary of this area, we build an inner buffer with a width of 50 km inside the coverage area (see Figure 3.2B) that defines the treatment area, and an outer buffer with a width of 50 km outside the coverage area (see Figure 3.2C). In the last step, we identify all the grid cells that lie within the inner or outer buffer areas and assign them to the treatment or control group, respectively.

Figure 3.1. Applying Viewshed analysis to contruct mobile phone coverage

Panel A. Mobile phone coverage Viewshed results

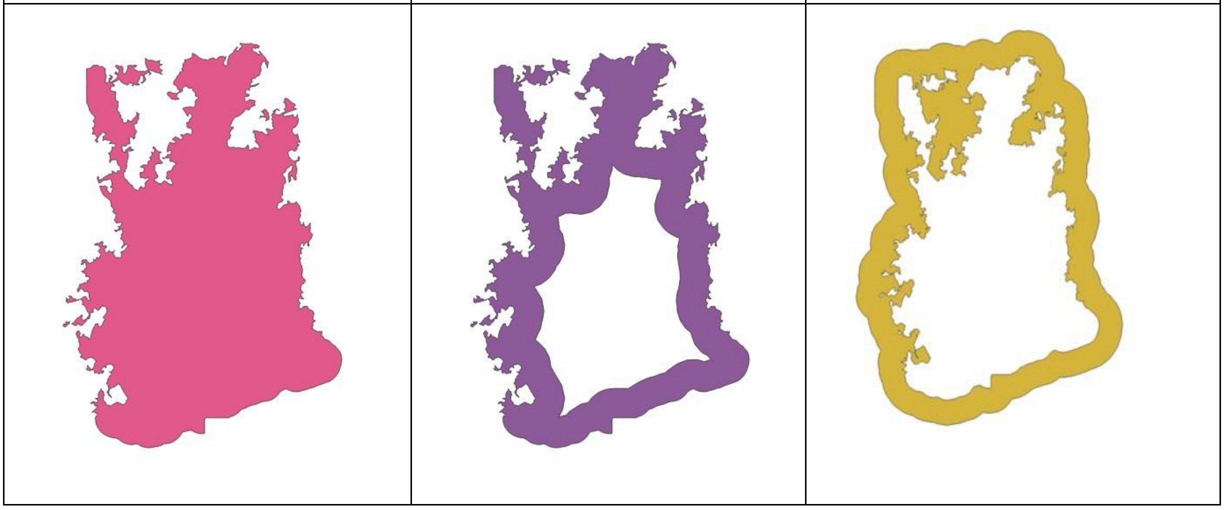
Panel B. Mobile phone coverage Viewshed results smoothened



Notes: Yellow dots are mobile phone towers. The light red area in Figure 3.1B is the area with mobile phone reception, and the light grey area is the area without mobile phone reception.

Figure 3.2. Example of using mobile phone coverage area (in Ghana) to define inner and outer buffers (50km Band).

Panel A. Mobile phone coverage	*Panel B. Inner buffer (50 km)*	*Panel C. Outer buffer (50km)*



3.4.3 Summary Statistics

3.4.3.1 Cross-section Data

For our cross-section data, the dependent variables are the change in *lnlight* and *dumlight* between the pre- and post-MM introduction years. *lnlight* is the logarithm of average night-time light plus 0.01 for pixel *p* in country *c* in year *t*. Following Michalopoulos and Papaioannou (2013) and Hodler and Raschky (2014), we add the constant 0.01 to the average night-time light to avoid losing pixels with zero or close to zero reported night-time light. *dumlight* is a dummy variable that equals 1 if night-time light in the pixel is greater than 0 and equals 0 otherwise.

Our main independent variable is *treat*, a dummy variable that equals 1 if the pixel is inside the mobile phone coverage boundary (in other words, *treat* = 1 if the pixel receives mobile phone signal) and equals 0 otherwise. We experimented with four levels of treatment cut-offs based on the distance from the centre of the pixel to the mobile phone coverage boundary (30 km, 50 km, 30–5 km and 50–5 km). We call the 30–5 km and 50–5 km treatment groups 'fuzzy' treatments because pixels at 5 km inside and outside the mobile phone coverage boundary could be noisy data. The *treat* variable has 5 km mobile phone coverage in our data but this may not accurately reflect reality. Therefore, we drop pixels that are 5 km inside or outside the mobile phone coverage boundary from our treatment and control groups to create the groups treat 30–5 km, treat 50–5 km, control 30–5 km and control 50–5 km. Table 3.4 reports the summary statistics for the main variables for the cross-section data.

Table 3.4. Descriptive statistics: Cross-section Data

Variable	Observations	Mean	SD	Min	Max
treat5km	1,970,253	0.10	0.30	0	1
treat10km	1,970,253	0.20	0.40	0	1
treat20km	1,970,253	0.33	0.47	0	1
treat30km	1,970,253	0.42	0.49	0	1
treat50km	1,970,253	0.53	0.50	0	1
treat30_5km	1,970,253	0.32	0.47	0	1
treat50_5km	1,970,253	0.43	0.50	0	1
pre_lnlight	1,970,253	–4.46	0.85	–4.61	4.14
post_lnlight	1,970,253	–4.44	0.94	–4.61	4.14
pre_dumlight	1,970,253	0.02	0.14	0	1
post_dumlight	1,970,253	0.03	0.15	0	1
changelnlight	1,970,253	0.03	0.37	–6.58	7.72
changedumlight	1,970,253	0.00	0.07	–1	1

Notes: This table presents the descriptive statistics of the main variables.

3.4.3.2 Panel Data

For our panel data, the dependent variables are *lnlight* or *dumlight*. *lnlight* is the logarithm of average night-time light plus 0.01 for pixel *p* in country *c* in year *t*. *dumlight* is a dummy variable that equals 1 if night-time light in the pixel is greater than 0 and equals 0 otherwise.

Our main independent variable is the interaction of *treat* and *post,* which captures the treatment effect of MM. *treat* is a dummy variable that equals 1 if the pixel is inside the mobile phone coverage boundary and equals 0 otherwise. *post* is a year dummy variable, standing for post-MM introduction year, and equals 1 if the year is after MM is introduced in the country. Table 3.5 reports the summary statistics for the main variables for the panel data.

Table 3.5. Descriptive statistics: Panel Data

Variable	Observations	Mean	SD	Min	Max
treat5km	41,375,313	0.10	0.30	0	1
treat10km	41,375,313	0.20	0.40	0	1
treat20km	41,375,313	0.33	0.47	0	1
treat30km	41,375,313	0.42	0.49	0	1
treat50km	41,375,313	0.53	0.50	0	1
treat30_5km	41,375,313	0.32	0.47	0	1
treat50_5km	41,375,313	0.43	0.50	0	1
lnlight	41,375,313	–4.47	0.88	–4.60	4.14
dumlight	41,375,313	0.02	0.15	0	1
post_treat30_5km	41,375,313	0.07	0.26	0	1
post_treat50_5km	41,375,313	0.10	0.29	0	1
post_treat 5km	41,375,313	0.02	0.15	0	1
post_treat 10km	41,375,313	0.04	0.21	0	1
post_treat 20km	41,375,313	0.07	0.26	0	1
post_treat 30km	41,375,313	0.09	0.29	0	1
post_treat 50km	41,375,313	0.12	0.32	0	1

Notes: This table presents the descriptive statistics of the main variables.

3.5 Empirical Strategy

Our empirical strategy applies the spatial regression discontinuity (SRD) of mobile phone coverage to identify treatment cut-offs. For cross-section data regressions, we follow the multidimensional discontinuity in longitude–latitude space approach by Dell (2010). We create the pre- and post-MM *lnlight* in each country by taking the average of *lnlight* four years before and four years after the introduction of MM. For panel data regressions, we apply the difference-in-differences (DID) approach to gauge the local average treatment effect. We are interested in data from 2000 onwards in each country.

3.5.1 Multidimensional, Semiparametric SRD Design

Since the late 1990s, regression discontinuity (RD) has been favoured by many analysts as a research design. Several empirical comparisons of randomised experiments and RDs have found that estimates from RD designs can be reasonably comparable to the results of randomised experiments (Berk, Barnes, Ahlman & Kurtz, 2010; Buddelmeyer & Skoufias, 2003; Shadish, Galindo, Wong, Steiner & Cook, 2011). According to Lee and Lemieux (2010) p. 282, assumptions in RD designs appear to be mild compared to those of other non-experimental designs and 'causal inferences from RD designs are potentially more credible than those from typical natural experiment strategies'.

In essence, RD design uses an observed continuous variable (referred to in the literature as the 'forcing' variable or 'running' variable) to assign treatment to a unit if their value exceeds a known cut-off point (Lee & Lemieux, 2010); units with a value exceeding the cut-off point are assigned to the treatment group, while units with a value below the cut-off point are assigned to the control group.

The fundamental feature of the RD design is that the probability of receiving the treatment changes suddenly at the known cut-off point. Because it can be assumed that units with the variable value just below the cut-off point are very similar and comparable to units with the variable value are just above the cut-off point, the difference in the outcome of interest among the treatment group and control group can be attributed solely to the treatment assignment (Skovron & Titiunik, 2015).

SRD is a special case of RD where geographic distance acts as the assignment variable and geographic borders act as sharp cut-off points. In our paper, the distance to the mobile phone coverage boundary acts as the running variable. The buffer cut-off acts as the known cut-off point. We divide the treatment zone into five sub-zones: 20km, 30 km, 50 km, 30-5 km and 50-5 km. We employ the SRD to assign units to the treatment or control group. Pixels inside the mobile phone coverage boundary are assigned to the treatment group, while the pixels outside the mobile phone coverage boundary are assigned to the control group.

We employ the multidimensional, semiparametric SRD approach of Dell (2010) in our cross-section data analysis. This approach projects the running variable in our study, the distance to the mobile phone coverage boundary in multidimensional space. According to this approach, the treatment assignment is a nonlinear and discontinuous function of longitude and latitude. Specifically, we report estimates from four baseline specifications.

In the first baseline specification, we test the relationship between the change in night-time light before and after MM is introduced without controlling for any other factors. In the second baseline specification, we control for a cubic polynomial in latitude and longitude as proposed by Dell (2010)[8] . In the third baseline specification, we control for a linear distance to the mobile phone coverage boundary. In the fourth baseline specification, we follow Dell (2010) in controlling for a Euclidean distance to the nearest point of the mobile phone coverage boundary[9] .

3.5.2 DID Approach

The DID method has also gained popularity in recent times. DID estimates the effect of a treatment (an independent variable) on an outcome (the dependent variable) by comparing the before and after changes in the outcome variable for the treatment group with the before and after changes in the outcome variable for the control group.

We apply the DID method in our panel data regressions to gauge the effect of MM on the economic activity of our seven African sample countries. The intervention or treatment here is the access to MM services in those countries, and we use access to mobile phone coverage as a proxy for access to MM services. By using DID, we compare the before and after changes in the economic activity of pixels that have mobile phone coverage with the before and after changes in the economic activity of pixels that do not have mobile phone coverage.

3.5.3 Common Trends Assumption

The DID approach used in this paper requires a common trends assumption (also referred to as parallel trends assumption). Common trends assumption requires that in the absence of MM, the difference in outcome variables between the treatment group and control group is constant over time. Figure 3.3 presents our test for the common trends assumption in our dataset.

Figure 3.3 confirms that visually, the common trends assumption holds in our dataset. As can be seen, the difference in night-time light between the treatment group and control group

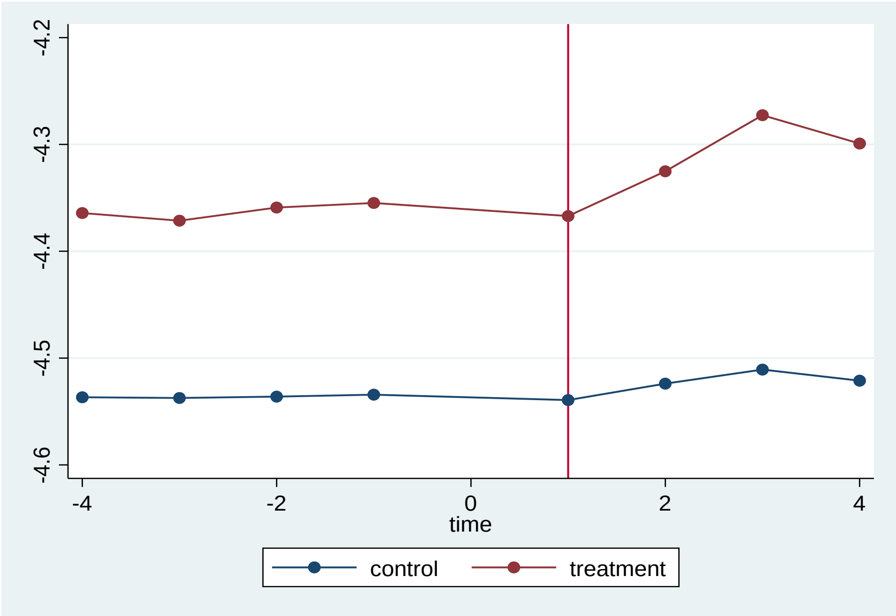
[8] Letting x and y denote the adjusted longitude and latitude of the observation after controlling for the mean longitudes and latitudes of all observations in the sample. Cubic polynomial in latitude and longitude is $x + y + x^2 + y^2 + xy + x^3 + y^3 + x^2y + xy^2$.

[9] Letting dist denote the distance to the mobile phone coverage boundary. Cubic polynomial in distance to the boundary is $dist + dist^2 + dist^3$

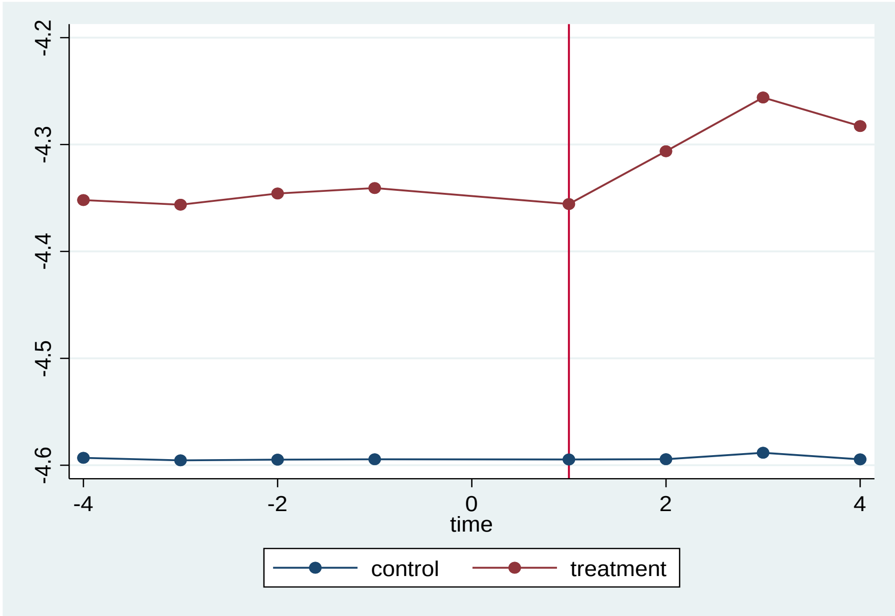
remains stable before the introduction of MM at time 1, but this difference suddenly widens after time 1, which could be inferred as the impact of MM on night-time light of the treatment group.

Figure 3.3. Common trends for 30 km and 50 km bands between treatment and control group.

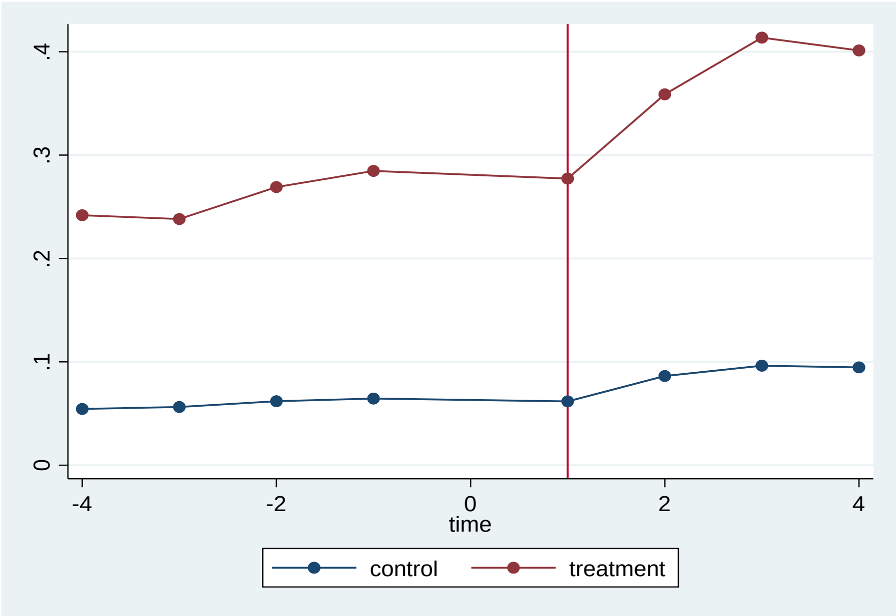
Panel A. Ln(light); 30km band



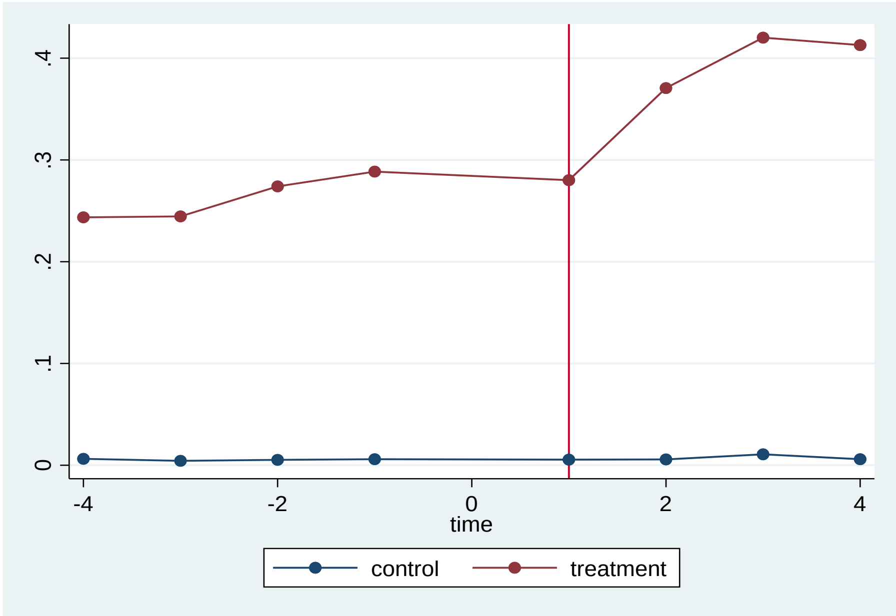
Panel B. Ln(light); 50km band



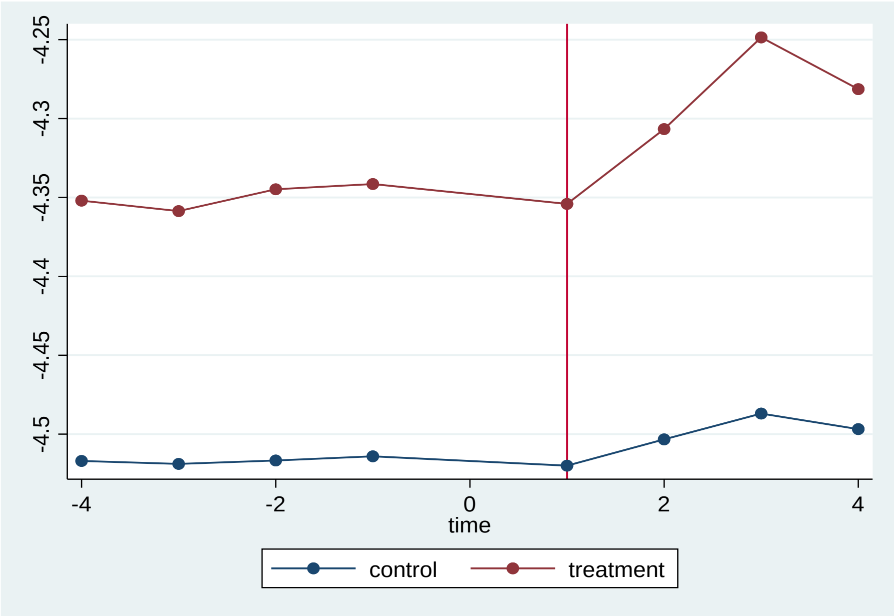
Panel C. light; 30km band



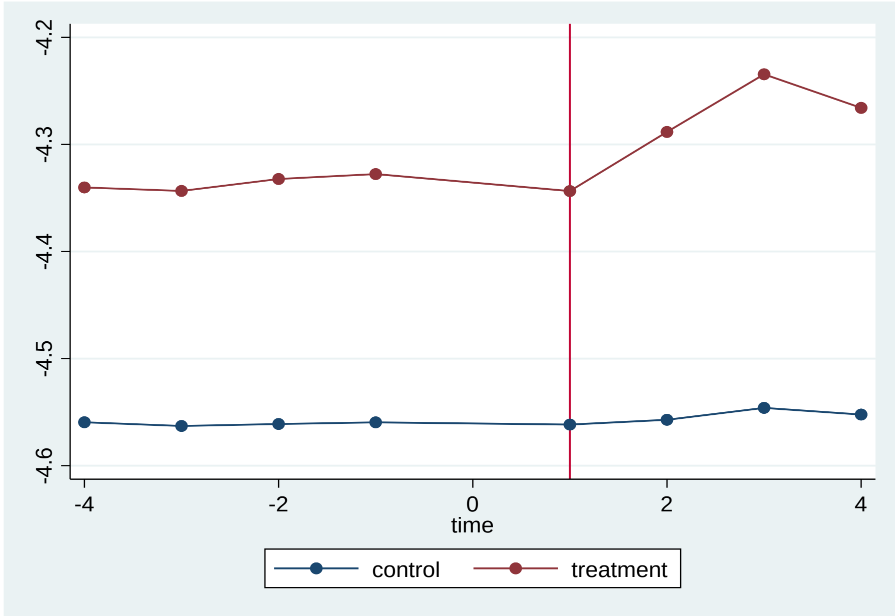
Panel D. light; 50km band



Panel E. Ln(light); 30-5km band



Panel F. Ln(light); 50-5km band



A key assumption in RD design is continuity assumption, which requires that the conditional expectation of a potential outcome is continuous at the cut-off point. In other words, the expected outcome of the treatment group and the control group at all points on the boundary should be very similar. Intuitively, the treatment and the control group should be very similar in all potentially relevant aspects at the cut-off point and they are only different in terms of the propensity to receive treatment. The literature often uses the balance test to test this assumption. We do not explicitly provide a test for this assumption in our paper but our panel data regressions with pixel fixed effects could control for all time invariant factors of the treated and control units. Another assumption often required in RD is no selective sorting over the treatment cut-off. We address this requirement by creating fuzzy treatment cut-offs (when treatment cut-offs are 30–5 km and 50–5 km). We drop all pixels that are 5 km inside or outside the mobile phone coverage boundary from our treatment and control group because there may be overlapping effects within 5 km of the boundary.

3.6 Empirical Analysis

3.6.1 Cross-section Analysis

The specification for cross-section data is given by:

$$\Delta light_{ibc} = \alpha + \beta(treat_{ibc}) + f(geographic\ location_i) + \mathrm{B}_{bc} + \varepsilon_{i_{bc}}, \qquad (1)$$

where $\Delta light_{ibc}$ is the outcome variable of interest for pixel i along segment b of the boundary in country c. It can take two forms, either change in *lnlight* and change in *dumlight* between post- and pre-MM introduction. *lnlight* is the logarithm of average night-time light plus 0.01 for pixel p in country c in year t. Following Michalopoulos and Papaioannou (2013) and Hodler and Raschky (2014), we add the constant 0.01 to the average night-time light to avoid losing pixels with zero or close to zero reported night-time light. *dumlight* is a dummy variable that equals 1 if night-time light in the pixel is greater than 0 and equals 0 otherwise. $treat_{ibc}$ is a dummy variable that equals 1 if the pixel is inside the mobile phone coverage boundary and equals 0 otherwise. $f(geographiclocation_i)$ is the RD polynomial, which controls for smooth functions of geographic location. Four specifications of $f(geographic\ location_i)$ were discussed in Section 3.5.1. B_{bc} is a vector of boundary segment dummies. $\varepsilon_{i_{bc}}$ is the error term.

3.6.2 Cross-section Regression Results

Table 3.6 shows that in all scenarios we experiment, MM has a positive and significant effect on economic activity. Column 3, row 1 of Table 3.6 estimates that a MM treatment effect increases the change in *lnlight* by 4.7%. The point estimates increase as the bands of the mobile coverage boundary increase. The treatment coefficients are greater in fuzzy treatment cut-offs (30–5 km and 50–5 km) compared to sharp treatment cut-offs (30 km and 50 km). The treatment coefficients are both economically and statistically significant across all specifications of the RD polynomials. It seems that the treatment effect is greatest in Panel A, when we do not control for any other factors, and is lowest in Panel B, when we include a cubic polynomial in latitude and longitude of the pixel (multidimensional RD).

Table 3.6. Cross-section results

Band	(1) 20 km	(2) 30 km	(3) 50 km	(4) 30–5 km	(5) 50–5 km
			A. Baseline		
			Δlight		
treat	0.0366***	0.0451***	0.0470***	0.0511***	0.0519***
	(0.0006)	(0.0005)	(0.0005)	(0.0007)	(0.0006)
			Post light		
treat	0.247***	0.276***	0.293***	0.296***	0.312***
	(0.0015)	(0.0014)	(0.0013)	(0.0016)	(0.0014)
			Pre light		
treat	0.211***	0.230***	0.246***	0.245***	0.260***
	(0.0014)	(0.0013)	(0.0011)	(0.0015)	(0.0013)
			B. Cubic polynomial in latitude and longitude		
			Δlight		
treat	0.0141***	0.0193***	0.0217***	0.0233***	0.0262***
	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)
			Post light		
treat	0.0792***	0.0960***	0.110***	0.110***	0.126***
	(0.0010)	(0.0011)	(0.0011)	(0.0015)	(0.0015)
			Pre light		
treat	0.0651***	0.0767***	0.0880***	0.0866***	0.100***
	(0.0010)	(0.0010)	(0.0010)	(0.0014)	(0.0014)
			C. Linear distance to the boundary		
			Δlight		
treat	0.0143***	0.0196***	0.0220***	0.0240***	0.0266***
	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)
			Post light		
treat	0.0807***	0.0987***	0.113***	0.114***	0.129***
	(0.0011)	(0.0011)	(0.0011)	(0.0015)	(0.0015)
			Pre light		
treat	0.0664***	0.0791***	0.0910***	0.0898***	0.103***
	(0.0010)	(0.0010)	(0.0010)	(0.0014)	(0.0014)
			D. Cubic polynomial in distance to the boundary		
			Δlight		
treat	0.0144***	0.0197***	0.0221***	0.0241***	0.0269***
	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)
			Post light		
treat	0.0807***	0.0988***	0.113***	0.114***	0.130***
	(0.0011)	(0.0011)	(0.0011)	(0.0015)	(0.0015)
			Pre light		
treat	0.0663***	0.0791***	0.0910***	0.0898***	0.103***
	(0.0010)	(0.0010)	(0.0010)	(0.0014)	(0.0014)
Observations	1,248,950	1,572,042	1,970,253	1,182,174	1,580,385

Band	(1) 20 km	(2) 30 km	(3) 50 km	(4) 30–5 km	(5) 50–5 km
Border FE	YES	YES	YES	YES	YES

Notes: Robust standard errors are in parenthesis. The dependent variable is change in *lnlight* between post- and pre-MM introduction. *lnlight* is the logarithm of average night-time light plus 0.01 for pixel *p* in country *c* in year *t*. *treat* is the treatment variable, which is a dummy variable that equals 1 if the pixel is inside the mobile phone coverage boundary, and is defined by different distances from the mobile phone coverage boundary (30 km, 50 km, 30–5 km and 50–5 km). We drop pixels that are 5 km inside or outside the mobile phone coverage boundary from our treatment and control group to create treat 30–5 km, treat 50–5 km, control 30–5 km and control 50–5 km because pixels 5 km inside or outside the mobile phone coverage boundary could be noisy data. In Panel A, we do not control for any other factors. In Panel B, we include a cubic polynomial in latitude and longitude of the pixel. In Panel C, we control for a linear distance to the mobile phone coverage boundary. In Panel D, we control for a cubic polynomial in Euclidean distance to the nearest point of the mobile phone coverage boundary. All regressions include boundary segment fixed effects (FE). *, **, *** = significant at 10%, 5% and 1% level, respectively.

The picture presented by Table 3.7 is similar to that of Table 3.6; MM has a positive and significant effect on economic activity across all specifications of the RD polynomials. Column 3, row 1 of Table 3.7 estimates that a MM treatment effect increases the change in *dumlight* by 0.0621%. We also observe the pattern of the treatment coefficients increasing as the bands of the mobile coverage boundary increase. In most cases, the treatment coefficients are greater in fuzzy treatment cut-offs (30–5 km and 50–5 km) compared to sharp treatment cut-offs (30 km and 50 km). It also holds that the treatment effect is greatest in Panel A, when we do not control for any other factors, and is lowest in Panel B, when we include a cubic polynomial in latitude and longitude of the pixel (multidimensional RD).

Table 3.7. Cross-section results: Light Growth

	(1)	(2)	(3)	(4)	(5)
Band	20 km	30 km	50 km	30–5 km	50–5 km
			Δlight		
			A. Baseline		
treat	0.00473***	0.00600***	0.00621***	0.00693***	0.00694***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
			B. Cubic polynomial in latitude and longitude		
treat	0.00199***	0.00277***	0.00309***	0.00338***	0.00377***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
			C. Linear distance to the boundary		
treat	0.00201***	0.00281***	0.00312***	0.00348***	0.00380***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
			D. Cubic polynomial in distance to the boundary		
treat	0.00201***	0.00283***	0.00314***	0.00349***	0.00386***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1,248,950	1,572,042	1,970,253	1,182,174	1,580,385
Border FE	YES	YES	YES	YES	YES

Notes: Robust standard errors are in parenthesis. The dependent variable is change in *dumlight* between post- and pre-MM introduction. *dumlight* is a dummy variable that equals 1 if night-time light in the pixel is greater than 0 and equals 0 otherwise. *treat* is the treatment variable, which is a dummy variable that equals 1 if the pixel is inside the mobile phone coverage boundary, and defined by different distances from the mobile phone coverage boundary (30 km, 50 km, 30–5 km and 50–5 km). We drop pixels that are 5 km inside or outside the mobile phone coverage boundary from our treatment and control group to create treat 30–5 km, treat 50–5 km, control 30–5 km and control 50–5 km because pixels at 5 km inside or outside the mobile phone coverage boundary could be noisy data. In Panel A, we do not control for any other factors. In Panel B, we include a cubic polynomial in latitude and longitude of the pixel. In Panel C, we control for a linear distance to the mobile phone coverage boundary. In Panel D, we control for a cubic polynomial in Euclidean distance to the nearest point of the mobile phone coverage boundary. All regressions include boundary segment fixed effects (FE). *, **, *** = significant at 10%, 5% and 1% level, respectively.

3.6.3 Panel Data Analysis

The specification for the panel data analysis is given by:

$$light_{ict} = \alpha_i + \beta(treat_{ic} \times Post_t) + \mathrm{CT}_{ct} + \varepsilon_{ict} \qquad (2)$$

where $light_{ict}$ is the night-time light variables. It can take the two forms, *lnlight* or *dumlight*. *lnlight* is the logarithm of average night-time light plus 0.01 for pixel p in country c in year t. *dumlight* is a dummy variable that equals 1 if night-time light in the pixel is greater than 0 and equals 0 otherwise. α_i denotes pixel-level fixed effects that cover all time-invariant differences at the pixel level (including access to mobile phone coverage). $treat_{ic}$ is a dummy variable that equals 1 if the pixel is inside the mobile phone coverage boundary and equals 0 otherwise. $Post_t$ is a year dummy variable standing for post-MM introduction year and equals 1 if the year is after MM is introduced in the country. The effect of the presence of mobile phone coverage and the period after MM introduction is captured by the interaction coefficient β, which is the causal effect of MM. CT_{ct} is a vector of the country year–level dummies. The underlying assumption for the above model, the error term, ε_{ict}, is assumed to have an expected zero value. That is, β, the causal parameter, gives the only remaining difference between the control and treatment group, which is MM presence.

3.6.4 Panel Regression Results

As can be seen from Table 3.8, in all scenarios we experiment, MM has a positive and significant effect on economic activity. The effect is both economically and statistically significant. The regression result shows that in the seven sample countries, on average, the introduction of MM increases local night-time light intensity by around 3.83% (equivalent to around a 1% higher level of local GDP) after we control for country and time fixed effects (Table 3.8, Panel A, Column 4, row 1).

We obtain a similar result that the impact of MM on economic activity is positive and significant when the independent variable is *dumlight*. Panel C, Column 4, row 1 of Table 3.8 shows that on average, the introduction of MM increases the likelihood that night-time light switches from zero to a positive value by around 0.45%, net of time fixed effects.

Table 3.8. Main Results: Panel Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Band	20 km		30 km		50 km		30–5 km		50–5 km	
	A. ln(0.01+light)									
PostTreat	0.0325***	0.0245***	0.0397***	0.0383***	0.0424***	0.0427***	0.0451***	0.0390***	0.0469***	0.0456***
	(0.0080)	(0.0061)	(0.0091)	(0.0081)	(0.0098)	(0.0090)	(0.0101)	(0.0084)	(0.0108)	(0.0097)
	B. light									
PostTreat	0.0949***	0.0777***	0.1041***	0.0995***	0.1086***	0.1068***	0.1105***	0.0926***	0.1143***	0.1064***
	(0.0179)	(0.0132)	(0.0189)	(0.0157)	(0.0190)	(0.0161)	(0.0204)	(0.0154)	(0.0201)	(0.0164)
	C. light(0/1)									
PostTreat	0.0036***	0.0026***	0.0047***	0.0045***	0.0050***	0.0051***	0.0055***	0.0047***	0.0057***	0.0055***
	(0.0012)	(0.0009)	(0.0013)	(0.0012)	(0.0015)	(0.0014)	(0.0015)	(0.0013)	(0.0016)	(0.0015)
Observations	16,236,350	16,236,350	20,436,546	20,436,546	25,613,289	25,613,289	15,368,262	15,368,262	20,545,005	20,545,005
# Grid cells	1,248,950	1,248,950	1,572,042	1,572,042	1,970,253	1,970,253	1,182,174	1,182,174	1,580,385	1,580,385
Grid Cell FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
CountryYear FEs	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Robust standard errors, adjusted for clustering by country year, are in parenthesis. The dependent variable is *lnlight*. *lnlight* is the logarithm of average night-time light plus 0.01 for pixel *p* in country *c* in year *t*. *treat* is the treatment variable, which is a dummy variable that equals 1 if the pixel is inside the mobile phone coverage boundary, and is defined by different distances from the mobile phone coverage boundary (30 km, 50 km, 30–5 km and 50–5 km). We drop pixels that are 5 km inside or outside the mobile phone coverage boundary from our treatment and control group to create treat 30–5 km, treat 50–5 km, control 30–5 km and control 50–5 km because pixels at 5 km inside or outside the mobile phone coverage boundary could be noisy data. *Post* is a year dummy variable standing for post-MM introduction year and equals 1 if the year is after MM is introduced in the country. The interaction variable *treat* x *post* captures the treatment effect of MM on the outcome variable. Regressions in Columns 1, 4, 7 and 10 include controls for year fixed effects (FE). Regressions in Columns 2, 5, 8 and 11 include controls for country x year FE. Regressions in Columns 3, 6, 9 and 12 include controls for border x year FE. *, **, *** = significant at 10%, 5% and 1% level, respectively.

3.7 Concluding Remarks

This paper empirically analyses the local economic impact of MM in Africa at the 1 x 1 km grid cell level. We combine the coordinates of mobile phone towers and the surrounding topography in a viewshed model to map granular mobile phone coverage boundaries in seven African countries. We then use these coverage boundaries in a spatial discontinuity approach to divide grids into control and treatment cells. Combining this information with yearly values of night-time light intensity, we obtain a balanced panel dataset of around 1.9 million grid cells for the period 2000–2012. We then use a standard DID method to estimate the effect of the introduction of MM on the treated cells. Our results show that MM increases local night-time light intensity by around 3.83%. Our results are robust to different bandwidths and assuming a sharp and a fuzzy discontinuity. Our paper complements the empirical literature on the importance of MM on economic development by presenting general equilibrium results for seven African countries. In general, our results confirm that the positive, partial equilibrium effects of MM also hold in the aggregate and are generalisable for a broader set of countries.

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Appendix

Table 3A.1. Mobile cellular subscriptions per 100 people and growth rate

	Tanzania		Ghana		Kenya		Uganda		Sub-Saharan Africa	
Year	Per 100 people	Growth	Per 100 people	Growth	Per 100 people	Growth	Per 100 people	Growth	Per 100 people	Growth
1996	0.0	158%	0.1	106%	0.0	24%	0.0	129%	0.2	73.4%
1997	0.1	124%	0.1	71%	0.0	139%	0.0	25%	0.3	55.8%
1998	0.1	88%	0.2	91%	0.0	59%	0.1	500%	0.6	108.3%
1999	0.2	34%	0.4	68%	0.1	121%	0.2	88%	1.0	72.9%
2000	0.3	117%	0.7	86%	0.4	436%	0.5	125%	1.7	171.8%
2001	0.8	149%	1.2	87%	1.8	371%	1.2	123%	2.5	307.8%
2002	1.7	120%	1.9	59%	3.5	98%	1.6	39%	3.6	201.1%
2003	3.6	114%	3.8	106%	4.6	34%	3.0	97%	4.9	82.5%
2004	5.2	50%	8.0	113%	7.1	60%	4.3	50%	7.3	101.8%
2005	7.7	53%	13.2	70%	12.6	81%	4.8	13%	11.9	77.7%
2006	14.2	89%	23.3	81%	19.5	59%	7.0	53%	17.2	68.7%
2007	20.3	47%	33.1	46%	29.3	55%	14.2	109%	22.9	48.8%
2008	31.1	58%	49.1	52%	41.0	44%	28.1	104%	31.4	52.3%
2009	40.6	34%	62.5	31%	47.3	19%	29.9	10%	37.0	33.0%
2010	47.3	20%	70.4	15%	59.4	29%	39.6	37%	44.6	30.2%
2011	56.2	22%	83.4	21%	65.0	12%	49.9	30%	52.8	31.7%
2012	57.8	6%	98.5	21%	69.3	9%	47.3	-2%	59.5	18.9%
2013	56.6	1%	105.3	9%	69.9	4%	50.6	10%	65.7	17.4%
2014	63.8	16%	111.5	8%	72.0	6%	55.2	13%	70.4	12.6%
2015	77.0	24%	125.7	15%	78.8	12%	52.9	-1%	75.7	12.2%
2016	75.5	1%	134.5	9%	79.5	3%	57.6	13%	73.7	0.4%
2017	73.1	0%	126.2	-4%	85.3	10%	60.6	9%	73.0	1.7%
2018	77.2	9%	137.5	11%	96.3	16%	57.3	-2%	71.1	-5.9%

Table 3A.1. Mobile cellular subscriptions per 100 people and growth rate (contd.)

	Rwanda		Zambia		Côte d'Ivoire		Sub-Saharan Africa	
Year	Per 100 people	Growth	Per 100 people	Growth	Per 100 people	Growth	Per 100 people	Growth
1996	0	NA	0.0	75.9%	0.1	NA	0.2	73.4%
1997	0	NA	0.0	67.2%	0.2	165.7%	0.3	55.8%
1998	0.1	NA	0.1	81.5%	0.6	153.4%	0.6	108.3%
1999	0.1	NA	0.3	241.3%	1.6	181.9%	1.0	72.9%
2000	0.5	254.5%	0.9	250.7%	2.9	83.9%	1.7	171.8%
2001	0.8	66.7%	1.1	22.6%	4.3	54.0%	2.5	307.8%
2002	1.0	26.8%	1.3	14.8%	6.0	41.0%	3.6	201.1%
2003	1.5	58.7%	2.1	73.3%	7.3	24.7%	4.9	82.5%
2004	1.6	5.0%	4.0	92.7%	9.3	30.7%	7.3	101.8%
2005	2.5	62.4%	8.0	104.5%	12.8	40.3%	11.9	77.7%
2006	3.5	40.9%	13.7	75.2%	21.7	73.0%	17.2	68.7%
2007	6.8	102.1%	21.1	58.7%	39.0	83.7%	22.9	48.8%
2008	13.9	108.2%	27.5	34.1%	53.3	39.9%	31.4	52.3%
2009	24.8	83.7%	33.3	24.5%	65.7	26.2%	37.0	33.0%
2010	35.3	46.1%	40.0	23.6%	76.0	18.3%	44.6	30.2%
2011	43.2	25.3%	58.2	49.9%	82.5	11.2%	52.8	31.7%
2012	53.9	28.0%	72.8	28.9%	84.0	4.4%	59.5	18.9%
2013	61.9	17.5%	69.6	-1.2%	87.8	7.1%	65.7	17.4%
2014	69.9	15.8%	65.7	-2.7%	97.6	14.0%	70.4	12.6%
2015	77.0	13.1%	72.8	14.3%	109.4	14.9%	75.7	12.2%
2016	76.5	1.8%	73.4	4.0%	115.2	8.0%	73.7	0.4%
2017	73.6	-1.1%	79.7	11.8%	129.9	15.6%	73.0	1.7%
2018	78.9	10.0%	89.2	15.1%	134.9	6.5%	71.1	-5.9%

Source: Own calculation using World Development Indicators database. Sub-Saharan Africa’s figures are population weighted averages. NA: not available

Table 3A.2. First time mobile money adopters in Africa between 2007 - 2013

	Country	Mobile money launch dates		Country	Mobile money launch dates
1	Benin	June 2010	21	Mali	June 2010
2	Botswana	June 2011	22	Mauritania	May 2013
3	Burkina Faso	July 2012	23	Morocco	January 2010
4	Burundi	March 2012	24	Mozambique	September 2011
5	Cameroon	September 2010	25	Namibia	September 2010
6	Chad	June 2012	26	Niger	June 2010
7	Congo	November 2011	27	Nigeria	February 2011
8	Congo Democratic Republic	February 2012	28	Rwanda	February 2009
9	Côte d'Ivoire	December 2008	29	Senegal	June 2010
10	Egypt	June 2013	30	Sierra Leone	January 2010
11	Ethiopia	February 2013	31	Somalia	June 2009
12	Gabon	March 2012	32	South Africa	November 2009
13	Ghana	July 2009	33	Swaziland	May 2011
14	Guinea	September 2012	34	Tanzania	April 2008
15	Guinea-Bissau	July 2010	35	Togo	August 2013
16	Kenya	March 2007	36	Tunisia	April 2010
17	Lesotho	September 2012	37	Uganda	March 2009
18	Liberia	September 2011	38	Zambia	March 2009
19	Madagascar	April 2010	39	Zimbabwe	March 2011
20	Malawi	February 2012			

Source: GSMA Deployment Tracker as of 31st July 2020, news outlets and country reports

Table 3A.3. Mobile money services

Country	First service launch year	Number of service	Current mobile money services		
			Mobile money product	Service provider	Launch year
Kenya	Mar 2007	5	Tangaza Pesa Mobile	Mobile Pay Ltd	Jan 2011
			Airtel Money	Airtel (Bharti Airtel)	Feb 2009
			M-PESA	Safaricom	Mar 2007
			Equitel	Equity Bank	Jul 2014
			T-Kash	Telkom (Helios)	Mar 2018
Tanzania	Apr 2008	6	ezyPesa	Zantel (Etisalat)	Feb 2009
			Airtel Money	Airtel (Bharti Airtel)	Apr 2012
			Tigo Pesa	Tigo (Millicom)	Aug 2010
			Vodacom M-pesa	Vodacom (Vodafone)	Apr 2008
			HaloPesa	Viettel eCommerce	Oct 2016
			T Pesa	TTCL	Aug 2017
Uganda	Jan 2009	7	M-Sente	UT Mobile (Uganda	Feb 2010
			Airtel Money	Airtel (Bharti Airtel)	Jan 2009
			MTN Mobile Money	MTN	Oct 2009
			EzeeMoney	EzeeMoney	Jan 2013
			MCash	MobiCash	Feb 2012
			Africell Money	Africell	Jan 2013
			Micropay Mobile Money	Micropay	Nov 2014
Ghana	Jul 2009	6	AirtelTigo Money	AirtelTigo	Mar 2012
			MTN Mobile Money	MTN	Jul 2009
			Vodafone Cash	Vodafone	Dec 2015
			Zeepay	Zeepay Ghana Limited	May 2016
			YUP	Société Générale	Jul 2018
			G-Money	Ghana Commercial Bank	Jan 2020
Zambia	Mar 2009	5	Zoona	Zoona	Mar 2009
			Airtel Money	Airtel (Bharti Airtel)	Aug 2009
			MTN Mobile Money	MTN	Jan 2012
			Zamtel Kwacha	Zamtel	Jun 2017
			Mangwee	Virtual Space Limited	May 2018
Rwanda	Feb 2009	3	MTN Mobile Money	MTN	Feb 2009
			Airtel	Airtel (Bharti Airtel)	Jul 2013
			Mcash	MobiCash	Feb 2015
Côte d'Ivoire	Dec 2008	6	Orange Money	Orange	Dec 2008
			MTN Mobile Money	MTN	Oct 2009
			Celpaid Cote d'Ivoire	Celpaid	Feb 2011
			Flooz	Moov (Etisalat)	Dec 2012
			Qash Mobile Banking	Qash Services	Nov 2013
			YUP	Société Générale	Sep 2017

Source: GSMA Deployment Tracker as of 31st July 2020

Chapter 4

Can Industrial Policy Change the Value Chain? Evidence from Vietnam's Supporting Industries Policies[1]

Nathaniel Lane[2] and Dung Le[3]

Abstract

Developing countries aspire to move into advanced industries, and to achieve this goal, policymakers often turn to industrial policy. Can industrial policy help developing countries to cultivate high value-added sectors? Our study evaluates the impact of Vietnam's Supporting Industries policies on industrial development. We do so using detailed information about the product markets targeted by the state and 15 years of micro-data on Vietnamese enterprises. We estimate the impact of the policies by comparing the evolution of manufacturers who are differentially exposed to the Supporting Industries policy - before and after its 2007 introduction. Our difference-in-differences estimates show significant development in treated firms across industrial development outcomes, including total revenue, employment, factor productivity and wages. However, we find only weak evidence that the policy significantly increased investment-related outcomes. This suggests that investment incentives per se may not be the consequential Supporting Industries policy; instead, we conjecture that labour-oriented policy may play an important role. Our future research will focus on opening the policy 'black box' to understand which policy mechanisms may be driving our results.

Keywords: industrial policies, supporting industries, difference-in-differences, Vietnam.

JEL classification: O14, O25

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4.1 Introduction

Vietnam embodies the success story of a modern, globalised economy - one that rapidly industrialised amid their integration into the global economy. From a relatively autarkic command economy, Vietnam has opened dramatically to trade since 1986. This has included the lifting of the US trade embargo in 1994 and participation in the Association of Southeast Asia Nations (ASEAN) Free Trade Area in 1995, followed by their membership to the Asia-Pacific Economic Community (APEC) in 1998 and the World Trade Organization in 2007.

Accordingly, since their economic 'Renovation' (Đổi Mới) in 1986, Vietnam's trade development has been impressive. Emerging not only as a significant trade economy but also a critical player in the global high-tech value chain, Vietnam has real gross domestic product (GDP) per capita (purchasing power parity–adjusted) increased ninefold over the past three decades (World Bank, 2020a) and their value of trade (as share of GDP) has increased a hundredfold. During this period, Vietnam also achieved something to which many middle-income economies aspire—it joined an impressive club of high-tech export economies. Specifically, between 2008 and 2018, Vietnam's high-tech exports (as share of manufacturing exports) jumped from eight per cent to 40 per cent (World Bank, 2020b).

Although this economic development is closely associated with liberalisation, the Vietnamese state has not been a passive actor. Alongside trade policy liberalisation, the government has frequently deployed industrial policy (IP) - intentional state action meant to allocate economy activity to key sectors (Lane, 2020). In particular, policies meant to promote their transition into high-tech manufacturing, including their so-called Support Industry (SI) policy.

Our study analyses Vietnam's SI IP intervention, exploring the impact of this policy on a panel of Vietnamese manufacturing firms from 2000 to 2014. Beginning in 2007, Vietnam's extensive SI intervention sought to promote the development of key domestic inputs into high-tech production. In particular, SI policy sought to promote foreign direct investment (FDI) and higher-value domestic production by addressing a critical bottleneck in the Vietnamese economy: the availability of high-quality domestic inputs into downstream production. In other words, a competitive SI could act as a stepping stone for Vietnam to 'move up' the global supply chain.

This study presents an initial analysis of SI, by first considering the effects of SI investment incentives on those products and firms affected directly by the intervention. Like many industrial policies, SI comprises a 'bundle' of incentives. Broadly, there are four categories of policies:

financial incentives, support in research and development (R&D) and technological transfer, human resource development and market development. Following Lane (2019), we focus on SI investment incentives and analyse those firms operating in product markets targeted (treated) by the SI policy intervention both before and after the policy intervention.

This study econometrically analyses the deployment of SI incentives and their corresponding impact on industrial development outcomes. This pilot study measures the impact of the policy by comparing the evolution of firms producing SI products (treated) to other industrial firms (controls), before and after its 2007 introduction, using a difference-in-differences (DID) methodology. We estimate these effects on a balanced firm-level dataset spanning the SI intervention (2000-2014), first considering investment-related outcomes, then corresponding firm-level development outcomes such as revenue and real wage growth.

Our DID estimates show a significant improvement in treated firms across industrial development outcomes, including total revenue, employment, factor productivity and wages. Although we find some significant upward trend in DID estimates of investment per unit of fixed assets, there is no significant development in total investment or other investment -related variables (i.e., total assets, total fixed assets and fixed assets per unit of labour) for treated firms. This suggests that our results are likely not driven by investment incentives per se, indicating that other policies may have played a role - such as policies aimed at promoting skilled-labour.

Our paper contributes to three strands of literature. First, we contribute to the limited empirical literature on the effects of IP on development. To date, this literature has mostly studied historical IP that no longer exists (for a comprehensive review, see Harrison & Rodríguez-Clare, 2010; Lane, 2020). What differentiates our paper is that we study IP in a contemporary setting, using data from Vietnam - a liberalised country - that has been a member of many international trade organisations. Such IP targets the SI sector, a key sector for industrial development, beginning in 2007 and still in progress.

Second, we complement the literature on the impacts of trade liberalisation on economic growth. Many studies have documented the role of trade liberalisation in development (Amiti & Konings, 2007; Billmeier & Nannicini, 2009; Goldberg & Pavcnik, 2003; McMillan & Rodrik, 2011; Melitz, 2003) and some papers have specifically examined Vietnam’s experience of liberalisation (Athukorala, 2006; McCaig, 2011; McCaig & Pavcnik, 2013; Minot & Goletti, 1998). These studies have indicated that free trade policies have positively transformed economic landscapes in Vietnam. We argue that trade liberalisation is just part of the story; IP may be another contributing factor. Our paper investigates the role played by IP in bolstering one niche of Vietnamese industrial sectors - the emerging SI.

Third, we contribute to the 'middle income trap' literature (see e.g., Bulman, Eden & Nguyen, 2017; Eichengreen, Park & Shin, 2014; Hausmann, Pritchett & Rodrik, 2005; Paus, 2012; Pritchett & Summers, 2014). The 'middle income trap' refers to the situation in which many middle-income countries aspire to move from commodity production to industrialised and hi-tech economies, but stagnate at middle-income status. This strand of literature provides some theoretical frameworks for why middle-income countries may face challenges in maintaining high growth rates, predicts some income thresholds at which growth slows and empirically suggests measures to overcome the dilemma. We expand this strand of literature by showing that, with IP targeting the SI sector, Vietnam is on its way to avoid stagnation.

In doing so, we hope to answer broader questions surrounding the use of IP to promote industrialisation, specifically in Southeast Asia. The rise of trade liberalisation and increased use of government policies to promote SI over the past decades are two significant phenomena that motivated us to formulate the following research questions: Was the growth in hi-tech exports attributed simply to trade liberalisation? Or was this the result of a combination of IP and trade openness? Can IP assist a developing country to cultivate high value-added sectors?

The paper is structured as follows. Section 4.2 provides background information about Vietnamese SI, Section 4.3 discusses our empirical strategy and Section 4.4 describes the data. Section 4.5 presents the results and Section 4.6 concludes the paper.

4.2 Background

4.2.1 Importance of Supporting Industries

The term SI is defined variously across different countries. Essentially, SI refers to all industries that manufacture production inputs for finished industries. When defined more broadly, SI also includes built-in support services such as logistics, insurance and warehousing distribution (Luu & Nguyen, 2014). This paper uses the definition provided by the Vietnamese prime minister's Decision 12/2011/QD-TTg, in which SI was specified as 'industries that produce materials, spare parts and accessories, semi-finished products to supply for industries that produce and assemble finished products’. For example, the SI for the footwear industry could produce leather, the SI for the computer manufacturing industry could produce computer chips as leather, and computer chips are production inputs to both footwear and computer manufacturing.

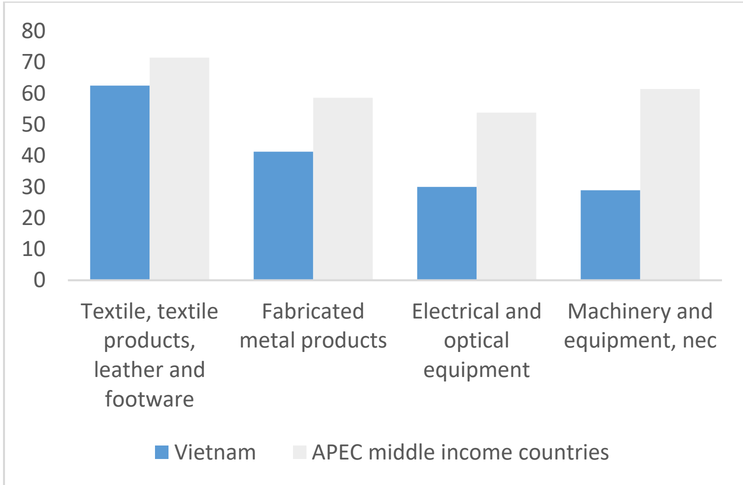
The concept of SI did not exist in Vietnam until the mid-1990s when foreign companies began investing in Vietnam and encountered difficulties in seeking production inputs. They approached the Vietnamese government to ask for appropriate measures to resolve this problem (Nguyen, 2007). Simultaneously, FDI inflow to Vietnam began to decrease after a period of minor pickup; it is believed that this reduction was partly accounted for by the weak SI in Vietnam.

The weak SI in Vietnam is illustrated in Figure 4.1, which shows that Vietnam has low localisation rates in manufacturing sectors compared to its peers. According to the latest available data (2011) from the Organisation for Economic Co-operation and Development (OECD) Trade in Value-Added (TiVA) database, Vietnam’s domestic value-added share of gross exports of some key manufacturing sectors is smaller, compared to other APEC middle-income countries.[4] For example, in 2011, in the machinery and equipment NEC sector, Vietnam’s share of domestic value-added share of gross exports was 28.9 per cent, compared to the share of 61.4 per cent found in other APEC middle-income countries. In the electrical and optical equipment sector, Vietnam’s share of domestic value-added share of gross exports was 30 per cent, whereas that of other APEC middle-income countries was approximately 54 per cent [5]. Although SI has been supported significantly by the government recently, Vietnamese SI firms still mostly conduct labour-intensive processes, low value-added activities and assembly work (Greene, 2014; Vietrade, 2015).

[4] Other APEC middle income countries include the Philippines, Indonesia, China, Malaysia, Mexico, Russia and Thailand. Countries are classified based on World Bank income classification as of June 2020.

[5] In Figure 4.1, the other APEC countries include China. If China is excluded, the relative difference still holds. We obtain similar patterns with or without China.

Figure 4.1. Share of domestic value added in gross exports in 2011



Source: Own calculation using the OECD TiVA database. Figures of APEC middle-income countries are averages. Assessed 17th November 2020.

The term SI officially appeared in Vietnam in 2003, when the Vietnam - Japan Joint Initiative was launched to discuss urgent measures to promote FDI to strengthen Vietnam's economic competitiveness. The first item of the Initiative action plan was 'development, introduction, and utilisation of supporting industries in Vietnam'.

Over time, it has become a consensus that SI is a key factor for promoting technological innovation and economic growth in Vietnam for various reasons. First, a competitive SI has become a key factor in the FDI location decisions of multinational companies (MNCs). Previously, key factors for FDI attraction included labour costs, labour skills, tax rates, size of the domestic market, exchange rate and political stability. Cheap labour costs were the driving factor for the influx of FDI into Southeast Asia in the 1970s and 1980s. However, as technology has advanced, input costs have become more important than labour costs. According to Kenich et al. (2006), in mechanical assembly-type manufacturing, the cost of parts usually accounts for 70-90 per cent of production costs, whereas labour costs occupy less than 10 per cent. Most MNCs have realised that operating in a country with cheap input costs is more cost competitive, compared to operating in a country with cheap labour costs.

Second, promoting SI is a direct measure to increase the competitiveness of a broad range of manufacturing industries. One of the characteristics of SI products is that many manufacturing industries share common SI products. For example, both consumer electronics products and motorbikes use plastic parts that are produced through a similar SI manufacturing process: injection moulding. Electronic products, motorbikes and automobiles all use metal pressing parts that are SI products (Mori, 2005). It has been said that SI plays a role as 'infrastructure' for primary manufacturing industries. Therefore, the promotion of SI will have a simultaneous promotion effect on a broad range of manufacturing industries.

Third, developing SI is a necessary step when a country participates in the globalisation process. The technological revolution and the process of globalisation have accelerated free trade and formed global value chains. The production process is now specialised on a global scale according to countries' comparative advantages, creating an international division of labour. A competitive SI will move Vietnam to higher value-added stages in the global supply chain.

Fourth, the development of SI would reduce imports of components and spare parts and limit the strain on the trade deficit. This would be extremely significant for Vietnam, which is known to have experienced chronic trade deficit since 2000.

Finally, the development of competitive SI promotes technological innovation, thereby increasing national competitiveness and welfare. Porter (1990) stated that one of four broad attributes that determine national advantage is having competitive related and supporting industries. Competitive related and supporting industries deliver "the most cost-effective inputs in an efficient, early, rapid and sometimes preferential way" to downstream industries. Having competitive related and supporting industries stimulates innovation and upgrading because suppliers and end-users in close proximity could enjoy quick and constant flow of communication and information and exchange ideas and innovations on an ongoing basis.

4.2.2 Timeline of Supporting Industries Policies

Since 2007, the Vietnamese government has issued several policies to promote the development of SI. The document that marks the government's first official attention to SI is Decision 34/2007/QD-BCN, issued in 2007 by the Ministry of Industry and Trade (MOIT). This document set the master plan to enhance SI until 2010, including a vision to 2020 with detailed targets and strategies for each of five industries: textiles and garments, leather and footwear, electronics, automobile and mechanical fabrication.

A subsequent key policy document is Decision 12/2011/QD-TTg, issued in 2011 by the prime minister on the development policies for prioritised SI. In this document, for the first time in history, SI was defined clearly. A sixth primary industry - hi-tech industry - was added, which SI was prioritised to promote. Specific measures and incentives to promote SI were put forward, focusing on six areas: market development, infrastructure, technology and science, human resources training, SI law and information provision and financial incentives. Related law documents were referred to by the document. Crucially, the document stipulated that the MOIT should have the leading role over other ministries to issue a list of prioritised SI products and update this list.

There are three key follow-up documents to Decision 12, spanning 2011 and 2012, that aimed to clarify and guide the implementation of some incentives proposed by Decision 12. The first follow-up document is Circular 96/2011/TT-BTC, issued by the Ministry of Finance in 2011 to guide the implementation of financial policies stipulated in Decision 12. Specific guidelines were provided for policies on import duty and export duty, borrowing of state development investment credit, financial assistance for small and medium enterprises (SMEs) and tax. The second follow-up document is Decision 1483/QD-TTg, issued by the prime minister in 2011. This document provided a clear list of SI products prioritised for development; in Decision 12, it was implicitly assumed that all SI products would receive incentives. Finally, in 2012, Decision 1556/QD-TTg was issued by the prime minister, which put together a comprehensive set of policies promoting SI SMEs with the target that, by 2020, Vietnam would have approximately 2,000 SI SMEs, meeting 50 per cent of the manufacturing industry's localisation demand. In 2015, Decision 9028/QD-BCT was promulgated by the MOIT, setting the master plan for developing SI up to 2020 and a vision to 2030. Compared to the master plan in Decision 34/2007/QD-BCN, more specific SI products were targeted.

The most recent, significant regulation regarding SI is Decree 111/2015/ND-CP, issued in 2015. This document amended and expanded specific incentives for SI, compared to Decision 12/2011/QD-TTg. It also encompassed an updated list of SI products prioritised for development. More SI products were included in this list, compared to the list in Decision 1483/QD-TTg. Decree 111/2015/ND-CP was accompanied by three circulars to guide the implementation of policies and one decision of the prime minister that detailed supporting plans and funds for SI firms. Circular 55/2015/TT-BTC provided guidance on the procedures for applying incentives for investment in SI projects. This document revised and updated the list of prioritised SI products. Remarkably, while in previous SI regulations, only product names are mentioned, in Circular 55, apart from product names, 8-digit trade codes of products are also included. Circular 01/2016/TT-NHNN provided instructions regarding granting loans to SI projects. Circular 21/2016/TT-BTC guided VAT tax and enterprise income tax incentives. Decision 68/QD-TTg, issued in 2017, is the latest regulation regarding SI. This document set out programs to improve SI from 2016 to 2025.

4.2.3 Scope of Supporting Industries Policies

To date, only SI that supports the following six primary industries is prioritised for development: textile, leather and footwear, electronics, automobile, mechanical fabrication and high-tech industry. The government promulgates and updates the list of SI products prioritised for development subject to changes in the global and domestic socio-economic context. The subjects of promotion incentives are projects for manufacturing SI products, including new investment projects, technology development and renovation projects, new production processes and new production projects with an increase in productivity of at least 20 per cent.

SI policies are comprehensive; however, in general, they can be categorised into the following groups.

4.2.3.1 Financial incentives

SI firms could enjoy preferential tax rates for a period. Fixed assets, raw materials and parts imported for the purpose of producing SI products can obtain import duty exemptions. SI firms are also entitled to exemption or reduction of land or water space rent (Circular 96/2011/TT-BTC). Additionally, SI firms could take out loans of up to 70 per cent of their project investments from the Vietnam Development Bank (Decree 75/2011/ND-CP).

4.2.3.2 Research and development and technological transfer

R&D activities could seek funds from the SI Development Program. Projects involving trial SI products could receive up to 50 per cent of the required funding. Projects for the construction of development and research of SI facilities could be given government land and could receive funding for up to 50 per cent of the research equipment investment from the SI Development Program (Decree 111/2015/ND-CP). SI technology transfers could receive partial funding. The government could provide up to 75 per cent of the technology transfer costs for SI projects using more than 85 per cent materials from domestic mineral processing and petrochemical products (Decree 111/2015/ND-CP).

4.2.3.3 Human resource development

SI firms could obtain funding for training activities from the SI Development Program. Institutes that provide training for SI human resources could receive funding from the Science, Technology and Training Fund (Decree 111/2015/ND-CP).

4.2.3.4 Market development

SI firms would be prioritised to participate in national trade promotion programs. SI firms were also eligible for partial funding from the SI Development Program for trademark registration, participation in domestic and overseas fairs or exhibitions and access to market information (Decree 111/2015/ND-CP).

4.3 Empirical Strategy

Our empirical strategy involves assigning firms into treatment and control groups and utilising the standard DID method to estimate the treatment impact. We assign a firm to the treatment group if it produces a product that belongs to the list of prioritised SI product for at least one year during the pre-treatment period. Otherwise, the firm is assigned to the control group. We utilise the list of prioritised SI products in Decision 1483/QD-TTg, issued by the prime minister in 2011, because this is the first comprehensive list directing the market.

The treatment assignment is performed in two steps. We only have product names in the list of prioritised SI products; therefore, the first step comprises converting these product names to 4-digit Vietnam Standard Industrial Classification (VSIC) by manual matching. A full list of prioritised SI products converted into VSIC codes is presented in Table 4A.1. It should be noted that VSIC has changed throughout our study period (2000-2014). From 1993 to 2006, VSIC was prepared based on the framework of International Standard Industrial Classification (ISIC) Revision 3 and detailed at the 4-digit level. From 2007 onwards, VSIC was developed based on ISIC Revision 4 and the ASEAN Common Industrial Classification and detailed at the 5-digit level. In the second step, we assign firms into either the treatment or control group. In our dataset, in each year, each firm reports a main sector code and eight other business sector codes. We develop the rule that, in each year, if any one of these nine codes is the same as a VSIC code in the list of prioritised SI products, the firm is said to produce a prioritised SI product in that year. Then, during the pre-treatment period (2000-2006), if a firm produces a prioritised SI product in at least one year, it is assigned to the treatment group and vice versa.

Our estimation strategy uses variations in the timing and exposure of the policy. As described in the timeline of SI policies (see Section 4.2.2), SI policies were not implemented until 2007; therefore, we consider changes in firm outcomes both before and after 2007. Moreover, we take advantage of differential exposure to the SI policy across firms. Specifically, we examine firms who were more or less exposed to SI by considering their outputs before the policy. We assume that firms producing a higher share of SI products are more 'exposed' to SI incentives. Thus, we use the timing of the policy and differences in exposure to identify the impact of SI on firm-level outcomes.

We estimate the impact of SI using a DID estimation strategy, comparing the relative changes in outcomes, before and after 2007, across firms more versus less exposed to SI incentives. Specifically, we estimate this using a standard two-way fixed effects model, with both firm and time fixed effects. The former (firm effects) control for all time-invariant firm effects. The latter—time effects—controls for period-specific, common shocks. Our identification relies on the assumption that, in the absence of SI policy, treatment and control firms would have evolved similarly following 2007. Accordingly, we assume that no other factors differentially affect treated firms in the treatment period. We chose 2007 as the cut-off year because the first SI policy was promulgated in 2007. Accordingly, we define the period from 2000 to 2006 as the pre-treatment period and the period including and after 2007 as the post-treatment period.

The main specification for our paper is given by:

$$Outcome_{it} = \alpha treat_i + \beta_t(treat_i \times year_t) + \gamma_1 + \delta_t + \varepsilon_{it} \quad (1)$$

where $Outcome_{it}$ is the inverse hyperbolic sine functions of a firm's outcome variables, which are total revenue, total labour, total revenue/total labour ratio, wages, total assets, total fixed assets, total fixed assets/total labour ratio (K/L ratio), total investment[6] and total investment/total fixed assets ratio (I/K ratio). $treat_i$ is a dummy variable, which equals 1 if the firm is treated and equals

[6] We calculated the nominal total investment value using the perpetual inventory method, as such total investment in period t would equal total fixed assets in period t – total fixed assets in period t –1 + total depreciation of fixed assets in period t.

0 in other cases. $year_t$ is a time variable, running from 2000 to 2014. γ_i and is firm fixed effects and time fixed effects. ε_{it} is the error terms.

Equation 1 is estimated with only industrial firms to ensure a logical comparison of treated firms and controlled firms. Specifically, we only include firms in the following sectors in our estimation: mining and quarrying, manufacturing, electricity, gas, steam and air conditioning supply, water supply, sewerage, waste management and remediation activities and construction.

The coefficient of interest in equation (1) is β_t, which shows the estimated impact of SI policies on a firm's outcomes. β_t measures the extra growth in a firm's outcome variables of SI firms, relative to non-SI firms, after SI policies were implemented relative to before. A positive value of β_t implies that, compared to non-SI firms, SI firms exhibit a greater increase in outcome variables after the introduction of SI policies, relative to before the introduction of such policies.

4.4 Data

4.4.1 Data Source

Our analysis is based on the Vietnam Enterprise Survey (VES), which has been conducted annually by the General Statistics Office (GSO) of Vietnam since 2000. The data covers firms in every economic sector that were in operation on 31st December of the previous year. Sample selection criteria differ slightly each year. However, in general, there are some categories of firms in which all firms must be surveyed, such as state-owned enterprises, medium and larger non-state enterprises, FDI, hospitality firms and all firms located in provinces with only a small number of enterprises. The list of sectors in which all firms must be surveyed can change every year. For other non-state enterprises, depending on the year and province, a certain percentage sample of enterprises was surveyed.

The data covers information on firm characteristics (name, establishment, firm type, business activity and director's information), labour, employees' compensation, assets, capital resources, business results (revenue and profit), the performance of obligation to the state and implemented development investment.

The data from GSO is annual; therefore, for this analysis, we developed a balanced panel dataset that comprises all firms that stayed consistently throughout our study period (2000-2014). The analysis of entry and exit of firms will be undertaken in our future research.

To develop the balanced panel dataset, we removed all significant outliers and harmonised all variables so that they have consistent names, definition and units across all years. Notably, because firms in yearly data have local identifiers—meaning that a firm with identifier ‘1’ in 2000 may be different to a firm with the same identifier in 2001—we created a firm identifier in the balanced panel dataset that is unique across all years. This identifier is created from a firm’s identification information, such as trade name, tax file number and address. The unique firm identifier allows us to track the firm over time.

Our balanced panel dataset covers the period 2000–2014 and comprises 157,770 yearly observations, indicating 10,518 firms per year. As indicated in Section 4.3, we run our estimation only on industrial firms in the balanced panel dataset, which accounts for 67,250 observations or, equivalently, 4,480 firms in a year.

4.4.2 Outcome Variables

For our analysis, we focus on two groups of a firm’s outcome variables: industrial development outcome variables and investment-related outcome variables. Industrial development outcome variables - which reflect the growth of firms - include total revenue, total labour, total revenue/total labour ratio and wages. Investment -related outcome variables include total investment, total investment/total fixed assets ratio (I/K ratio),[7] total assets, total fixed assets and total fixed assets/total labour ratio (K/L ratio).

Except for total labour, all other variables with monetary values are deflated by the Producer Price Index (PPI)[8] from the GSO of Vietnam, with 2010 as the base year. For our analysis, we employ the inverse hyperbolic sine functions of all outcome variables. The advantage of an inverse hyperbolic sine function is that it can accommodate a dataset that has variables with many zero values and normalise a skewed distribution.

[7] I/K ratio is calculated by taking total investment divided by total fixed assets in the previous period because total fixed assets also includes total investment for the current period.

[8] PPI of each sector is matched with our balanced panel dataset by VSIC2007 codes. There are two different VSIC systems in the dataset throughout the study period; therefore, to ensure consistency, we convert VSIC1993 codes to VSIC2007 codes before matching PPI to our data. PPI data is available at various levels: 2-digit, 3-digits and 4-digit. We prioritise codes with more digits in our PPI matching. For sectors where PPI is unavailable, we employ general PPI.

4.4.3 Summary Statistics

Table 4.1.Pre-intervention descriptive statistics of main outcome variables

Variable	Treatment			Control		
	Observation	Mean	Standard deviation	Observation	Mean	Standard deviation
Total revenue (million VND)	12,440	10.90	2.30	53,964	10.30	2.29
Total labour (number of workers)	12,452	5.35	1.71	54,090	4.99	1.65
Total assets (million VND)	12,452	10.83	2.22	54,075	10.50	2.06
Wages (million VND)	12,444	3.99	0.71	54,046	3.92	0.79
Total fixed assets (million VND)	12,387	9.67	2.30	53,574	9.10	2.32
Total investment (million VND)	12,291	8.81	4.26	52,742	7.60	5.22
I/K ratio	11,370	1.08	0.87	48,222	1.04	0.93
Revenue/Labour ratio	12,439	6.24	1.32	53,961	6.00	1.38
K/L ratio	12,386	5.03	1.39	53,572	4.82	1.50

Note: These are descriptive statistics of the main variables in the pre-treatment period. All main variables are in inverse hyperbolic sine functions.

4.5 Results

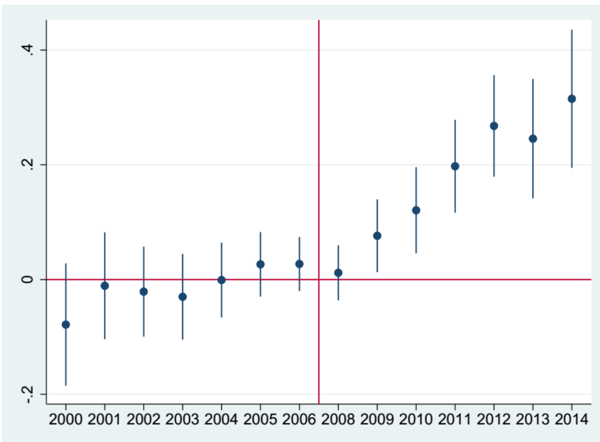
4.5.1 Industrial Outcome Variables

The regression results of equation (1) with industrial outcomes variables—total revenue, total labour, total revenue/total labour ratio, wages, total assets, total fixed assets and total fixed assets/total labour ratio (K/L ratio)—are reported in Table 4A.2. In Table 4A.2, each coefficient in a given year gives the difference between the outcomes of the treatment and control groups of that year, relative to the difference between the outcomes of the treatment and control groups of 2007 (the intervention year). To better visualise the trend of the treatment and control groups over time in interested variables, we plot the coefficients of interaction between treatment and year: βt in equation (1).

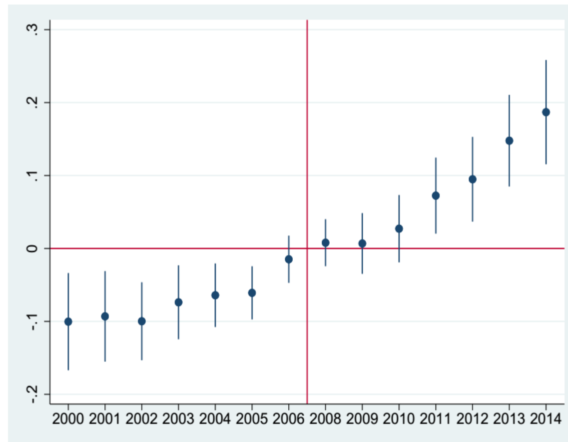
Figure 4.2 plots the estimated coefficients presented in Table 4A.2 and the 95 per cent confidence intervals of these estimated coefficients. A clear pattern is observed across all industrial outcome variables from the coefficient plots in Figure 4.2. After the introduction of SI policies, relative to control firms, treated firms have seen significant development in their total revenue, total labour, labour productivity (proxied by the revenue/labour ratio) and wages. The increase in total labour of treated firms is the most remarkable result (see Figure 4.2b). After SI policies were implemented in 2007, there was a constant, significant increase in the total labour of treated firms; further increases were observed in later years. Total revenue followed a similar trend, although there was a minor drop in 2013 (see Figure 4.2a). The estimated coefficients of total revenue were close to zero and insignificant in the pre-treatment period; then, they gradually increased following 2007 and began to be significant from 2009 onwards. Notably, while both total revenue and total labour of treated firms increased, the total revenue/total labour ratio, which is typically considered as a proxy for labour productivity, also rose significantly (see Figure 4.2c). The coefficients of wages were significant and positive throughout the study period (see Figure 4.2d). These coefficients began at high values in 2000-2012, indicating that, initially, treated firms tend to have higher wages than control firms. Then, the wages of treated firms followed a downward trend from 2003-2005 before picking up entirely in the post-treatment period.

Figure 4.2. Point estimates and confidence intervals of coefficients of industrial outcome variables using the inverse hyperbolic sine functions of the firms' outcome variables.

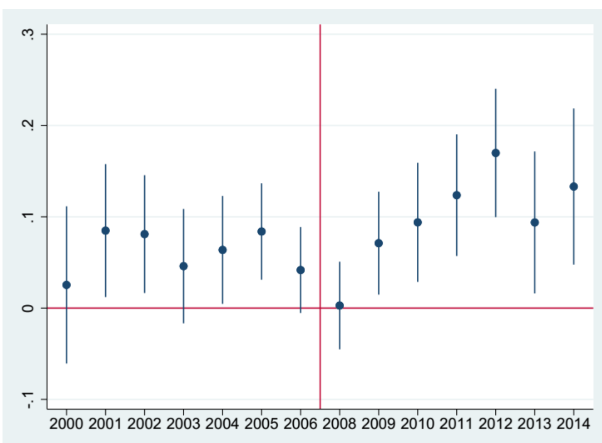
(a) Total revenue



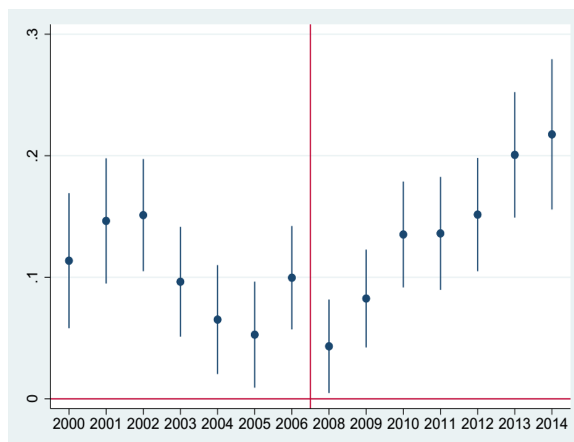
(b) Total labour



(c) Total revenue/total labour ratio



(d) Wages



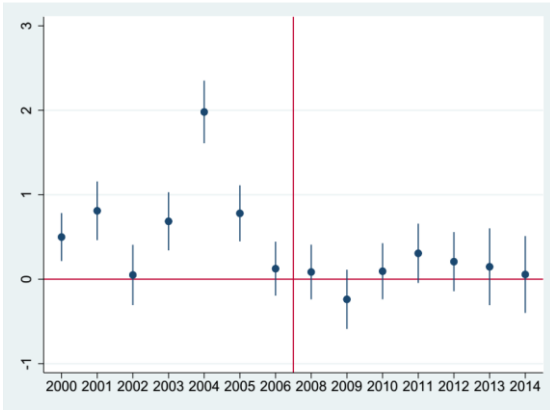
4.5.2 Investment - Related Outcome Variables

The regression results of equation (1) with investment-related outcome variables - total investment, total assets, total fixed assets, total fixed assets/total labour ratio (K/L ratio) and total investment/total fixed assets (I/K ratio)—are reported in Table 4A.3.

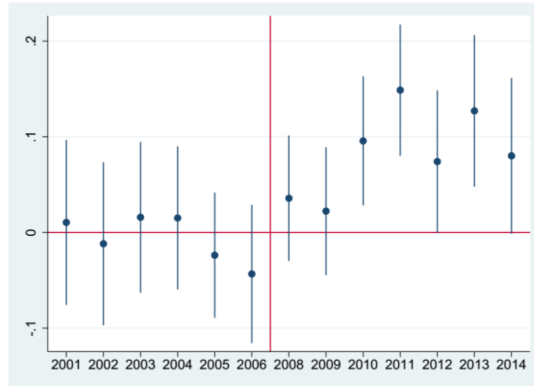
The picture regarding investment -related outcome variables is not as clear as for the industrial outcome variables. Although we observe a significant upward trend in the I/K ratio in the post-treatment period (see Figure 4.3b), total investment—the key policy outcome variable that could act as a proxy for the actual implementation of SI policies—did not show any significant improvement in the post-treatment period. There was no particular trend associated with this variable in the pre-treatment period, and associated coefficients were not significant and close to zero in the post-treatment period (see Figure 4.3a). There was an upward trend in the total assets of treated firms (see Figure 4.3c); however, the coefficients of total fixed assets—a more refined outcome variable, which is normally considered as capital (K) in economic growth models—underwent many fluctuations in the post-treatment period (see Figure 4.3d). Finally, the K/L ratio (see Figure 4.3e), which shows fixed assets per unit of labour, experienced a steady decrease throughout the study period.

Figure 4.3. Point estimates and confidence intervals of coefficients of investment -related outcome variables using the inverse hyperbolic sine functions of the firms' outcome variables

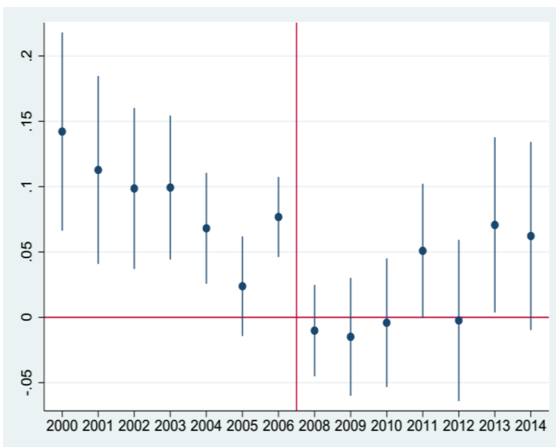
(a) Total investment



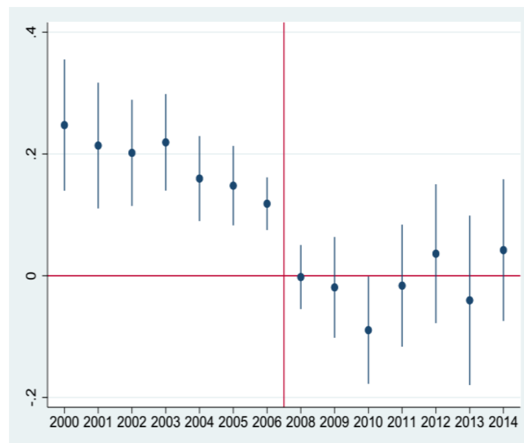
(b) I/K ratio



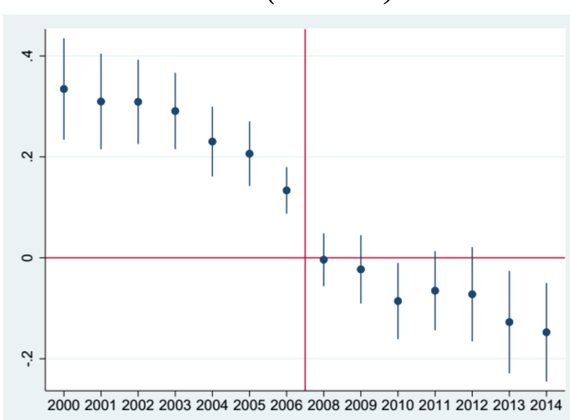
(c) Total assets



(d) Total fixed assets



(e) Total fixed assets/total labour ratio (K/L ratio)



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We also run equation (1) using a different form of data transformation. Rather than using the inverse hyperbolic sine functions of the firms' outcome variables, we use the logarithm of the firms' outcome variables, and we add the constant one to the outcome variables to avoid losing observations with zero or near-zero values. Outcome variables with monetary values were also deflated by PPI, with the base year 2010. The results using logarithm functions are presented in Tables 4A.4 and 4A.5. Coefficient plots using logarithm functions are shown in Figures 4A.1 and 4A.2. The principal results are similar if the variables are measured using logarithm functions.

The results suggest that investment incentives may not be the driving channel that leads to growth in industrial outcome variables[9]. It can be seen that there is a significant improvement in labour-related outcome variables of treated firms such as total labour, revenue/labour ratio and wages. Also, as discussed in Section 3.2.3, the Vietnamese government has issued a number of policies promoting skilled labour in SI. Therefore, we conjecture that labour-oriented policy may play a key role in boosting firm industrial development.

There are several possible explanations for these results. First, the literature often states that low domestic demand is one of the key barriers impeding Vietnamese SI from expanding investment and production capacity. For example, the statistics provided by Kenich et al. (2006) showed that Vietnam's domestic consumer electrical and electronics market is tiny compared to those of other ASEAN countries. For example, domestic consumers in Vietnam purchase approximately 1.4–1.5 million TV sets per year, whereas Thai consumers purchase 2.2–2.4 million sets per year. When including exports in measuring the market size, the difference increases further. In 2003, Vietnam produced 2.2 million TV sets (Kenich et al., 2006), while Malaysia produced 9.9 million, Thailand produced 6.5 million and Indonesia produced 5.6 million (News Net Asia, 2005). A small domestic demand makes it impossible to achieve economies of scale for cost reduction and to remain competitive. For this reason, MNC part-makers prefer to export parts from their existing factories in Malaysia, Thailand and Indonesia and have not made significant investments in Vietnam. Similarly, domestic suppliers have chosen to be subcontractors and not to invest significantly in SI fixed assets.

[9] Tran (2020) also independently finds similar results on a slightly different sample. While her paper investigates investment and related variables using an investment dataset directly reported by firms in VES, in our paper, we calculate the nominal total investment value of firms using the perpetual inventory method. Therefore, in our method, investment is derived from total fixed assets.

Another possible reason for the pattern we find is that there may be contemporaneous policies implemented in the study period that also favour firms in other sectors at the same time (Tran, 2020), potentially making the DID coefficients insignificant and close to zero. One such policy is Decree 43/1999/ND-CP, issued in 1999 and later replaced by Decree 106/2004/ND-CP, Decree 151/2006/ND-CP, Decree 75/2011/ND-CP and Decree 32/2017/ND-CP. According to this policy, firms that invest in prioritised projects are eligible for loans from the Vietnam Development Bank with preferential interest rates and tenures. The list of prioritised projects is revised periodically by the government, based on the socio-economic conditions of Vietnam. Generally, it includes projects in infrastructural, agricultural and industrial sectors and projects implemented in some extremely poor areas. Another contemporaneous policy example is the set of policies promoting SME firms. Key SME policies include Decree 90/2001/ND-CP, which was replaced by Decree 56/2009/ND-CP and Decree 39/2018/ND-CP, and Decisions 236/2006/QD-TTg and 1231/QD-TTg. These policies provide similar incentives to SME firms, as compared to SI policies, such as support for market extension, technology improvement, human resource development and financial incentives.

4.6 Conclusion

This paper empirically analyses the effect of the introduction of SI policies on firms' development during 2000-2014. Using an annual firm census dataset conducted by the GSO, we develop a balanced panel dataset that comprises firms in all sectors that consistently remain from 2000 to 2014. We run our estimation on a subset of the balanced panel dataset that includes only industrial firms and comprises 67,250 observations over 15 years or, equivalently, 4,480 firms per year. We assign a firm into the treatment group if, during the pre-treatment period, it produces a prioritised SI product in at least one year and assign a firm into the control group otherwise. We select 2007 as the intervention year because this was when the first SI policy became official. Subsequently, we use the standard DID method to estimate the effect of the introduction of SI policies on the treated firms.

Our results show that treated firms experienced significant growth in industrial development outcomes, including total revenue, employment, factor productivity and wages. Although we find some significant upward trend in the DID estimates of the I/K ratio, we do not find evidence of a significant trend or improvement in policy outcomes (proxied by investment) or other investment

-related variables (total assets, total fixed assets or K/labour ratio) of treated firms relative to control firms. This suggests that investment incentives per se may not be the driving channel that leads to growth in the industrial outcomes of treated firms; instead, we conjecture that labour-oriented policy might play a significant role.

This paper presents results from the first cut of a complicated dataset and provides a preliminary analysis of the impacts of SI policies. We have neither addressed the entry and exit analysis of firms in the aggregate census dataset nor controlled for some other key variables affecting firm outcomes. Additionally, the issue of contemporaneous policies or labour-oriented policy could be explored further. These issues will be addressed in our future research, with the aim of further opening the policy ‘black box’.

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Appendix

Table 4A.1. List of prioritised SI products with 4-Digit VSIC codes (Decision 1483/QD-TTg in 2011)[9]

Names of products in SI policy documents	VSIC1993	VSIC2007
I. TEXTILE & GARMENT INDUSTRY		
Natural fibre: cotton, silk, jute, hemp fibre	1711	1311
Synthetic fibre: PE, viscose	2430	2030
Fabric: technical fabric, non-woven and woven fabric, knitted fabric	1730	1321
Chemicals, auxiliary chemicals, fabric dyes	2429	2029
Accessories: buttons, zippers		
II. FOOTWEAR: LEATHER INDUSTRY		
Leather	1820	1511
Leatherette	1730	1321
Shoe soles, shoelace, toe shoe	1920	1520
Chemicals used in leather tanning	2429	2029
Salty leather		
Sewing thread for shoe		
III. ELECTRONICS INDUSTRY		
Basic electronics: optoelectronics components, transistors, integrated circuits, sensors, resistors, capacitors, diodes, antennae, thyristor	3320 3210	2670 2610
Quartz components		

[9] This technical appendix was prepared by the Research Assistant Chau Hai Le for the project to investigate the impacts of Vietnamese SI IP on firm financial development, which is a collaboration between Nathaniel Lane, Dung Le, Van Anh Tran and Chau Hai Le. This appendix was also used in Van Anh Tran's Master thesis 'Industrial policy and implementation: A study of Supporting Industry in Vietnam' submitted to Monash University in 2020.

Names of products in SI policy documents	VSIC1993	VSIC2007
IC		
Material used for manufacturing electronic components: semiconductors, hard magnetic materials, active insulators	3692	2680
Electronic products components: plastic components, rubber components, glass components, mechanical-electronic components	3210	2610
Laptop battery and cell phone battery	3410	2720
IV. AUTOMOBILE INDUSTRY		
Engine and engine components: piston, crankshaft, connecting rod, gear, exhaust, cylinder, cylinder head assembly kits, camshaft, rings, engine valves	3410	2910
Lubrication system: oil filters, coolers, radiators, oil pumps, valves	3420	2920
Cooling system: radiators, thermostat valves, water pumps, air cooling fans	3430	2930
Fuel supply system: fuel tanks, fuel filter	2812	2512
Frame – hull – door: punch –late-shaped components, trunk, chassis, doors, doorstep		
Suspension system: tweezers, springs, dampers		
Wheels: tires, aluminium rims	2511	2211
Transmission system: clutch, gearbox, axles, propeller shaft		
Driving system		
Braking system		
Electric: electronic components	3210	2610

Names of products in SI policy documents	VSIC1993	VSIC2007
Power supply: generators, accumulators	3210	2610
Ignition system: spark plug, high voltage transformer	3210	2610
+ Starter relay, electric starter	3210	2610
+ Wires, connectors, fuses, sensors, automatic control devices, processors	3210	2610
Lighting system and signals: indicators, horns, gauges		
Automobile exhaust treatment system		
Plastic components		
Rubber components, buffering material	2511	2211
V. MECHANICAL FABRICATION SECTOR		
Moulds, fixtures: processing fixtures, testing fixtures,	2731	2431
stamping moulds, casting moulds	2732	2432
Tools/cutters: drill, turning cutters, milling cutters	2922	2822
	2922	2818
Mechanical processing components and accessories, welders	2892	2592
Measurement devices: rulers, 3D coordinate–measuring machines, metal analysers, ultrasonic welding machines	3312	2651
Other machine components: high-strength bolts, high-tensile fasteners, bearings, silver lining, valves, joints, punch plates, variable speed boxes, hydraulic cylinders		
Fabricated steel	2710	2410
VI. SUPPORTING PRODUCTS USED IN HI-TECH INDUSTRY		
Types of mould: high-precision moulds, high-precision	2731	2431
mould for plastic casting	2732	2432

Names of products in SI policy documents	VSIC1993	VSIC2007
	2520	2220
	2520	2220
High standard mechanical parts: types of nuts, bolts, screws	3210	2610
and high-precision equipment used in electronics,	3311	2660
mechanical-electronic parts, medical electronics, industrial	3320	2670
robots	3692	2680
Types of electronic components, electronic circuits used for	3210	2610
creating equipment: peripheral equipment, computers,	3000	2620
electronic appliances, audiovisual equipment, solar cells,	3220	2630
microprocessors, controllers (programmable logic		
controllers PLC, CNC)		
Components and accessories used for new power generator	3110	2710
and renewable generator	3110	2710
High-quality plastic components: high-precision drive train,	2520	2220
durable, heat-resistant and wear-resistant plastic components	2520	2220

Table 4A.2.The impact of SI policies: Inverse hyperbolic sine functions of industrial development outcome variables

	(1)	(2)	(3)	(4)
VARIABLES	Total revenue	Total labour	Wages	Revenue/labour ratio
treat x 2001	–0.0108	–0.0931***	0.146***	0.0849**
	(0.0475)	(0.0317)	(0.0263)	(0.0371)
treat x 2002	–0.0211	–0.0998***	0.151***	0.0811**
	(0.0400)	(0.0273)	(0.0235)	(0.0329)
treat x 2003	–0.0300	–0.0738***	0.0963***	0.0459
	(0.0381)	(0.0259)	(0.0230)	(0.0319)
treat x 2004	–0.000784	–0.0641***	0.0652***	0.0637**
	(0.0332)	(0.0222)	(0.0229)	(0.0301)
treat x 2005	0.0266	–0.0609***	0.0528**	0.0839***
	(0.0287)	(0.0186)	(0.0223)	(0.0269)
treat x 2006	0.0272	–0.0148	0.0996***	0.0417*
	(0.0240)	(0.0165)	(0.0217)	(0.0240)
treat x 2008	0.0118	0.00790	0.0432**	0.00281
	(0.0245)	(0.0165)	(0.0196)	(0.0245)
treat x 2009	0.0763**	0.00684	0.0825***	0.0711**
	(0.0324)	(0.0212)	(0.0205)	(0.0288)
treat x 2010	0.121***	0.0271	0.135***	0.0939***
	(0.0383)	(0.0236)	(0.0222)	(0.0333)
treat x 2011	0.198***	0.0724***	0.136***	0.124***
	(0.0413)	(0.0266)	(0.0237)	(0.0340)
treat x 2012	0.268***	0.0949***	0.152***	0.170***
	(0.0451)	(0.0296)	(0.0238)	(0.0359)

	(1)	(2)	(3)	(4)
VARIABLES	Total revenue	Total labour	Wages	Revenue/labour ratio
treat x 2013	0.246***	0.148***	0.201***	0.0938**
	(0.0531)	(0.0320)	(0.0263)	(0.0397)
treat x 2014	0.315***	0.187***	0.218***	0.133***
	(0.0614)	(0.0365)	(0.0316)	(0.0436)
Observations	66,345	66,483	66,431	66,341
R-squared	0.862	0.899	0.624	0.723
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: This table reports DID estimates relative to the 2007 baseline level of industrial firms in the sample. Coefficients are reported with robust standard errors, clustered at the firm level, in parentheses. All outcome variables are in inverse hyperbolic sine functions, and outcome variables with monetary values are deflated by PPI, with the base year 2010. Treat is a dummy variable that equals 1 if the firm is treated and equals 0 in other cases. All regressions include firm fixed effects and year fixed effects (FE). *, **, *** = significant at 10, 5 and 1 per cent levels.

Table 4A.3. The impact of SI policies: Inverse hyperbolic sine functions of investment -related outcome variables

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Total investment	I/K ratio	Total assets	Total fixed assets	K/Labour ratio
treat x 2001	0.810***		0.113***	0.214***	0.310***
	(0.177)		(0.0367)	(0.0527)	(0.0484)
treat x 2002	0.0502	–0.0118	0.0986***	0.202***	0.309***
	(0.182)	(0.0435)	(0.0314)	(0.0445)	(0.0426)
treat x 2003	0.686***	0.0159	0.0994***	0.219***	0.291***
	(0.176)	(0.0402)	(0.0281)	(0.0405)	(0.0386)
treat x 2004	1.980***	0.0151	0.0681***	0.160***	0.230***
	(0.189)	(0.0382)	(0.0216)	(0.0356)	(0.0352)
treat x 2005	0.780***	–0.0238	0.0238	0.148***	0.206***
	(0.169)	(0.0334)	(0.0194)	(0.0333)	(0.0327)
treat x 2006	0.125	–0.0434	0.0768***	0.118***	0.134***
	(0.163)	(0.0369)	(0.0156)	(0.0221)	(0.0235)
treat x 2008	0.0850	0.0358	–0.0101	–0.00218	–0.00375
	(0.165)	(0.0335)	(0.0178)	(0.0268)	(0.0267)
treat x 2009	–0.239	0.0223	–0.0149	–0.0191	–0.0229
	(0.179)	(0.0341)	(0.0230)	(0.0422)	(0.0345)
treat x 2010	0.0942	0.0957***	–0.00410	–0.0894**	–0.0857**
	(0.169)	(0.0344)	(0.0251)	(0.0450)	(0.0385)
treat x 2011	0.307*	0.149***	0.0509*	–0.0163	–0.0653
	(0.179)	(0.0350)	(0.0262)	(0.0511)	(0.0400)
treat x 2012	0.208	0.0741*	–0.00237	0.0362	–0.0722

VARIABLES	(1) Total investment	(2) I/K ratio	(3) Total assets	(4) Total fixed assets	(5) K/Labour ratio
	(0.179)	(0.0380)	(0.0314)	(0.0582)	(0.0476)
treat x 2013	0.147	0.127***	0.0707**	–0.0404	–0.127**
	(0.232)	(0.0405)	(0.0342)	(0.0710)	(0.0517)
treat x 2014	0.0560	0.0801*	0.0622*	0.0421	–0.148***
	(0.232)	(0.0415)	(0.0367)	(0.0594)	(0.0499)
Observations	64,971	59,549	66,468	65,900	65,897
R-squared	0.375	0.297	0.922	0.810	0.658
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Note: This table reports DID estimates relative to the 2007 baseline level of industrial firms in the sample. Coefficients are reported with robust standard errors, clustered at the firm level, in parentheses. All outcome variables are in inverse hyperbolic sine functions, and outcome variables with monetary values are deflated by PPI, with the base year 2010. Treat is a dummy variable, which equals 1 if the firm is treated and equals 0 in other cases. Note that the I/K ratio is calculated by taking total investment divided by total fixed assets in the previous period. All regressions include firm fixed effects and year fixed effects (FE). *, **, *** = significant at 10, 5 and 1 per cent levels.

Table 4A.4. The impact of SI policies: Log transformation of industrial development outcome variables

	(1)	(2)	(3)	(4)
VARIABLES	Total revenue	Total labour	Wages	Revenue/ Labour ratio
treat x 2001	–0.0108	–0.0931***	0.146***	0.0849**
	(0.0475)	(0.0317)	(0.0263)	(0.0371)
treat x 2002	–0.0211	–0.0998***	0.151***	0.0811**
	(0.0400)	(0.0273)	(0.0235)	(0.0329)
treat x 2003	–0.0300	–0.0738***	0.0963***	0.0459
	(0.0381)	(0.0259)	(0.0230)	(0.0319)
treat x 2004	–0.000784	–0.0641***	0.0652***	0.0637**
	(0.0332)	(0.0222)	(0.0229)	(0.0301)
treat x 2005	0.0266	–0.0609***	0.0528**	0.0839***
	(0.0287)	(0.0186)	(0.0223)	(0.0269)
treat x 2006	0.0272	–0.0148	0.0996***	0.0417*
	(0.0240)	(0.0165)	(0.0217)	(0.0240)
treat x 2008	0.0118	0.00790	0.0432**	0.00281
	(0.0245)	(0.0165)	(0.0196)	(0.0245)
treat x 2009	0.0763**	0.00684	0.0825***	0.0711**
	(0.0324)	(0.0212)	(0.0205)	(0.0288)
treat x 2010	0.121***	0.0271	0.135***	0.0939***
	(0.0383)	(0.0236)	(0.0222)	(0.0333)
treat x 2011	0.198***	0.0724***	0.136***	0.124***
	(0.0413)	(0.0266)	(0.0237)	(0.0340)
treat x 2012	0.268***	0.0949***	0.152***	0.170***

	(1)	(2)	(3)	(4)
VARIABLES	Total revenue	Total labour	Wages	Revenue/ Labour ratio
	(0.0451)	(0.0296)	(0.0238)	(0.0359)
treat x 2013	0.246***	0.148***	0.201***	0.0938**
	(0.0531)	(0.0320)	(0.0263)	(0.0397)
treat x 2014	0.315***	0.187***	0.218***	0.133***
	(0.0614)	(0.0365)	(0.0316)	(0.0436)
Observations	66,345	66,483	66,431	66,341
R-squared	0.862	0.899	0.624	0.723
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: This table reports DID estimates relative to the 2007 baseline level of industrial firms in the sample. Coefficients are reported with robust standard errors, clustered at the firm level, in parentheses. We use the logarithm of the firm's outcome variables, and we add the constant 1 to the outcome variables to avoid losing observations with zero or near-zero values. Outcome variables with monetary values are deflated by PPI, with the base year 2010. Treat is a dummy variable, which equals 1 if the firm is treated and equals 0 in other cases. All regressions include firm fixed effects and year fixed effects (FE). *, **, *** = significant at 10, 5 and 1 per cent levels.

Table 4A.5. The impact of SI policies: Log transformation of investment -related outcome variables

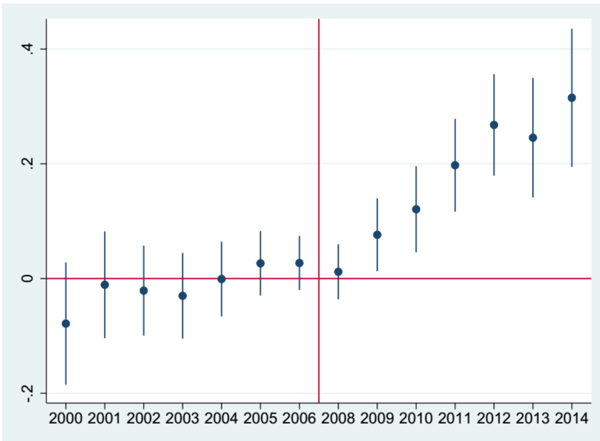
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Total investment	I/K ratio	Total assets	Total fixed assets	K/Labour ratio
treat x 2001	0.676**		0.113***	0.218***	0.312***
	(0.342)		(0.0367)	(0.0527)	(0.0484)
treat x 2002	–0.0587	–0.0647	0.0986***	0.207***	0.313***
	(0.345)	(0.0472)	(0.0314)	(0.0446)	(0.0426)
treat x 2003	0.667**	–0.0315	0.0994***	0.225***	0.294***
	(0.337)	(0.0446)	(0.0281)	(0.0405)	(0.0386)
treat x 2004	1.876***	–0.0411	0.0681***	0.162***	0.232***
	(0.347)	(0.0437)	(0.0216)	(0.0357)	(0.0352)
treat x 2005	0.668**	–0.0881**	0.0238	0.149***	0.207***
	(0.330)	(0.0395)	(0.0194)	(0.0333)	(0.0327)
treat x 2006	0.870**	0.00328	0.0768***	0.119***	0.134***
	(0.339)	(0.0405)	(0.0156)	(0.0221)	(0.0235)
treat x 2008	0.161	0.0392	–0.0101	–0.00246	–0.00401
	(0.332)	(0.0360)	(0.0178)	(0.0269)	(0.0268)
treat x 2009	–0.184	–0.00423	–0.0149	–0.0190	–0.0228
	(0.350)	(0.0354)	(0.0230)	(0.0423)	(0.0345)
treat x 2010	0.140	0.0397	–0.00410	–0.0883**	–0.0850**
	(0.358)	(0.0354)	(0.0251)	(0.0450)	(0.0385)
treat x 2011	0.193	0.0880**	0.0509*	–0.0148	–0.0645
	(0.347)	(0.0437)	(0.0262)	(0.0511)	(0.0400)
treat x 2012	0.108	0.0130	–0.00237	0.0553	–0.0621

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Total investment	I/K ratio	Total assets	Total fixed assets	K/Labour ratio
	(0.339)	(0.0450)	(0.0314)	(0.0601)	(0.0482)
treat x 2013	0.0158	0.0672	0.0707**	–0.00567	–0.107**
	(0.367)	(0.0466)	(0.0342)	(0.0716)	(0.0520)
treat x 2014	–0.0593	0.0198	0.0622*	0.0778	–0.127**
	(0.380)	(0.0472)	(0.0367)	(0.0609)	(0.0505)
Observations	65,849	60,297	66,468	66,079	66,073
R-squared	0.324	0.261	0.922	0.805	0.656
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

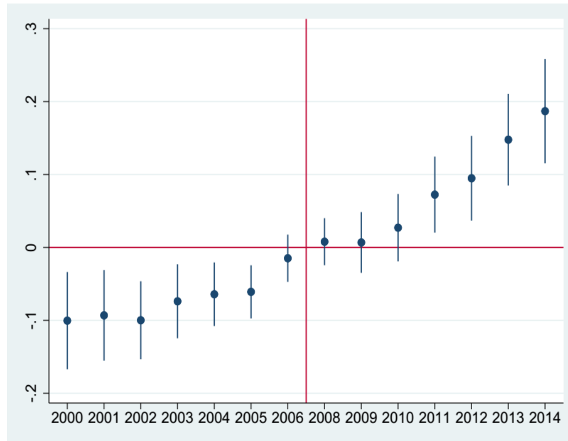
Note: This table reports DID estimates relative to the 2007 baseline level of industrial firms in the sample. Coefficients are reported with robust standard errors, clustered at the firm level, in parentheses. We use the logarithm of firm's outcome variables, and we add the constant 1 to the outcome variables to avoid losing observations with zero or near-zero values. Outcome variables with monetary values are deflated by PPI, with the base year 2010. Treat is a dummy variable, which equals 1 if the firm is treated and equals 0 in other cases. Note that the I/K ratio is calculated by taking total investment divided by total fixed assets in the previous period. All regressions include firm fixed effects and year fixed effects (FE). *, **, *** = significant at 10, 5 and 1 per cent levels.

Figure 4A.1. Point estimates and confidence intervals of coefficients of industrial outcome variables using the logarithm of firms' outcome variables + 1.

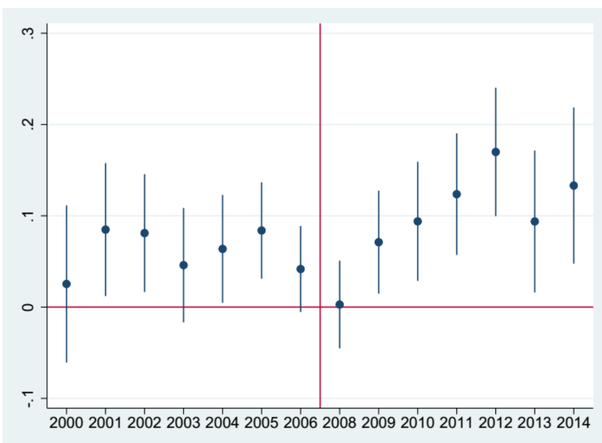
(a) Total revenue



(b) Total labour



(c) Total revenue/total labour ratio



(d) Wages

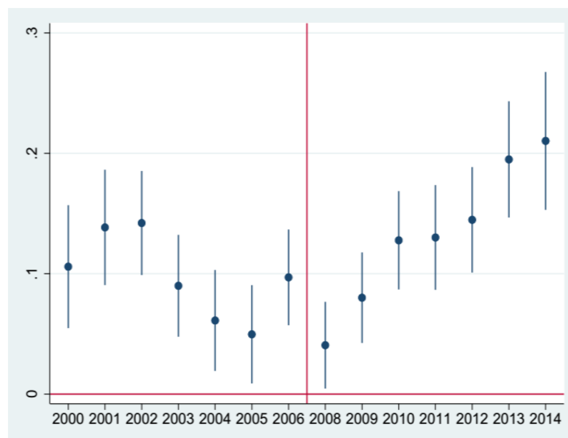
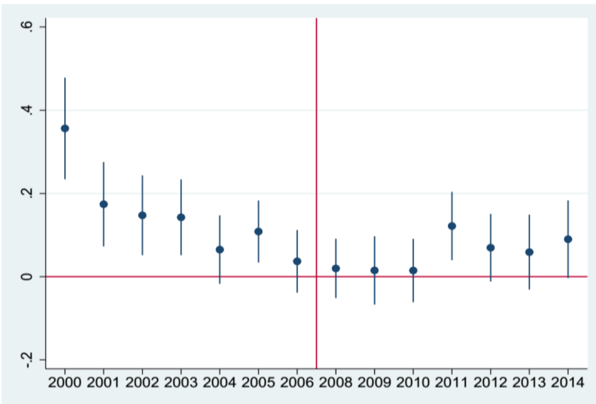
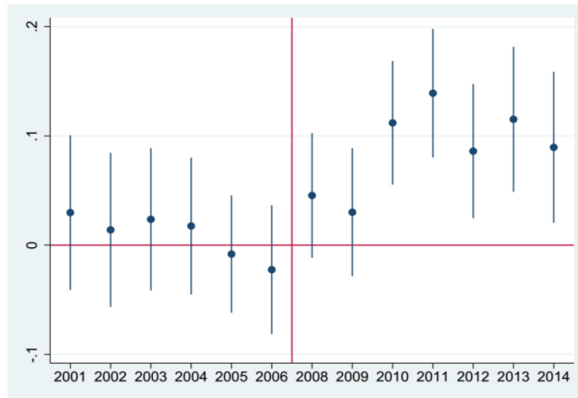


Figure 4A.2. Point estimates and confidence intervals of coefficients of investment -related outcome variables using logarithm of firms' outcome variables + 1.

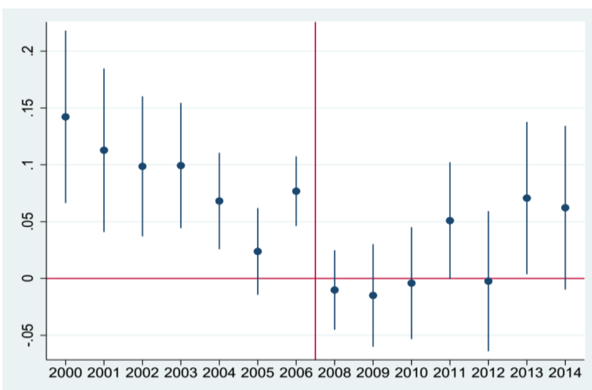
(a) Total investment



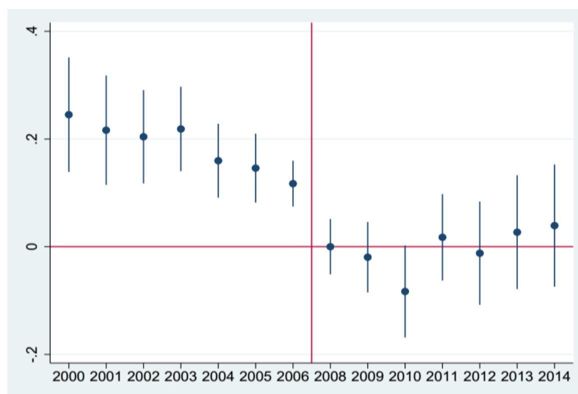
(b) I/K ratio



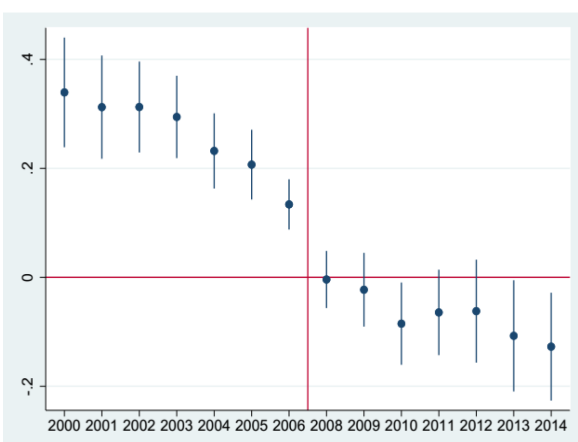
(c) Total assets



(d) Total fixed assets



(e) Total fixed assets/total labour (K/L) ratio



Chapter 5

Conclusion

Economic development and income inequality are among the key problems that economists have tried to address for centuries. One strategy on how countries have attempted to improve economic development and reduce income inequality is through some form of government policy. This thesis's theme is to examine how government intervention fosters economic development and reduces income inequality. It does so by looking at the impact of three different types of government intervention into the economy. The first paper (chapter 2) looks into the impacts of government policies to increase education expansion on income inequality. The second paper (chapter 3) examines empirically the effects of government-initiated infrastructure improvement on local economic activity. In particular, the chapter investigates the aggregate impact on local economic activity of mobile money service developed using a mobile phone platform that has been brought about by the dramatic increase in mobile phone coverage. The third paper (chapter 4) explores the impacts of industrial policy in boosting the industrialization process and transition into hi-tech manufacturing.

5.1 Summary of the Chapters and Findings

Chapter 2 examines the impact of education expansion on income inequality through three channels: level effects, dispersion effects, and interaction between technological progress and tertiary education.

Our paper makes three main contributions to the literature. Firstly, we augment the educational Gini with educational attainment dispersion across age cohorts at all levels of education. In contrast to the conventional education inequality measures which only account for education inequalities between *all* adults, our augmented measure allows for education inequality at all levels of education between all age cohorts in the 23-65 age bracket (working age population). This augmentation is necessary as generational educational inequalities are not negligible and have had significant effects on overall educational inequality as shown in our paper.

Secondly, we overcome the problem of using cross-country or cross-state data in previous studies by employing a unique long time-series data set for 21 OECD countries for the periods 1870–2016 (regression analysis) and 1818–2016 (data required to estimate educational inequality starting from 1870). In previous studies, the conventional education inequality measures were calculated from a cross-section of countries or a few observations per country (typically 3-5). Long data is more desirable than cross-country or cross-state data because they: 1) are much less influenced by the medium-term movements than data of a few decades and, thus, would better reflect the structural nexuses between variables; 2) enable us to identify a structural break around WWII and identify factors affecting income inequality; and 3) enable us to identify a Kuznets (1955) curve for educational attainment.

Thirdly, to the best of our knowledge, this paper is the first empirical attempt at the macro level that allows for the direct effects of technological progress and the interaction between technological progress and tertiary educational attainment on income inequality. The interaction term allows us to examine whether tertiary education strengthens the income inequality effects of technological progress and vice versa.

Our empirical analysis is carried out for 21 OECD countries in three periods 1870–2016, 1870–1940 and 1940–2016. The split of the regressions into two periods with a breaking point in 1940 allows us to improve the inference of the relationship as there is a structural break in the relationship between income inequality and education around 1940. Robustness tests are carried out on a dataset of 61 countries, categorized into three approximately equally sized income groups: high-income countries, middle-income countries and low-income countries. We also employ a simulation analysis to break down the contribution of each of the variable: educational inequality, technological progress, education, tariffs and unionization to the income inequality over the periods 1870-1940, 1940-2016 and 1980-2016.

Our empirical analysis shows that there is a structural break in the association between educational inequality and income inequality in around WWII. This association is positive before WWII and negative thereafter. We also find evidence that the interaction between tertiary education and technological progress has contributed to the increase in income inequality since WWII.

Chapter 3 investigates the impact of mobile money (MM) service on local economic activity at the 1 x 1 km grid cell level using a balanced panel dataset of around 1.9 million grid cells of seven Sub-Saharan African countries for the period 2000-2012.

Numerous empirical studies have examined the impacts of MM at the microeconomic level. Our paper complements these microeconomic studies by looking at the aggregate impact of MM on local economic activity. Prior studies often analyze the impact of MM on a single economic indicator (such as consumption or investment) and utilise data from a single area or country. Therefore, their results are partial equilibrium. We make contribution to the literature by studying data from seven countries and generating general equilibrium results which are more generalisable.

We use night-time light intensity as a proxy for economic activity and mobile phone coverage as a proxy for access to MM service. We construct granular mobile phone coverage boundaries by combining the coordinates of mobile phone towers and the surrounding topography in a viewshed model. We use the discontinuity at the mobile phone coverage boundary as a spatial discontinuity to assign grids into control and treatment groups. The DID method is then employed to measure the effect of the introduction of MM on the treated cells. Our paper finds that the impact of MM on local economic activity is robust, positive and both statistically and economically significant.

Chapter 4 evaluates the impact of Vietnam's Supporting Industries (SI) policy on firm industrial development using a balanced dataset of industrial firms for the period 2000-2014. Our paper contributes to the literature in three different aspects. Firstly, we contribute to the very thin empirical literature on the impacts of industrial policy (IP). While most of previous studies examine historical IP that happened a long time in the past and no longer exist, our paper investigates IP impacts in a contemporary setting - IP that targets the SI sector, a key sector for industrial development in Vietnam, beginning in 2007 and still in progress.

Secondly, we complement the literature on the impacts of trade liberalisation on economic development. Literature have indicated a positive role of trade liberalisation in development (Amiti & Konings, 2007; Billmeier & Nannicini, 2009; Goldberg & Pavcnik, 2003; McMillan & Rodrik, 2011; Melitz, 2003) and some papers have specifically looked into liberalisation impacts in Vietnam (Athukorala, 2006; McCaig, 2011; McCaig & Pavcnik, 2013; Minot & Goletti, 1998). We hypothesize that the positive change in economic growth is not only brought by trade liberalisation, IP may be another contributing factor. Our paper examines the efficiency of IP in fostering the development of one niche of Vietnamese industrial sectors - the emerging SI.

Thirdly, we enrich the 'middle income trap' literature (see e.g., Bulman, Eden & Nguyen, 2017; Eichengreen, Park & Shin, 2014; Hausmann, Pritchett & Rodrik, 2005; Paus, 2012; Pritchett & Summers, 2014). The 'middle income trap' refers to the situation in which many middle-income countries aspire to move from commodity production to industrialised and hi-tech economies, but could not find efficient ways to do it and stagnate at middle-income status. Existing literature provides theoretical frameworks explaining this stagnation, predicts some income thresholds at which growth slows and empirically suggests measures to escape the stagnation. Our paper contributes to literature by showing that, with IP targeting the SI sector, Vietnam is on its way to avoid stagnation.

We estimate the impact of the policy by comparing the evolution of firms producing SI products (treated) to other industrial firms (controls), before and after its 2007 introduction, using the standard DID methodology. The empirical exercise finds that there is a significant improvement in treated firms in industrial development outcomes, but there is weak evidence of an improvement in investment-related outcomes.

5.2 Policy implications and further research avenues

In Chapter 2, we find that the association between educational inequality and income inequality has switched from positive before WWII to negative thereafter. Nowadays, with the rise of advances in technology and high level of complexity and the sophistication of work tasks due to the structural break in labor productivity in advanced countries after WWII (Greasley, Madsen, & Wohar, 2013), it seems that education equality is not leading to reduced income inequality anymore. Other factors, such as the rise of residual inequality (Acemoglu, 2002), have surpassed education to become the driving factors of income inequality. We are not of the opinion that our paper results indicate educational expansion policies are ineffective in reducing income inequality, but we are for the belief that improvements in education equality are not a sufficient condition to reduce income inequality. There are factors that affect unobserved skills and residual inequality that need to be addressed.

This chapter proposes the idea that we need to take into account intergenerational education inequality and demonstrates that this augmented education Gini is a significantly more reliable measure of education inequality than the conventional education Gini. This idea could be explored and applied using other data sources to obtain a better understanding of education inequality and draw credible policy directions. This chapter also highlights the importance of allowing for the direct effects of technological progress and the interaction between technological progress and tertiary educational attainment on income inequality. In the era of rapid technological advancement today, this approach could potentially be a methodological avenue that sheds lights on a better understanding of what factors drive income inequality.

Chapter 3 demonstrates that the improvement of infrastructure (mobile phone coverage), together with technology innovations (the advent of MM service) play an important role in increasing the local community welfare. It reinforces the finding in literature that investment in physical infrastructure matters to economic development (Aschauer, 1989; Duffy-Deno & Eberts, 1991; Eisner, 1991; Munnell, 1990; Ratner, 1983). This has policy implications towards investing more in infrastructure and technological research. In addition, in the chapter, following Doll, Muller, and Morley (2006); Elvidge et al. (2009); Henderson, Storeygard, and Weil (2012); Hodler and Raschky (2014), satellite data of night-time light is used as a proxy for economic activity. The chapter illustrates that the use of alternative data sources such as satellite images could address the data quality and availability challenges when drawing economic inferences at subnational levels or from less developed countries. Thus, the chapter highlights the importance of investment in alternative data sources, which could potentially improve how we see the world and make economic inferences. While there is a plethora of empirical studies examining micro-level MM impacts, studies on the aggregate or macro impact level of MM are scarce. To the best of my knowledge, this chapter is the first empirical study attempting to estimate the impact of MM at the aggregate level. Further research could direct towards this area to allow for a comprehensive understanding of MM impacts. Moreover, another avenue for further research is to explore the mechanisms through which MM leads to higher, local economic development.

Chapter 4 shows that industrial policy has improved firm industrial development, therefore it highlights how important government policies are in allocating economic activity to targeted sectors to boost economic development. However, we find only weak evidence that the policy significantly increased investment-related outcomes, suggesting that our results are not driven by investment incentives per se. We conjecture that labour-oriented policies, such as policies aimed at promoting skilled labour may play a critical role. This could be an avenue for future research to dive in, to understand which policy mechanisms may be driving our results.

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