Understanding the effects of human capital on economic growth

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by

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To my parents

Στους γονείς μου

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Marianna
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CHAPTER 1

Introduction

THERE is a strong consensus in the literature regarding the importance of education, and therefore human capital, for the economy and society as a whole. Education is highly valued, not only because of its potential to generate monetary returns but also because of the social (non-pecuniary) returns it entails, such as the effects on crime, health, mortality, fertility, voting or political participation (e.g. Moretti, 2005; Lochner, 2011). Little surprise that education holds such a central role in economic and policy debates.

The core aim of this thesis is to examine the importance of education and, therefore, human capital in facilitating faster growth. As such, it can be positioned within the broader, and recently resurgent, literature that calls for a better understanding of human capital in order to identify its effects on growth (e.g. Fraumeni, 2015; Lucas, 2015). Various theories exist with respect to the channels through which human capital impacts economic growth (e.g. Nelson & Phelps, 1966; Mankiw, Romer, & Weil, 1992) and empirical research has commonly examined this relationship by adopting a rich set of data sets, empirical set-ups and methodologies (cross-section, panel, time-series country cases, non-parametric).[1]

Each chapter in this thesis answers a specific question that relates to the effects of human capital on economic growth. The canonical model in the cross-country growth literature is the tried-and-tested approach of growth accounting inspired by Solow (1957) and developed in a refined form by Jorgenson and associates (Jorgenson, Gollop, & Fraumeni, 1987). The basic assumption underlying this neo-classical approach is that the contribution of a worker is reflected in her wage which is assumed to equal marginal productivity. I take this approach as the starting point and extent it in three directions.

[1] For reviews on the role of human capital for economic growth, see: Krueger and Lindahl (2001); Sianesi and van Reenen (2003); Savvides and Stengos (2009); Benos and Zotou (2014); Delgado, Henderson, and Parmeter (2014); Glewwe, Maïga, and Zheng (2014).

In **Chapter 2**, I apply a new measure of human capital that accounts for vintage effects. In this way, I loosen up the assumption that a year of schooling delivers a constant amount of human capital over time. Instead, I allow for the fact that new cohorts of graduates may differ from previous ones with respect to the quantity of labor services per hour worked they supply. The results show that the introduction of these vintage effects in growth accounting increased the measure of labor services by high-skilled workers in the United States and the United Kingdom compared to the standard growth accounting. Conversely, the measured contribution of human capital to growth in the Continental European countries declined between 1995 and 2005. As such, human capital vintage effects appear to be much more important in accounting for the trans-Atlantic productivity growth difference during that period.

In **Chapter 3**, I depart from the assumption that the contribution of human capital can be measured by its private rates of return as reflected in wages. Possible social returns on top of the private ones will show up as total factor productivity (TFP) in standard growth accounting exercises. To trace potential externalities, I use an econometric method relating human capital to TFP growth. I find evidence of externalities stemming from tertiary-educated people and also that these externalities depend greatly on a country's level of technological development.

In **Chapter 4**, I investigate potential *international* spill-overs of human capital, thereby departing from the assumption that human capital effects can only be realized within a focal country. I analyse the impact of migration on the home country's human capital by econometrically relating a country's emigrant population with its growth in knowledge-intensive industries. I find that countries with higher emigration rates of skilled workers show faster growth in knowledge-intensive manufacturing industries. Perhaps surprisingly, this suggests evidence for a 'brain gain' rather than 'brain drain'.

In the remainder of this introductory chapter I elaborate on the background and extant literature for the main chapters of this thesis, and discuss my findings in some more detail.

1.1 Growth Accounting

The canonical empirical model for analysing the contribution of human capital to economic growth is growth accounting. Growth accounting allows us to track down the sources of a country's output growth over time.[2] Formally formulated first by Solow (1957), a growth accounting exercise decomposes growth in output into growth

[2]For a review of the growth accounting literature, see Hulten (2010).

in inputs and productivity. A production function constitutes the starting point:

$$Y = f(A, K, L) \tag{1.1}$$

where Y denotes a country's output, K capital and L labor. A is the "Solow residual", multi or total factor productivity (MFP or TFP) (Hulten, 2010), or the "measure of our ignorance" (Abramovitz, 1956), and captures the efficiency with which the factors of production are used. In formal notation and assuming competitive factor markets, full input utilization and constant returns to scale, it holds that[3]:

$$\Delta logY = \Delta logA + \alpha \Delta logK + (1-\alpha)\Delta logL \tag{1.2}$$

where Δ is the difference operator and α and $(1-\alpha)$ are the capital and labor income shares respectively. Hence, growth is calculated as the logarithmic difference between two points in time, for example t and T, and the capital and labor income shares are averages of the same period.

Furthermore, in the standard growth accounting framework, it holds that:

$$\Delta logL = \sum_{j=1}^{N} w_j \Delta logH_j \tag{1.3}$$

where j denotes a particular type of worker, w_j the share of total labor compensation flowing to that type of worker and H_j the hours worked by that type of worker. As before, growth is calculated as the logarithmic difference between t and T and w_j is the average of that same period. By distinguishing between labor types j, this formulation takes into account the composition of the labor force: labor input is not homogeneous but rather encompasses different types of labor depending for example on age, gender, education and/or experience (Hulten, 2010). The productivity of each worker is measured by her wage.

In a recent contribution, Barro and Lee (2015) conduct a growth accounting exercise in a sample of 83 advanced and developing countries (for every decade) between the 1961-2010 period. They find that human capital grew annually by 0.6% and explained a bit more than one-fifth of the world's per worker GDP growth. The average annual growth rate of the latter amounted to 2.6%. The contribution of human capital is found to be slightly larger among advanced economies (it explains approximately one-fourth of their average annual growth rate) and somewhat smaller for the developing world (approximately one-fifth). Jorgenson, Ho, and Samuels (2016) show that, between

[3] Inklaar, Timmer, and van Ark (2008, p. 181).

1947 and 2010, only 0.24 percentage points of the US' average annual growth rate of 3.23% can be attributed to improvements in human capital. C. I. Jones (2016) provides similar estimates. While not unimportant, human capital is not identified as the main driver of output growth in growth accounting exercises.

An often used variant of growth accounting is the so-called development (or level) accounting. It addresses the question 'what explains the observed, vast income differences across countries'. This is perhaps the most frequently asked one in the field of economics, and development accounting is the standard tool used to answer this question (e.g. Hall & Jones, 1999; Caselli, 2005; Hsieh & Klenow, 2010). Development accounting assesses how much of the observed income differences can be attributed to differences in factors of production and how much to differences in the efficiency with which these factors are used. Hence, it provides an indication as to whether policies should primarily address factor accumulation or efficiency (Caselli, 2005).

Efficiency is consistently found in the literature to drive income differences, with its contribution amounting to 50%-70% (Hsieh & Klenow, 2010).[4] Klenow and Rodríguez-Clare (1997) pay special attention to the construction of their human capital measure[5] and attribute to productivity at least half of the observed cross-country GDP differences. After a barrage of robustness tests, Caselli (2005, p. 737) overwhelmingly replies "no, way no" to the question whether production factors are responsible for the large cross-country income disparities. Hall and Jones (1999) also identify the Solow residual as primarily responsible for the large disparities in output per worker. With its contribution ranging from 6% to 20%, Barro and Lee (2015) confirm that human capital is not the main source of cross-country income differences.[6]

From the discussion above, it follows that a standard growth (or development) accounting assumption is that an hour worked by a worker of a given type delivers a constant quantity of labor services over time. However, this assumption may be violated due to vintage effects: new graduates may differ from previous cohorts in terms of the quantity of labor services per hour worked they supply. This may be for instance due to improving schooling or on-the-job training. Bowlus and Robinson (2012) show that vintage effects have been important in the United States (for

[4]One exception to this consensus comes from Mankiw et al. (1992) who attribute to the augmented-with-human-capital Solow model 78% of the cross-country variation in income. Note, however, that they reach this conclusion based on OLS regressions which might suffer from endogeneity (e.g. reverse causality, omitted variable bias).

[5]They take into account different levels of schooling, experience and the quality of education, evidence that the production of human capital is labor-intensive, as well as information from Mincerian regressions.

[6]Other contributions in this field with similar conclusions come from Hendricks (2002) and Mutreja (2014).

example, labor services per hour worked of high-skilled workers have increased over time). As a result, growth of human capital has been underestimated and that of TFP overestimated. In **Chapter 2**, we apply the Bowlus and Robinson (2012) method for identifying vintage effects, in order to compare the United States to six European countries (France, Germany, Italy, the Netherlands, Spain and the United Kingdom). We find that adjusting for vintage effects leads to increases in labor services per hour worked by high-skilled workers in the United States and United Kingdom. In contrast, decreases occur in Continental European countries between 1995 and 2005. During this period, human capital vintage effects were important in explaining the productivity growth advantage the US and the UK have developed vis-à-vis Continental Europe.

1.2 Externalities from Human Capital

However important they are as diagnostic tools, growth and development accounting ignore any *in*direct contribution of human capital. Interactions between efficiency, physical and human capital accumulation are not captured in such exercises (Caselli, 2005; Barro & Lee, 2015) and, as a result, not the full role of human capital is picked up.[7] These indirect channels imply the existence of externalities.

Externalities from human capital emerge when the social returns to education exceed the private ones (e.g. Krueger & Lindahl, 2001).[8] This implies that the benefits of human capital are not limited to the person who acquires the education, but extend to one's co-workers, community, country, and even other countries. Studying only the private returns to education would, as a result, understate the importance of human capital and potentially misguide government policies such as the provision of public education.

The empirical literature that estimates the private returns to schooling is vast and largely relies on the famous Mincerian wage equation (Mincer, 1974):

$$log(w_i) = \beta_0 + \beta_1 \cdot S_i + \beta_2 \cdot E_i + \beta_3 \cdot E_i^2 + \varepsilon_i \tag{1.4}$$

where w is the wage of individual i, S her years of schooling, E labor market experience and ε the error term. The β_1-coefficient is interpreted as the average

[7]Human capital, for example, impacts physical capital (Lucas, 1990) and TFP growth (Benhabib & Spiegel, 1994).

[8]Naturally, the concept of externalities implies that the social return is higher than the private one, but that is not necessarily always the case. Krueger and Lindahl (2001, p.1107) state that the social return is lower when education is merely a credential and does not add to productivity.

private rate of return to one additional year of schooling (Psacharopoulos, 1994) and captures one's incentive to invest in education (Psacharopoulos & Patrinos, 2004).[9]

This semi-logarithmic earnings function has been estimated for many countries. Reviewing the literature, Psacharopoulos (1994) finds that the global average rate of return to an additional year of schooling is about 10%, although there are differences between countries (Krueger & Lindahl, 2001). His work, followed by that of Psacharopoulos and Patrinos (2004) and Montenegro and Patrinos (2014), also concludes that low- and middle-income countries experience the highest, whereas high-income the lowest returns. Looking at different regions, high returns are recorded in Latin America and the Caribbean, as well as Sub-Saharan Africa. The returns in Asia are analogous to the global average. Low returns are found in OECD and non-OECD European, Middle East and North African countries. Important to note is that these private returns also vary with gender, level of education (tertiary, secondary, primary) and over time (Psacharopoulos, 1994; Psacharopoulos & Patrinos, 2004; Montenegro & Patrinos, 2014).

Although the Mincerian wage equation is informative about the private returns to education, it does not allow us to draw inferences regarding externalities from human capital. Their existence is manifested in the literature in two ways: the first addresses the feature of human capital to spill-over and increase the productivity of others (e.g. Lucas, 1988), and the second links human capital to technological progress and technology adoption (e.g. Nelson & Phelps, 1966; Romer, 1990).

First, in Lucas (1988), human capital is a factor of production, the presence of which entails externalities. Human capital is formed at school and makes workers more productive. But less-educated workers also learn from their higher-skilled counterparts and become more productive themselves. In other words, a higher level of *aggregate* human capital entails larger benefits in terms of increased productivity. This is a form of externality since human capital not only benefits the workers who invest in its accumulation but, via increased aggregate productivity, the economy as a whole. This form of externalities is empirically documented in Moretti (2004a) and Moretti (2004b). In the former study, the author compares wages of workers and in the latter productivity of plants, in cities with different shares of college graduates. However, Acemoglu and Angrist (2001), who use compulsory schooling laws in the US as instruments to estimate the relationship between average (state-level) schooling

[9]Endogeneity has been identified as a potential problem of the Mincerian wage equation. Unobserved personal characteristics, such as ability, affect one's earnings and correlate with schooling, giving rise to omitted variable bias. However, there is 'surprisingly little evidence' in the literature that ability bias significantly overstates returns to schooling (Krueger & Lindahl, 2001, p. 1101).

and individual wages, fail to find evidence of sizeable externalities.

Second, human capital facilitates technological progress and technology adoption, giving rise to externalities. Nelson and Phelps (1966) argue that education makes workers more innovative and, hence, human capital endogenously determines the rate of technological progress. Accordingly, Redding (1996) asserts that human capital and R&D are complements. Romer (1990) distinguishes between skilled and unskilled workers and links the former to R&D. According to Benhabib and Spiegel (1994), human capital is a determinant of TFP growth rather than an input to the production function. In Acemoglu (2002), a high-skilled workforce triggers skilled-biased technological change.

The fact that the link between human capital and technological progress appears to better fit a story of an advanced economy does not mean that human capital lacks a role in the developing world – on the contrary. Less advanced economies rely on the adoption (imitation) of new and more productive technologies to catch-up. Human capital is instrumental in this process (Nelson & Phelps, 1966; Benhabib & Spiegel, 1994, 2005). More specifically, the common thread between these theories is the complementarity of human capital with technology, either the emergence of new, or the employment of already existing. This becomes clear in Nelson and Phelps (1966) and Benhabib and Spiegel (1994) where a technological leader innovates and pushes the technological frontier, and a follower benefits from the diffusion of technology and the imitation thereof, and catches up to the leader. Human capital stock facilitates both processes. Externalities emerge since human capital promotes the development of new technologies, which in turn diffuse to the imitating countries. According to Nelson and Phelps (1966, p. 75), this implies divergence between the private and social return to education.

Chapter 3 of this thesis revisits the ability of human capital to bring about externalities by facilitating technological progress and technology adoption. Empirical research on this topic has produced mixed results (e.g. Vandenbussche, Aghion, & Meghir, 2006; Inklaar et al., 2008). In this chapter, I examine the effect of education on TFP growth for countries at different distances from the world technology frontier. My sample consists of 106 countries in the 1970-2010 period. The contribution of Chapter 3 lies exactly in the use of state-of-the-art TFP data that is purged of private returns to education and thus, allow us to draw inferences regarding the existence of externalities.

My analysis points to broader evidence of externalities than the literature so far. It also finds that not all types/levels of education (tertiary, secondary, primary) uniformly affect TFP growth, namely that the composition of human capital matters.

Hence, allowing for heterogeneity in human capital is important for identifying the link between education and growth. More specifically, the results suggest externalities from tertiary education for all countries, even those far from the technology frontier. Furthermore, the marginal effect of tertiary education on TFP growth is U-shaped: large for countries far from the world technology frontier, decreasing as countries move closer to it and, from a point onwards, marginally increasing again. Externalities from secondary education are also present but limited to a number of middle- and/or low-income countries.

1.3 International Effects of Human Capital

Trade, FDI and migration constitute the globalization forces/channels through which technology diffuses across countries. Human capital, in turn, facilitates this diffusion through its effect on the absorptive capacity of the economy (e.g. Keller, 2004). The case of migration appears complicated: as people cross borders, the level of human capital of both the home and host country is affected. The direction to which the *home* country's human capital will be affected is a priori unknown. There are both negative and positive forces at play: on the one hand, if high-skilled people migrate, human capital will be negatively impacted ('brain drain'). On the other hand, there is growing evidence that emigration facilitates human capital creation at home via feedback mechanisms such as return migration, remittances, network and incentive effects ('brain gain').[10] Given human capital's central role for economic growth, identifying the direction to which migration affects it, is of great significance.

The question is thus ultimately an empirical one: what is the effect of emigration on the home country's human capital? In **Chapter 4**, I try to understand human capital's role in a highly globalized world where decisions to migrate affect a country's level of human capital and, thus, growth potential. For example, there is ample empirical evidence as to how remittances and migrants' networks (diaspora) affect the home country. Remittances can compensate a sending country for its loss of human capital (Docquier & Rapoport, 2012, p. 683) in particular if they are directed to investments in education. Return migration has also been suggested as another beneficial feedback mechanism. This literature is scarcer due to data limitations but on the rise (e.g. Dustmann, Fadlon, & Weiss, 2011). The level of human capital increases as migrants return to their home country with newly-acquired skills, after a spell abroad. This inflow of skills can also facilitate technology adoption and lead to productivity

[10]For a review of the 'brain drain' literature, see: Docquier and Rapoport (2012).

growth (Docquier & Rapoport, 2012). A more pessimistic view, however, asserts that it is only those migrants who do not succeed abroad that decide to return (Faini, 2003). Furthermore, networks formed by migrants foster the diffusion of knowledge and ideas (also of goods and/or factors) between home and host country (Docquier & Rapoport, 2012). Kerr (2008, p. 518) shows, for example, that ethnic research communities in the US indeed facilitate knowledge diffusion to foreign countries of the same ethnicity.

Emigration can also improve the incentives to acquire or improve skills: if the opportunity to migrate improves the expected returns to education, the incentives to actually get an education improve, leading to an increase in human capital in the home country. Mountford (1997) and Stark, Helmenstein, and Prskawetz (1997, 1998) were the first to theoretically establish this 'brain gain' argument based on the idea that "expectations about future migration opportunities affect education decisions" (Docquier & Rapoport, 2012, p. 701). Empirical contributions that try to test this hypothesis have also recently appeared in the literature: Beine, Docquier, and Rapoport (2008) find evidence for the incentive effect and show that the sign of the net gain or loss depends on the level of human capital and rate of emigration. Beine, Docquier, and Oden-Defoort (2011) also find evidence for a significant incentive effect which depends on a country's income. Docquier, Faye, and Pestieau (2008), however, are less optimistic and argue that the incentive effects have been overestimated in the literature. According to their estimations, post-secondary education decreases in the developing world by 2.7% because of skilled emigration (Docquier et al., 2008, p. 264). Also according to Faini (2003), there is only little evidence that educational achievements improve with high-skilled emigration. Studying the effect of migration on the level and composition of human capital, Di Maria and Lazarova (2012) conclude that emigration has potentially detrimental impacts on economic growth, depending on a country's level of technological sophistication. Turning to the micro-level literature, the case of Cape Verde provides supporting evidence for the incentive effect: the probability of completing intermediate secondary schooling increases with the perceived probability of future migration (Batista, Lacuesta, & Vicente, 2012).[11]

From the discussion above, it becomes apparent that, although the debate is far from settled, there is growing evidence favouring the 'brain gain' hypothesis. This research has only focused on high-skilled migration however, thereby ignoring any impacts that might stem from migration of medium-skilled workers. Moreover it is also largely silent on the overall impacts of migration on the economy. **Chapter**

[11] High-skilled emigration has also additional consequences for the countries of origin. Bhargava, Docquier, and Moullan (2011), for example, study its effects on human development indicators.

4 of this thesis takes up on these issues and employs a new strategy to assess the impact of migration on the home country's human capital. It does so by studying the overall impact of migration on a country's specialization patters. More specifically, I analyse how emigration impacts growth in more knowledge-intensive industries. I find evidence in favour of 'brain gain', as countries with higher emigration show faster growth in human capital intensive industries. Notably, my findings for total migration can be traced to the migration of the high- *as well as* medium-skilled, with no positive effect from low-skilled migration. Hence, I find that 'brain gain' is more widespread than currently thought, in part, because of the effects from high- as well as medium-skilled workers.

1.4 Concluding Remarks and Future Research

This thesis contributes to the broader literature on the importance of human capital for economic growth. It starts by relaxing the standard growth accounting assumption that an hour worked by a worker of a given type delivers a constant quantity of labor services over time. Allowing for these vintage effects in a growth accounting exercise helps us better understand the divergent productivity growth paths Europe and the US have embarked upon during the 1995-2005 period. It, then, examines the effect of human capital on TFP growth and finds evidence of externalities within countries. Finally, this thesis studies international human capital spill-overs, by revisiting the consequences of migration on the sending country's human capital. Evidence of 'brain gain' is presented.

Future research could be done in various other dimensions. One of the most active fields pertaining to human capital is that on education quality. As school systems vary across countries, we cannot assume that one year of schooling results in the same amount of human capital in all countries (e.g. Hanushek & Kimko, 2000). Therefore, quality of schooling plays an important role for growth and cross-country income differences (Hanushek & Woessmann, 2012; Schoellman, 2012; Islam, Ang, & Madsen, 2014; Kaarsen, 2014). In order to measure schooling quality, researchers usually use the results of international test scores conducted during primary or secondary education.[12] Alternative measures include the pupil-teacher ratio and educational expenditures (Caselli, 2005). Information on adult skills is also used sometimes (Hanushek, Schwerdt, Wiederhold, & Woessmann, 2015). As data were becoming available, more and promising research on education quality has emerged. The

[12] The tests are in math, reading, and science. For a discussion, see: e.g. Hanushek and Woessmann (2012).

consensus of this stream of literature is that quality of schooling is an important component of human capital and determinant of economic growth (Hanushek & Kimko, 2000; Hanushek & Woessmann, 2011, 2012; Delgado et al., 2014; Barro & Lee, 2015; Hanushek, Ruhose, & Woessmann, 2017).

The potential presence of endogeneity is also a recurring issue in this field. Measurement error in education and the difficulty to prove (the direction of) causality between education and growth and development are the primary reasons. Econometrically alleviating a potential endogeneity problem has proven to be a challenge in the literature. The latter is to a great extent because finding suitable instruments for education is hard (Madsen, 2014). Attempts to address this issue include, among others, the work of Bils and Klenow (2000); Hanushek and Kimko (2000); Krueger and Lindahl (2001); Vandenbussche et al. (2006); Ang, Madsen, and Islam (2011); Hanushek and Woessmann (2012); Islam et al. (2014) and Madsen (2014). Krueger and Lindahl (2001) devote particular attention to measurement error in the education series and the most recent version of the widely-used Barro and Lee (2013) education dataset addresses various concerns that have been raised on earlier versions of it. Finally, instruments for different education variables (quantity and quality ones) that have been suggested in the recent literature include among others: public expenditures on education (Vandenbussche et al., 2006), institutional characteristics of a school system (Hanushek & Woessmann, 2012), pathogen stress outcomes (Islam et al., 2014), the length of compulsory schooling, life expectancy at birth and urbanization (Madsen, 2014). Still, proving causality is a contentious issue in the field.

Finally, it is important to note that human capital also entails non-production benefits that are not *directly* reflected in economic measures such as output or productivity.[13] One prominent effect is its two-way relationship with health. Health, for example, affects one's longevity, productivity and learning abilities (Weil, 2014), thereby raising human capital. But education also leads to better health for individuals and their children (Currie & Moretti, 2003). It raises awareness with respect to birth control, and empirical estimates show a negative impact of (female) schooling on fertility rates (Barro & Lee, 1994, 2015). Even though the literature on health as human capital is less vast than that on education as human capital (Becker, 2007), the recent research focus of, for example, O'Mahony and Samek (2016) and Weil (2014) has brought this topic to the forefront again.

Education might also discourage criminal behavior. Going to school limits the opportunities and time available for criminal activities, and raises opportunity costs

[13]For reviews, see: Lochner (2011) and Oreopoulos and Salvanes (2011). For the effects on fertility and democracy, see: Barro and Lee (2015).

through foregone earnings (Machin, Marie, & Vujić, 2011; Anderson, 2014). As social networks are shaped in schools, the propensity to criminal behavior decreases if educated people interact more with each other or act as role models for the less-educated ones (Lochner, 2011). Schooling also improves civic participation (Milligan, Moretti, & Oreopoulos, 2004) and promotes democracy (Lipset, 1959; Barro & Lee, 2015). Empirical support for this relationship is found by Glaeser, La Porta, Lopez-de Silanes, and Shleifer (2004), but contradictory results are presented in Acemoglu, Johnson, Robinson, and Yared (2005) and the debate is ongoing.[14]

To summarize, we know a lot about the possible benefits – monetary and non-monetary – of education at the individual as well as the national and even international level. Further research will help individuals and the society as a whole to better weight the benefits against the costs and will guide policy makers accordingly.

[14]For a discussion and recent elaborate analysis, see: Barro and Lee (2015).

CHAPTER 2

Vintage Effects in Human Capital: Europe versus the United States*

2.1 Introduction

Improvements in human capital have long been thought to contribute only modestly to economic growth, following the growth accounting method of Jorgenson and Griliches (1967).[1] For example, Jorgenson et al. (2016, Table 4) show that the United States economy grew at an average annual rate of 3.23 percent between 1947 and 2010 and that human capital improvements only contributed 0.24 percentage points to this total, with little variation in this contribution over time.[2] Growth accounting relies on the assumption that an hour worked by a person of given type – distinguished by education, age and gender – provides a *constant quantity of labor services over time*. Yet this assumption is increasingly challenged on both theoretical and empirical grounds as the quality of education and post-education accumulation of human capital may change over time; see Lucas (2015). Bowlus and Robinson (2012) contribute to this literature by modifying the growth accounting method to accommodate vintage effects, whereby new graduates may differ from previous cohorts in terms of the quantity of labor services per hour worked that they supply, for instance due to improved schooling or on-the-job training.[3] Applying their method to data for the United States between 1963 and 2008, they find that the quantity of labor services per hour worked by college-educated workers increased substantially. As a consequence, they argue that there is a larger role for human capital in accounting for US growth than based

*This chapter is based on Inklaar and Papakonstantinou (2017). We would like to thank Raquel Ortega-Argilés, Marcel Timmer and seminar participants at the University of Groningen (2016) for helpful comments and suggestions.

[1]See Hulten (2010) for a more recent survey.

[2]C. I. Jones (2016, p. 11) shows very similar estimates.

[3]We use the term 'vintage effects' throughout, but the literature also refers to these as 'cohort effects'.

on the traditional 'constant quantity' assumption.

An important question is whether the Bowlus and Robinson (2012) results can be generalized to a broader set of countries. A comparison with European countries is especially interesting as productivity growth in the US accelerated in the mid-1990s, while European productivity lagged behind. Standard growth accounting shows no important role for differences in human capital improvements in accounting for these differences (Timmer, Inklaar, O'Mahony, & van Ark, 2010), but if vintage effects led to higher growth of (effective) labor input in the United States but not in Europe, that could provide a more focused target for analysis and economic policy.

To address this question, we apply the Bowlus and Robinson (2012) method to a more recent period for the United States, covering the 1975–2014 period (using data from the Current Population Survey, CPS) and for six European countries – France, Germany, Italy, the Netherlands, Spain and the United Kingdom – covering the period from the mid-1990s to 2013 (with coverage varying by country) using the Luxembourg Income Study (LIS) database. In standard growth accounting, the quantity of labor services provided by a given type of worker is assumed to be constant over time. Observing an increase in workers' wages then automatically means that the price of that type of human capital – the price per unit of labor services – has increased. The novelty of the Bowlus and Robinson (2012) method is that it drops the assumption that an hour worked by a worker of a given skill level delivers a constant amount of labor services over time and thus that increases in wages are increases in the price of human capital. The method does so by drawing on the literature on life-cycle earnings (in particular Ben-Porath (1967)) and earlier work by Heckman, Lochner, and Taber (1998). The key assumption of Bowlus and Robinson (2012) is that changes in the price of human capital for a particular educational level can be identified only for workers at a late stage in their life cycle since these older workers no longer increase their productivity over time. Put differently, there is a period in a worker's life cycle during which worker productivity is constant, a so-called flat spot range. If wages of younger workers increase more rapidly than for older workers (of the same educational level) in this flat spot, then the conclusion should be that the labor services per hour worked of these younger workers has increased. The Bowlus and Robinson (2012) method thus provides a time series of prices per unit of labor services for each educational level that can be compared to wages by educational level to track changes in the quantity of labor services per hour worked.

The main finding in Bowlus and Robinson (2012) is that, starting around 1980, wages of high-skilled workers in the United States increased relative to the price of high-skilled labor (i.e. the wages of workers in the flat-spot range), while the wages of medium-skilled and (especially) low-skilled workers declined relative to the price of each labor type.[4] So labor services per hour worked by high-skilled workers increased, while labor services per hour worked by medium- and low-skilled workers declined. Combined with the increased share of high-skilled work, this implies that standard growth accounting substantially underestimates the contribution of improvements in human capital to US growth and overestimates the role of (multifactor) productivity growth, which is determined as a residual. Indeed the Bowlus and Robinson (2012) results indicate that uncounted human capital improvements may have been large enough to eliminate productivity growth entirely. The Bowlus and Robinson (2012) method does not reveal the underlying drivers of the changes in labor services per hour worked, but the authors mention that selection effects could play a role, whereby, for instance, the distribution of innate ability of college students has changed as enrollment has increased. Another possibility they mention is changes in the human capital production function, that would allow high-skilled workers to more rapidly accumulate human capital during their working life.

We find that vintage effects continue to be important in the United States in recent years. Between 1975 and 2014, labor services per hour worked of high-skilled workers have increased by 25 percent when applying the Bowlus and Robinson (2012) method. By contrast, labor services per hour worked of medium-skilled workers have declined by 9 percent and those of low-skilled workers have declined by 20 percent. The declines for medium- and low-skilled workers were concentrated in the first half of the period, until 1995. The increase for high-skilled workers was concentrated in the period 1995–2005, which coincides with the period during which US labor productivity growth was (temporarily) higher.[5]

Within Europe, the United Kingdom's experience is most similar to that of the United States, with increases of labor services per hour worked by high-skilled workers between 1995 and 2005. The Continental European countries – France, Germany, Italy and the Netherlands – instead show declines of 10 to 14 percent in labor services per hour worked by high-skilled workers over this same period. The differences between the Anglo-Saxon and Continental European countries remain throughout the sensitivity analyses that change key assumptions or modify the treatment of the basic data.

These differences suggest that human capital vintage effects were an important

[4]High-skilled workers have completed tertiary education (ISCED levels 5 or 6), medium-skilled workers have completed secondary education (ISCED levels 3 or 4), and low-skilled workers have not completed secondary education (ISCED levels 0, 1 or 2).

[5]See e.g. Byrne, Fernald, and Reinsdorf (2016) on the timing of US productivity growth episodes.

factor in accounting for the productivity growth difference between Europe and the United States between 1995 and 2005, the topic of a sizeable literature.[6] Under standard growth accounting methods, the US and UK had a productivity growth advantage over the Continental European countries in our analysis – France, Germany, Italy, Netherlands, and Spain. Accounting for the increases in the quantity of labor services per hour worked in the UK and US and the decreases in the Continental European countries eliminates most of the differences. Only Italy and Spain remain exceptional, with declining productivity over this period. Recent research on this topic has emphasized a deterioration in the capital allocation process in Italy and Spain, suggesting theirs was the exceptional productivity growth experience rather than the UK or US.[7] The method of Bowlus and Robinson (2012) does not clarify the source of the vintage effects – and thus also not why the US and UK show increases in labor services per hour worked by high-skilled workers, while the Continental European countries show declines between 1995 and 2005. However, the possible explanations for the vintage effects are probably less numerous than for differences in the (Solow residual) productivity growth measure. This would be an interesting avenue for future research.

In measuring vintage effects for human capital, this paper adds to a recent, growing literature on this topic. Lagakos, Moll, Porzio, Qian, and Schoellman (2016) show that experience-earnings profiles are much steeper in high-income economies than in lower-income economies. Their analysis is based on a similar approach as that of Bowlus and Robinson (2012) and ours, but applied in a cross-country setting. They conclude that workers in high-income countries – and especially high-skilled workers – are able to accumulate human capital more rapidly during their career than workers in low-income countries. In a similar vein, Manuelli and Seshadri (2014) find that workers in high-income countries have 'higher quality' human capital, which may also be due to more rapid accumulation of human capital on the job. Further empirical support for systematically higher quality of education in high-income countries is provided by Kaarsen (2014). Hanushek and Woessmann (2012) show that a higher quality of education leads to faster economic growth. These are specific examples of studies in a more general trend to accommodate a large role for human capital in accounting for growth or income level differences; see e.g. Lucas (2015) for a general discussion of this stream of literature and B. F. Jones (2014) as another prominent example of

[6]See e.g. Ortega-Argilés (2012) for a survey or van Ark, O'Mahoney, and Timmer (2008) for a notable contribution.

[7]See Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez (2017) and Cette, Fernald, and Mojon (2016).

how the traditional growth accounting method is likely to understate human capital's importance by emphasizing imperfect substitutability between workers with different skill levels. Fraumeni (2015) provides a more in-depth overview of how different measures of the amount of human capital in a country can lead to very different rankings across countries, emphasizing that measurement choices in this area matter substantially. Finally, O'Mahony (2012) is an example of what can still be achieved within the scope of the growth accounting method by using data about on-the-job training to infer investments in human capital during workers' careers. She also finds that failure to account for these investments understates the contribution of human capital to economic growth.

2.2 Methodology

2.2.1 The price of labor services

The methodology used to calculate the price per unit of labor services is based on the work of Bowlus and Robinson (2012). It starts from the premise that the hourly wage of an individual (with a given educational level) of age i in period t ($w_{t,i}$) is the product of the price of a unit of labor services in that period (p_t) and the quantity of labor services the individual supplies per hour of work ($q_{t,i}$):

$$w_{t,i} = p_t \cdot q_{t,i} \tag{2.1}$$

Between two periods, $t-1$ and t, changes in wages will thus be determined by changes in prices and quantities as:

$$\Delta log(w_{t,i}) = \Delta log(p_t) + \Delta log(q_{t,i}) \tag{2.2}$$

with Δ as the difference operator. The problem with the above-outlined relationships is that only the hourly wage is observed and the price and quantity of labor services are not, leading to an under-identification problem. To overcome this, Bowlus and Robinson (2012) use the insight of the Ben-Porath (1967) model that the quantity of labor services remains constant at a late stage in a person's working life. When young, people invest in their human capital in the formal education system, while no time is spent on work. As they grow older, they allocate their time to both working and producing further human capital through on-the-job training. With the age of retirement approaching, the incentive to further invest in human capital disappears, so time is now solely spent on work. As a result, the quantity of labor services enters a flat spot range. Without any change in quantity between two periods within this flat spot, one can derive changes in prices directly from changes in wages, i.e. $\Delta log(w_{t,i}) = \Delta log(p_t)$. For example, if the flat spot range starts at 51, the price change can be inferred by comparing the hourly wage of 51-year olds in year 1 to the wage of 52-year olds in year 2.

More specifically, let us assume that all individuals of a given age (and education level) in our sample[8] are homogenous, so we can summarize the wage within each age-education cell as the median across all workers in this cell, denoted by $log(\tilde{w}_{t,i})$ for age i at time t. Depending on the length of the flat spot range and the frequency of the surveys we have N wage differences in the flat spot range. For example, if the length of the flat spot range is 10 years and we have annual surveys, $N = 9$ because we compared the wage of 51-year olds in year 1 to the wage of 52-year olds in year 2 all the way to comparing the wage of 59-year olds in year 1 to the wage of 60-year olds in year 2. If surveys are several years apart, N will be smaller so denote the number of wage differences in the flat spot range between years t and τ as $N_{t,\tau}$. Given this notation, the price series from $t = 0, \ldots, T$ for labor services per hour worked can be computed as:

$$\begin{aligned}
t &= 0 \qquad && log(p_0) = 0 \\
t &= 1 \qquad && log(p_1) = \frac{\sum_{i=1}^{N_{1,0}} [log(\tilde{w}_{1,i}) - log(\tilde{w}_{0,i})]}{N_{1,0}} + log(p_0) \\
t &= 2 \qquad && log(p_2) = \frac{\sum_{i=1}^{N_{2,1}} [log(\tilde{w}_{2,i}) - log(\tilde{w}_{1,i})]}{N_{2,1}} + log(p_1) \\
&\vdots \\
t &= T \qquad && log(p_T) = \frac{\sum_{i=1}^{N_{T,T-1}} [log(\tilde{w}_{T,i}) - log(\tilde{w}_{T-1,i})]}{N_{T,T-1}} + log(p_{T-1})
\end{aligned} \tag{2.3}$$

As discussed below, the length of the flat spot range is set to ten years. For example, for those who have completed tertiary education in the US, it lies between the ages of 50 and 59. This results in a total of nine wage differences when data for adjacent years are available. We average across these wage differences to derive the price per unit of labor services.

Bowlus and Robinson (2012) estimate prices of labor services. Therefore, in the

[8] The analysis is limited to male workers that work for the full year and have a full time job; see below for further discussion.

example above, we are comparing the (logarithm of the) median hourly wage of high-skilled (tertiary-educated) 51-year olds in year 2000 to the median hourly wage of high-skilled 52-year olds one year later. We estimate prices per unit of labor services for seven high-income countries (France, Germany, Italy, the Netherlands, Spain, UK, US) for various years, and three types of workers, distinguished by educational attainment (low, medium and high).

2.2.2 The flat spot range

Bowlus and Robinson (2012) establish the flat spot range based on (cross-sectional) experience-earnings profiles. They conclude that, for high-skilled workers in the US, the flat spot occurs between the ages of 50 and 59. To infer the flat spot range for workers with lower levels of education, they choose the period at which those worker types would have the same length of (post-education) work experience, which means shifting the flat spot range back by three years for medium-skilled (so ages 47–56) and six for low-skilled (44–53) while keeping the length of the range at ten years.[9] The important question in our context is whether the US flat spot range is suitable for the other countries in the analysis. The flat spot range is the outcome of the workers' investment in human capital during the working life and an optimizing worker would endogenously choose to stop investing in human capital as the end of the working life approaches. This means that the flat spot range in a country will be affected by the (expected) retirement age of a person. These differ across countries suggesting that the flat spot needs to be adjusted accordingly, as earlier retirement decreases the length of the working life and affects investment in human capital through on-the-job training (Jacobs, 2010).

To account for differences in the expected retirement age across countries, we adjust the flat spot range using information on the effective age of retirement among males. The OECD defines this as "the average effective age at which older workers withdraw from the labor force".[10] This differs from the official age of retirement (which does not show much variation across the countries of our sample) and better captures retirement expectations. Table 2.1 below shows the median effective age of retirement among males in the seven countries over the period 1990-2012 (OECD, 2013).[11]

[9] The US context typically distinguishes groups 'with some college' and 'high school graduates', but we group these together for the three-category breakdown more prevalent in international research. Sensitivity analysis for the US shows that this compression of the educational categories does not lead to qualitatively different results; results are available upon request.

[10] Source: `http://www.oecd.org/els/emp/average-effective-age-of-retirement.htm`

[11] For Germany, the data begin in 1996.

Table 2.1: Effective Age of Retirement and the Flat Spot across Countries

		Flat Spot		
	Retirement Age	Low-skilled	Medium-skilled	High-skilled
United States	64.7	44-53	47-56	50-59
France	59.3	39-48	42-51	45-54
Germany	61.2	40-49	43-52	46-55
Italy	60.8	40-49	43-52	46-55
Netherlands	61.0	40-49	43-52	46-55
Spain	61.6	41-50	44-53	47-56
United Kingdom	62.8	42-51	45-54	48-57

Sources: Effective retirement age: OECD (2013). Flat spot range United States: Bowlus and Robinson (2012); other countries: own calculations.

We know already the flat spot range of the US from Bowlus and Robinson (2012). We retain the assumptions that the flat spot (a) lasts for a period of ten years and (b) that it occurs earlier for those with a lower education level. We calculate the distance between the median value of the US high-skilled flat spot (54.5) and the retirement age (64.7) and observe that the high-skilled people reach the middle point of their flat spot range approximately ten years before retirement. We assume that the same distance applies to the other countries, identify the middle point of their high-skilled flat spot and the respective upper and lower bound and move the flat spot back accordingly to determine its range for the low- and medium-skilled.[12] Table 2.1 presents the results by country and level of education (low, medium, high). These are the country-specific flat spot ranges we subsequently use for the calculation of the price per unit of labor services and, although not very different between countries, they provide us with a consistent country-ranking based on retirement patterns.

The flat spot ranges we have determined are assumed constant over time. This means that we assume that, in the period under examination, the effective age of retirement has not changed sufficiently to affect decisions on investment in human capital. Indeed, the data show that the effective retirement age in the countries of the sample has remained rather stable, with only a slow upward trend after 2006. Assuming that human capital investment patterns change gradually after changes in retirement patterns, we do not expect that the modest increase in the effective retirement age affects our flat spot identification in the time frame we are focusing on.

[12]The numbers are rounded to the closest integer to best capture the age range.

2.3 Data

The data we use in order to calculate the price per unit of labor services are from the Luxembourg Income Study Database (LIS, 2017) for the six European countries in our analysis – France, Germany, Italy, the Netherlands, Spain, and the United Kingdom. Data for the United States are drawn from the US Current Population Survey, as made available through IPUMS-CPS.[13] LIS collects and harmonizes survey data on socio-demographic and labor market characteristics, as well as income, at both the individual- and household-level.[14] Data are available for forty-nine countries over multiple years between 1967 and 2014.

We focus on six European countries over the 1990-2013 period, prioritizing the larger European countries.[15] In processing these data, we have taken special care to ensure consistency over time in variable definitions, to ensure comparability across countries and over time. Table 2.2 below lists the main LIS variables we employ alongside a short definition.

The sample we analyze in order to construct the prices per unit of labor services consists of men of an age that falls within the country-specific flat spot range we have identified. Following Bowlus and Robinson (2012), females are excluded because of the fluctuations in their labor force participation. The self-employed are excluded as well. Furthermore, we only keep those employed full-time, full-year with a positive income (larger than one). As full-time full-year, we define those with at least thirty-five weekly hours and forty annual weeks worked. Income variables are deflated using the consumer price index and (for euro area countries) converted to euros for the full period. The hourly wage is constructed using information on the annual paid employment income (*pmile*) and a person's weekly hours (*hours*) and annual weeks (*weeks*) worked.[16]

Based on a person's completed level of education (*educ*), we derive prices for three categories of workers, as defined in Table 2.2. We calculate the median hourly wage by age and education level, and subsequently its log change between two points in time. Based on the methodology outlined above (equation 2.3), we then infer changes in the price per unit of labor services. A limitation of the LIS data is that it does not

[13]See Flood, King, Ruggles, and Warren (2015); this allows us to have an annual time series covering the period since 1975.

[14]LIS uses as data sources national surveys such as the German Socio-Economic Panel (GSOEP) and the UK's Family Resources Survey (FRS).

[15]Expanding the set of countries would lead to shorter time coverage, since complete information on the required variables is typically a problem, especially when moving back in time.

[16]For the United Kingdom, data on the number of weeks worked is missing, so 'full-year' employment cannot be used as a criterion and we can only divide the overall employment income by weekly hours.

Table 2.2: List of LIS Variables and Definitions

LIS Variable	LIS Variable Definition
age	Age in years
sex	Sex
educ	Highest completed education level This variable is recoded into three categories: (a) low: less than secondary education completed (never attended, no completed education or education completed at the ISCED levels 0, 1 or 2) (b) medium: secondary education completed (completed ISCED levels 3 or 4) (c) high: tertiary education completed (completed ISCED levels 5 or 6)
pmile	Paid employment income Monetary payments received from regular and irregular dependent employment
hours	Weekly hours worked, any information Regular hours worked at all jobs currently held (including family work and overtime, whether paid or unpaid)
weeks	Annual weeks worked, any information Number of weeks worked during the year in any job
emp	Employed Dummy that distinguishes the employed from the non-employed
status1	Status in employment (in first job) Variable that distinguishes the dependent-employed from the self-employed

Sources: Documentation-LIS (available online at: `http://www.lisdatacenter.org/wp-content/uploads/our-lis-documentation-variables-definition.xlsx`) provide an annual series of surveys. We can directly implement the procedure from equation 2.3 for the United States, and thus have nine changes in wages to average over the flat spot range. For the European countries, there is a survey in (for instance) 1993 and 1999 for the Netherlands,[17] which means that rather than comparing the wage of a 49-year old to that of a 50-year old in the next year, the comparison is between a 49-year old in 1993 and a 55-year old in 1999. Since the data for the United States are available annually from the CPS, but also at similar intervals in the LIS data, we use a comparison between calculations based on the two sources to establish that the price series based on gaps in survey coverage are comparable to those based on annual survey data.

In the UK, data on the variable *educ* are missing for the year 1994, but not for other years in our analysis. We do have information on an individual's age when completed education for 1994, as well as in other years.[18] To incorporate data for 1994 in the analysis, we identify the typical education level at a given age of education completion. Based on this, we find that low-skilled workers are those who complete their education at or before the age of 15, medium-skilled between ages 16 and 20 and high-skilled are those who complete their education after age 21.

2.4 Results

2.4.1 The price and quantity of labor services per hour worked – United States

An important outcome of our analysis is estimates of the price per unit of labor services for workers of different educational backgrounds. Bowlus and Robinson (2012, Figure 3) find that, in the United States, the price per unit of labor services evolves similarly for each skill level, which leads them to conclude that changes in relative wages between skills levels represent (primarily) changes in the relative quantity of labor services per hour worked, rather than changes in relative prices. In Table 2.3, we show that our own calculations for the US provide a perspective that is not notably different. The first line shows our estimates for the 1975-2014 period, the full length of our study period for the United States. While the price of high-skilled units of labor services has declined by less than that of medium- and low-skilled labor services, this is not a persistent difference.[19] The second line shows estimates based on the annual CPS

[17] See Table A.1 of the appendix for the list of LIS surveys per country that we use in our analysis.
[18] "When he/she last attended continuous full-time education", variable *edcage* in LIS.
[19] Our results also closely match those of Bowlus and Robinson (2012, Figure 3).

data for 1991-2013, which corresponds to the period for which LIS data are available. The third line shows results based on LIS data for the 1991-2013 period.

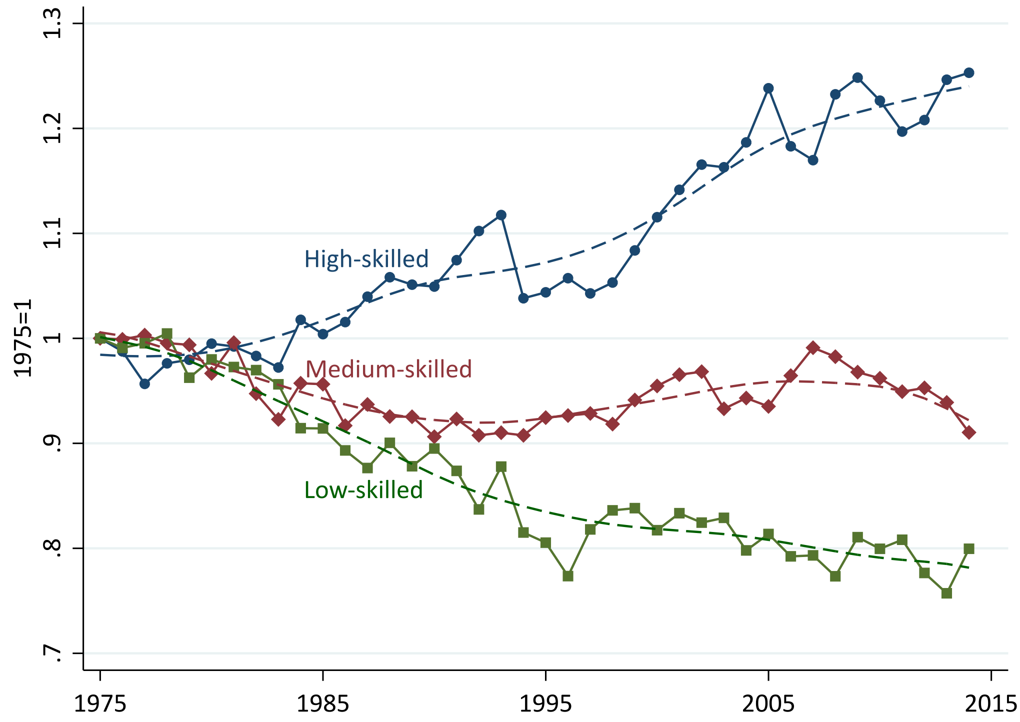
Table 2.3: The Change in the Price per Unit of Labor Services in the United States

		Change in the Price per Unit of Labor Services		
Source	Period	Low-skilled	Medium-skilled	High-skilled
CPS	1975-2014	-0.24	-0.20	-0.18
CPS	1991-2013	-0.01	-0.11	-0.06
LIS	1991-2013	-0.02	-0.18	-0.04

Source: Computations based on LIS data (LIS, 2017) and CPS data from IPUMS-CPS (Flood et al., 2015).
Notes: The price per unit of labor services is computed based on equation 2.3 and the flat spot ranges in Table 2.1. Each entry in the table indicates the change in price over the stated period, relative to the change in the country's consumer price index.

The LIS data, for both the US and Europe, are not available annually but at intervals of typically three or four years, so lines two and three are useful to gauge the impact of annual data vs. multi-year gaps in the time series. The main difference is that the computation of price changes (equation 2.3) can use fewer wage changes if there are gaps in the time series. For example, with annual data, the wage of 50-year old high-skilled workers in year 1 can be compared to 51-year old high-skilled workers in year 2, all the way to 58-year olds in year 1 and 59-year olds in year 2. As a result, the price change is based on the average of nine wage changes. In contrast, if wages are observed in year 1 and next in year 4, the price change is an average of 7 wage changes, comparing 50 year old to 53 year old high-skilled workers until 56 year old to 59 year old workers. There is no reason to suspect that this would impart a systematic bias to the price change estimates, but comparing lines 2 and 3 in Table 2.3 allows us to verify this. For low-skilled and high-skilled workers, the differences are small; for medium-skilled workers the differences are larger. Yet, as we show in Figure A.1 of the appendix by charting the full time series for the three skill levels, this larger difference is not a sign of a systematic deviation between the two sources but a one-off outlier. This gives us greater comfort in relying on LIS data for the analysis of the European countries, below. At the same time, the results in Table 2.3 (as well as those for the European countries, in Table 2.5 below) suggest that the conclusion of 'no relative price changes' by Bowlus and Robinson (2012) seems not warranted in general. So while Bowlus and Robinson (2012) explicitly disregard relative price movements when analyzing changes in the quantity of labor services per hour worked, we will simply use the observed price changes from Table 2.3 (and Table 2.5) when decomposing the overall wage into a price and quantity component, as in equation 2.1.

Figure 2.1: Labor Services per Hour Worked in the United States, 1975-2014



Source: Computations based on CPS data from IPUMS-CPS (Flood et al., 2015). *Notes*: The solid lines show the annual time series of labor services per hour worked, the dashed line is the LOWESS trend estimate (bandwidth of 0.5). Labor services per hour worked are computed by dividing the median wage of full-time, full-year male workers between the ages of 26 and 60 of a given educational attainment by the price per unit of labor services of that educational level (see Table 2.3) and normalized to one in the initial year, 1975.

Figure 2.1 shows the quantity of labor services per hour worked in the United States between 1975 and 2014, computed by dividing the median wage of (full-time, full-year male) workers between the ages of 26 and 60 of a given educational attainment by the price per unit of labor services for that level of educational attainment, i.e. by applying equation 2.1. The figure shows the annual series (solid line) as well as an estimate of the longer-run trend, computed using a LOWESS smoother with a bandwidth of 0.5.[20] The labor services per hour of high-skilled workers increased substantially over this period, rising by 25 percent compared to 1975, with most of this increase (19 percent)

[20]The LOWESS smoother creates a curve to best capture the trend of labor services per hour worked. It is the result of a locally weighted regression of labor services per hour worked on time/year.

occurring between 1995 and 2005. There has been a decline in labor services per hour worked of medium-skilled workers of approximately 10 percent, with a sustained decline between 1975 and 1995 and fluctuations around this level in the subsequent period. Labor services per hour worked of low-skilled workers also declined, by 20 percent, with sustained declines between 1975 and 1995. This periodization is somewhat arbitrary, also given the, sometimes large, year-to-year fluctuations in the series. The estimated trends suggest that salience of the 1975-1995 period for medium- and low-skilled workers and of the 1995-2005 period for high-skilled workers may not be as large, but notable differences remain in the pattern of changes over time.

Table 2.4: Linear Time Trend of Labor Services per Hour Worked in the United States, 1975-2014

	Low-skilled	Medium-skilled	High-skilled
Age 26-60	-0.0067***	-0.0007	0.0069***
	(0.0004)	(0.0004)	(0.0003)
Age 26-35	-0.0044***	-0.0015**	0.0052***
	(0.0007)	(0.0007)	(0.0004)
Age 36-45	-0.0058***	-0.0025***	0.0056***
	(0.0005)	(0.0003)	(0.0005)

Notes: N=40. Each entry in the table is the coefficient of a linear time trend on the log of labor services per hour worked in a given age range and level of educational attainment. Robust standard errors are given in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

To establish that the patterns in Figure 2.1 are not mere noise in a statistical sense, the first row of Table 2.4 shows the coefficients of a linear time trend for the (log of) labor services per hour worked for the age range 26 to 60. This shows a significant negative time trend for low-skilled workers, no significant time trend for medium-skilled workers, and a positive time trend for high-skilled workers. The subsequent rows test the sensitivity of this result and show that similar time trends can be observed for narrower age ranges, though with a significantly negative time trend for medium-skilled workers as well. This indicates that the patterns are observed broadly across the (male) population.

2.4.2 The price and quantity of labor services per hour worked – Europe

We next turn to the European countries, analyzing the trends in relative price and then quantities of labor services. The price developments, shown in Table 2.5, are more mixed than in the US, with, for example, France showing similar price trends across educational categories, Germany showing price declines for low-skilled and price increases for high-skilled and the United Kingdom showing the reverse pattern of price increases for low-skilled and price decreases for high-skilled labor services. This variety of patterns remains intact through a range of sensitivity checks (see below) and does not lend itself to easy explanation. This more firmly establishes the need to account for these price changes when analyzing the trends in the quantity of labor services per hour worked.

Table 2.5: The Change in the Price per Unit of Labor Services in Europe

		Change in the Price per Unit of Labor Services		
Country	Period	Low-skilled	Medium-skilled	High-skilled
France	1994-2005	0.12	0.17	0.14
Germany	1994-2013	-0.15	0.07	0.36
Italy	1991-2010	0.04	0.01	0.12
Netherlands	1990-2013	0.07	0.06	0.13
Spain	2007-2013	-0.01	0.15	0.10
United Kingdom	1994-2013	0.11	-0.24	-0.27

Source: Computations based on LIS data (LIS, 2017). *Note*: The price per unit of labor services is computed based on equation 2.3 and the flat spot ranges in Table 2.1. Each entry in the table indicates the change in price over the stated period, relative to the change in the country's consumer price index.

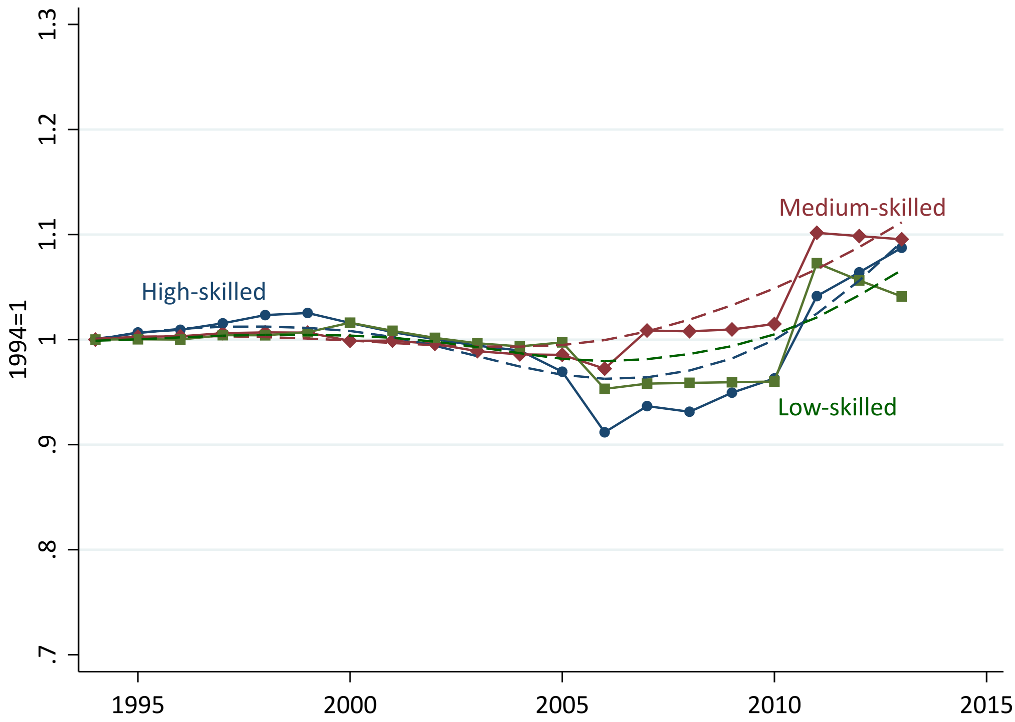
To analyze the trends in the quantity of labor services per hour worked across European countries, we first pool the country-level results. We compute a weighted average across the six European countries of labor services per hour worked, first linearly interpolating between LIS-covered years and then using the share of each country in total employment by educational attainment as weights.[21] Due to variation

[21] Using data from the WIOD Socio-Economic Accounts (Timmer, Dietzenbacher, Los, Stehrer, & de Vries, 2015). We assume that workers in the UK work 40 weeks per year to accommodate missing data on this variable in LIS.

in country coverage over time, we construct a 'Europe' series starting in 1994 and ending in 2013.

Figure 2.2 shows the development of the quantity of labor services per hour worked for the six European countries, on the same scale as Figure 2.1 for the United States. There is no clear trend over time in the quantity of labor services per hour worked for any level of educational attainment. This is especially true when taking the year-to-year swings into account, i.e. it is hard to discern a trend if an increase or decrease of 6 percent in labor services per hour worked can be observed.[22]

Figure 2.2: Labor Services per Hour Worked in Europe, 1994-2013



Source: Computations based on LIS data (LIS, 2017). *Notes*: The solid lines show the annual time series of labor services per hour worked, the dashed line is the LOWESS trend estimate (bandwidth of 0.5). Labor services per hour worked are computed by dividing the median wage of full-time, full-year male workers between the ages of 26 and 60 of a given educational attainment by the price per unit of labor services of that educational level (see Table 2.5) and normalized to one in the initial year, 1994. The figure shows a weighted average of labor services per hour worked across the six European countries covered (see Table 2.5), using total employment by educational attainment of a country as weights.

This is further confirmed in Table 2.6, which shows the results from regressions of

[22] Although there seem to be increases in recent years (after the Great Recession), these may be (at best) the start of a longer trend rather than an established pattern. Moreover, there is no difference by skill level, so even if this were a clear trend, it would be one of a different pattern.

a linear time trend on the log of labor services per hour worked for all observations for the six European countries. The regressions include country fixed effects as the period covered in each country differs (though results are not substantively different without fixed effects). The only common finding across age groups is that labor services per hour worked of low-skilled workers have declined, though the rate of decline is smaller than observed in the US (cf. Table 2.4).

Table 2.6: Linear Time Trend of Labor Services per Hour Worked in Europe, 1990-2013

	Low-skilled	Medium-skilled	High-skilled
Age 26-60	-0.0026*	0.0000	-0.0033
	(0.0012)	(0.0027)	(0.0037)
Age 26-35	-0.0062**	-0.0035	-0.0084*
	(0.0022)	(0.0036)	(0.0039)
Age 36-45	-0.0041**	-0.0019	-0.0036
	(0.0011)	(0.0022)	(0.0040)

Notes: N=33. Each entry in the table is the coefficient of a linear time trend on the log of labor services per hour worked in a given age range and level of educational attainment. All 33 observations as well as country fixed effects for the six European countries are included in each regression. Robust standard errors are given in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Despite these inconclusive patterns for the period as a whole and the full set of European countries, a clearer distinction becomes apparent when zooming in on the period of 1995 to 2005. For the United States, this was the period in which the largest increases in labor services per hour worked by high-skilled workers could be seen, in Figure 2.1, and this is shown in the first line of Table 2.7. When selecting the LIS survey years of each European country to most closely match the 1995-2005 period,[23] the United Kingdom stands out amongst the European countries in showing a 25 percent increase in labor services per hour worked by high-skilled workers, while the four Continental European countries show declines of 10 to 14 percent. For low-skilled and medium-skilled workers the changes in the quantity of labor services per hour worked are typically smaller than for high-skilled workers, though the UK also shows

[23] Spain is not shown in the table because its price series is only available from 2007 onwards, see Table A.1 of the appendix.

Table 2.7: The Change in the Quantity of Labor Services per Hour Worked in Europe and the United States between the mid-1990s and mid-2000s

		Change in the Quantity of Labor Services per Hour Worked		
		Low-skilled	Medium-skilled	High-skilled
United States	1995-2005	0.01	0.01	0.19
United Kingdom	1994-2004	-0.09	0.22	0.25
France	1994-2005	-0.04	-0.10	-0.14
Germany	1994-2004	0.01	-0.04	-0.10
Italy	1995-2004	0.00	0.00	-0.09
Netherlands	1993-2004	0.02	0.02	-0.10

Notes: See Notes to Figures 2.1 and 2.2. Spain is not shown because its data series starts in 2007.

a notable increase for medium-skilled workers. Before turning to the implications of the differences for high-skilled workers for measured productivity, we first assess the sensitivity of the results to the assumptions and choices we made.

2.4.3 Sensitivity analysis

Computing the prices per unit of labor services involves a series of choices and judgements, as the preceding discussion has already illustrated. Of particular note is the determination of the flat spot range. Bowlus and Robinson (2012) devote considerable attention to this topic, for instance by showing that moving the flat spot range for high-skilled workers to earlier ages would pick up some of the upward-sloping wages in a standard, concave earnings-experience profile. We have anchored our own analysis to that of Bowlus and Robinson (2012) by using their US flat spot range and adjusting it to reflect differences in effective retirement age. An alternative is to directly use the US flat spot range for European countries.

In addition, we consider a range of treatments of the European LIS data. What our results for the United States (Table 2.3) already indicated is that the frequency of survey data availability is not an important source of sensitivity, nor is the number of educational categories considered (four in Bowlus and Robinson (2012), three in this study). A potential concern could be that the price series we estimate are 'contaminated' with noise. A reason could be a small number of full-time full-year male survey respondents in an education/age cell, which could give wage outliers an undue influence on the final price series. By taking the median wage of each education/age cell, we already limit the scope for such outlier-induced noise.

Table 2.8: Sensitivity Analysis for the Change in Labor Services per Hour Worked for High-skilled Workers in Europe and the United States Between the mid-1990s and mid-2000s

		Baseline	US Flat Spot	Industry	Services	Trimmed	Unrestricted
United States	1995-2005	0.19	0.19	0.18	0.16	0.18	0.21
United Kingdom	1994-2004	0.25	0.15	0.23	0.19	0.23	0.30
France	1994-2005	-0.14	-0.34	n.a.	n.a.	-0.15	-0.15
Germany	1994-2004	-0.10	-0.13	-0.09	-0.09	-0.09	-0.05
Italy	1995-2004	-0.09	-0.06	n.a.	-0.03	-0.07	-0.11
Netherlands	1993-2004	-0.10	0.03	-0.23	-0.03	-0.08	-0.13

Notes: The baseline column corresponds to the final column of Table 2.7. 'US flat spot' uses the flat spot range for the United States from Table 2.1 instead of country-specific flat spot ranges. 'Industry' and 'Services' estimates prices using only wage information of workers in those particular sectors, which eliminates any impact of pay differentials between broad sectors. 'Trimmed' removes the top and bottom 2.5 percent of wage information in the entire flat spot range before computing the prices for labor services as in equation 2.3. 'Unrestricted' includes all (male) workers with at least 5 weekly hours worked and 5 weeks worked per year, rather than the full-time, full-year restriction. Missing estimates for 'Industry' or 'Services' are due to missing industry classifier variables or lack of observations.

In this sensitivity analysis, we consider three additional approaches. The first is to trim the top and bottom 2.5 percent of wages in the entire flat spot range (e.g. US high-skilled workers between the ages of 50 and 59). The other two are computed using only wage information for workers within industry (manufacturing, construction) or only within services[24] as shifts between sectors could conceivably skew the results. Finally, we explore to what extent the results are influenced by the selection of only (male) workers that work full-time for a full year. As an 'unrestricted' alternative, we compute prices based on the sample of male workers that work at least 5 weekly

[24]A more fine-grained industrial classification was not feasible. As it is, the number of observations per age/education/sector cell sometimes makes computation of sensible price series infeasible. For one-off occurrences, we use the baseline price trend. For France and Italy, it is not possible to compute price change for the full period due to missing industry classifier variables.

hours and 5 weeks per year. In Table 2.8, we show how the baseline results in the final column of Table 2.7 change for these alternatives.[25]

As the table shows, the different price series influence the change in the quantity of labor services per hour worked relative to the baseline estimate. Yet the overall pattern remains similar: the United States and United Kingdom show increasing labor services per hour worked for high-skilled workers, while the Continental European countries show predominantly declines. Relying on the US flat spot range rather than our country-specific ranges has a varied impact on the Continental European countries, with larger declines in France but even a small increase in the Netherlands. Selecting workers only in Industry or in Services leads to somewhat smaller changes in the quantity of labor services per hour worked in some of the countries, but again, no substantive changes. Outliers in wage data do not seem to have a systematic impact as the change in the quantity of labor services per hour worked for the Trimmed series is barely different from the baseline. Finally, using a less restrictive sampling of workers to compute the change in price of labor services per hour worked leads to somewhat larger changes, but again, no substantial deviation from the baseline results.

2.4.4 Implications for Europe-US productivity growth comparisons

Our main finding is that labor services per hour worked of high-skilled workers in the United States and United Kingdom increased by 19-25 percent between 1995 and 2005, while Continental European countries register declines of 10-14 percent over the similar period. This is a finding that can have important implications for productivity growth comparisons between Europe and the United States. Standard growth accounting assumes constant labor services per hour worked over time in estimating (multifactor) productivity growth, but if this assumption is violated, productivity growth will have been overestimated in the United States and United Kingdom and underestimated in Continental European countries. Between 1995 and 2005, productivity growth in the United States was much higher than before or since (Byrne et al., 2016; Syverson, 2017) and much higher than in Europe (e.g. van Ark et al., 2008). If we zoom in on the market economy – which excludes government, health, education and real estate – US productivity growth was 1.4 percent on average per year between 1995 and 2005, while growth averaged a mere 0.6 percent between 1975 and 1995

[25]The estimates for low and medium-skilled workers do not show a clear pattern and are therefore omitted. These data are available on request.

and 0.1 percent between 2005 and 2014.[26] In contrast, European countries showed notably lower productivity growth over this period, see also Table 2.9, below. A large literature has aimed to explain this growth gap focusing on explanations such as lower investment in R&D and stricter regulations or the role of ICT-producing and ICT-using industries; see e.g. the survey of Ortega-Argilés (2012). Yet our analysis points to a hitherto underappreciated element. While differences in human capital accumulation have typically been found wanting as an explanatory factor, relaxing the 'constant labor services per hour worked' assumption may provide greater heft to this factor.

To gauge the importance of our findings for the Europe-US productivity growth difference, consider the following expression for (Solow residual) productivity growth:

$$\Delta logA = \Delta logV - \alpha\Delta logK - (1-\alpha)\Delta logL \tag{2.4}$$

where Δ is the difference operator, A is productivity, V is value added, K is capital input, L is labor input, and α is the output elasticity of capital – typically assumed to be equal to the share of capital income in value added. This implies assuming perfect competition in factor and output markets and a constant returns to scale production function. Labor input is typically distinguished by type of worker, assuming that a given type of worker (denoted by j) provides a constant quantity of labor services per hour worked over time. If that type of worker's marginal product equals its marginal cost, the share of total labor compensation flowing to that type of worker (w_j) can be used to weight the growth in hours worked by that type of worker,H_j:

$$\Delta logL = \sum_{j=1}^{N} w_j \Delta logH_j \tag{2.5}$$

But if, as we have established, the effective labor input per hour worked of a particular type of worker changes over time, we should adjust our computation of the growth in overall labor services:

$$\Delta logL^* = \sum_{j=1}^{N} w_j \Delta log(H_j \cdot E_j) \tag{2.6}$$

Here E_j is an estimate of effective labor services per hour worked. Note that the labor compensation share w_j of each labor type is the same in both equations, as total

[26] The 1975-2005 data are drawn from the 2012 version of the EU KLEMS database; see O'Mahony and Timmer (2009). The 2005-2014 average is computed using BLS data for the private business sector, which showed similar growth as the EU KLEMS market economy between 1995 and 2005.

labor compensation does not depend on the division of that sum between a price and a quantity component. Denote as $\Delta logA^*$ the estimate of productivity growth based on adjusted growth in labor services, so substituting $\Delta logL$ by $\Delta logL^*$ in equation 2.4:

$$\Delta logA^* = \Delta logV - \alpha\Delta logK - (1-\alpha)\Delta logL^* \tag{2.4'}$$

To implement equations 2.5 and 2.6, we use data on hours worked (H_j) and the share of labor compensation (w_j) of low-, medium-, and high-skilled workers for the United States and the six European countries.[27] All E_j are set equal to one, except for those of high-skilled workers between 1995 and 2005. For those years and that type, we set the annual E_j such that the quantity of labor services per hour worked by high-skilled workers increases by the amount shown in the final column of Table 2.7. This assumes that our estimates of the increase in labor services per hour worked of (full-time, full-year) male workers is applicable for all workers. As discussed in Bowlus and Robinson (2012), this may be an overestimation, because of changes in the degree of discrimination of women in the labor market. Such changes, though, may be relatively modest over a ten year period.

Table 2.9 presents standard growth accounting results based on EU KLEMS as well as figures adjusted for the vintage effects for high-skilled workers that we found in Table 2.7 for the period 1995 to 2005. The average annual growth of high-skilled labor input is shown first, with changes in total hour worked shown under 'Standard Growth Accounting' and changes in total labor services under 'Adjusted for Vintage Effects'. So, for example, total hours worked of high-skilled workers grew at an average annual rate of 1.9 percent in the US over this period. The final column in Table 2.7 showed that labor services per hour worked of US high-skilled workers increased by 19 percent over this 10-year period, which corresponds to an average annual increase of 1.8 percent. Therefore, labor services of high-skilled increased at an average annual rate of 3.7 percent, as shown under 'Adjusted for Vintage Effects'. We can then apply equations 2.5 and 2.6 to show that total labor services grew 0.7 (1.7-1.0) percentage points faster when adjusting for vintage effects than based on standard growth accounting assumptions.[28] This translates to an average annual TFP

[27]These data are not available in the 2012 version of EU KLEMS, but are presented in WIOD's Socio-Economic Accounts (Timmer et al., 2015), so we use those data and combine them with TFP growth estimates from EU KLEMS. Also note that these shares are not constant over time, so we compute two-period average compensation shares to implement equations 2.5 and 2.6 as a Törnqvist index. Similarly, we use the two-period average share of capital income in value added in implementing equations 2.4 and 2.4'.

[28]Labor compensation of high-skilled workers accounted for, on average, 31 percent of total labor compensation in the US over this period.

growth of 0.8 percent when adjusting for vintage effects versus 1.3 percent under standard growth accounting.

Table 2.9: The Impact of Changes in the Quantity of Labor Services per Hour Worked by High-skilled on Productivity Growth in Europe and the US, Average Annual Growth 1995-2005

	Standard Growth Accounting			Adjusted for Vintage Effects		
	High-skilled	Total Labor	TFP Growth	High-skilled	Total Labor	TFP Growth
United States	1.9	1.0	1.3	3.7	1.7	0.8
United Kingdom	4.2	1.2	1.0	6.6	1.9	0.5
France	4.4	1.3	0.8	2.9	0.8	1.1
Germany	1.5	-0.5	0.7	0.5	-0.9	0.9
Italy	7.1	1.3	-0.6	6.0	1.2	-0.5
Netherlands	5.9	1.3	0.9	4.9	1.1	1.1
Spain	8.8	4.1	-0.8	7.6	3.8	-0.6

Sources: Growth in high-skilled hours worked and the share in total labor compensation from the WIOD Socio-Economic Accounts (Timmer et al., 2015); TFP growth from the EU KLEMS 2012 version (O'Mahony & Timmer, 2009). *Notes*: High-skilled labor input growth under standard growth accounting is the average annual growth of hours worked by high-skilled; adjusted for vintage effects uses the average annual change in the quantity of labor services per hour worked of high-skilled workers from the final column in Table 2.7 to adjust the trends in hours worked. For Spain we assume the same change in the quantity of labor services per hour worked as for Italy. Total labor input under standard growth accounting is based on equation 2.5; adjusted for vintage effects is based on equation 2.6. TFP growth is based on equation 2.4 for standard growth accounting; adjusted for vintage effects is based on equation 2.4′.

Under standard growth accounting assumptions, the United States showed notably faster TFP growth between 1995 and 2005 than the Continental European countries, and the United Kingdom also had a growth advantage. Within Continental Europe, the performance of Italy and Spain is notable, with declines in productivity. After adjusting for vintage effects, TFP growth in France and the Netherlands outstrips that of the other countries. Growth in the United States and United Kingdom is slower than in Germany, though still higher than in Italy and Spain. As recently argued by Gopinath et al. (2017) and Cette et al. (2016), the productivity declines in Italy and Spain can be traced to a deterioration of the capital allocation process. That deterioration, in turn, was triggered by the decline in real interest rates in the run-up to Italy and Spain joining the euro. In other words, the productivity declines in these countries were due to exceptional circumstances, while the other five countries in the table had broadly comparable productivity growth rates between 1995 and 2005. This implies that the most notable difference between Anglo-Saxon and Continental European countries is in their human capital vintage effects.

2.5 Conclusions

This paper has contributed to a growing literature that emphasizes human capital accumulation after formal education as an important factor for understanding the role of human capital in the process of economic growth and for understanding cross-country income differences. In growth accounting (or development accounting) a standard assumption is that an hour worked by a worker of given type, e.g. high-skilled males, represents a constant amount of labor services per hour worked over time. Yet if there are vintage effects, this assumption may be violated. Our starting point is recent research that identified vintage (or cohort) effects for the United States (Bowlus & Robinson, 2012) and we extended their methodology to six European countries. The starting point in their methodology is that the 'constant labor services per hour worked' assumption only holds for workers in the later stage of their working life, when the incentive to invest in human capital has disappeared – the so-called flat spot range. Vintage effects can then be identified from wage changes for younger workers relative to wage changes of workers in the flat spot range.

We confirm the findings for the United States of Bowlus and Robinson (2012) of vintage effects, with declining labor services per hour worked for low- and medium-skilled workers between 1975 and 1995 and rapidly increasing labor services per hour worked by high-skilled workers between 1995 and 2005. We find similar vintage effects in the United Kingdom, with even larger increases in labor services per hour worked by high-skilled workers over the same period. In contrast, we find evidence of declining labor services per hour worked by high-skilled workers in the Continental European countries, in a notable divergence.

This divergence in vintage effects has a notable impact on the productivity growth difference between the US and UK, on the one hand, and the Continental European countries – France, Germany, Italy, Netherlands and Spain – on the other hand. The increases of labor services per hour worked in the US and UK imply faster growth of labor input and, hence, smaller productivity growth. The opposite is the case for the Continental European countries. The net result of these adjustments is that the US and UK no longer show faster productivity growth than the Continental European countries.

On one level, this is an encouraging result, because it provides a novel perspective on the Europe-US productivity growth difference and because the set of reasons for why productivity growth is high or low can be considerably larger than the set of reasons for why vintage effects were so different in the US and UK compared to the Continental European countries. At the same time, the Bowlus and Robinson (2012) methodology only pinpoints vintage effects but it does not provide an explanation for why they occur. It is also an open question to what extent the evidence for male workers can be generalized to female workers. We leave these important issues for future research.

APPENDIX A

Appendix Chapter 2

Figure A.1: Price Series for the United States Based on CPS and LIS Data for 1991-2013

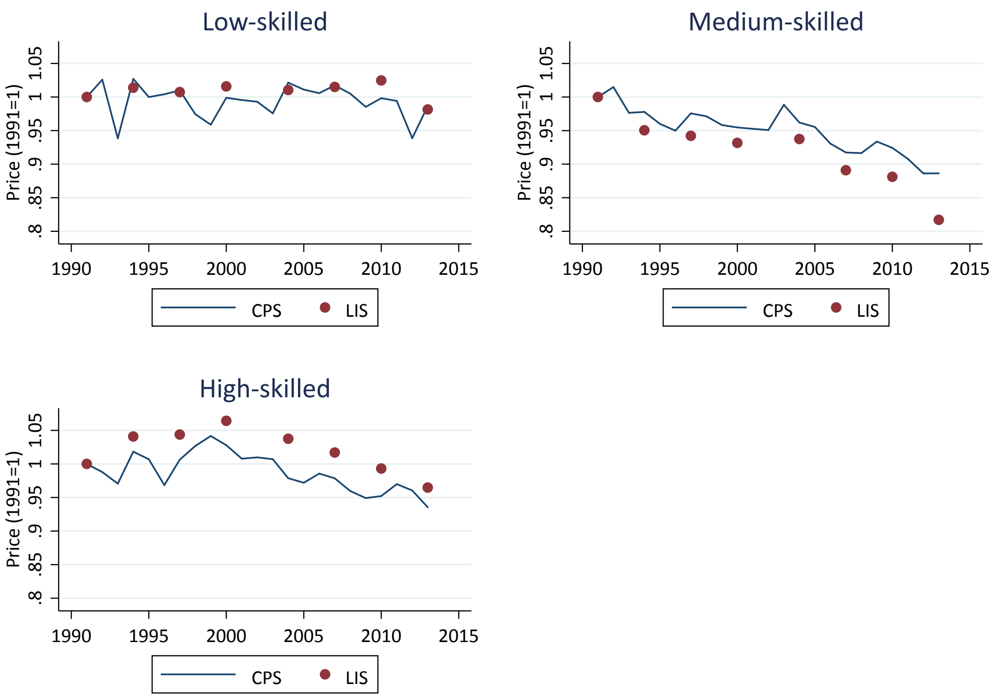


Table A.1: Coverage of LIS Survey Years

	LIS Survey Years Covered
France	1994, 2000, 2005
Germany	1994, 2000, 2004, 2007, 2010, 2013
Italy	1991, 1993, 1995, 1998, 2000, 2004, 2008, 2010
Netherlands	1990, 1993, 1999, 2004, 2007, 2010, 2013
Spain	2007, 2010, 2013
United Kingdom	1994, 1999, 2004, 2007, 2010, 2013

CHAPTER 3

Composition of Human Capital, Distance to the Frontier and Productivity*

3.1 Introduction

HUMAN capital, commonly captured in empirical research by a country's level of education, has been identified as a key determinant of economic growth: it triggers innovation (Romer, 1990), facilitates the adoption of new technologies developed by the world's technological leader (Nelson & Phelps, 1966) and affects output directly being itself a factor of production (Mankiw et al., 1992).[1] Yet, in a seminal contribution, Krueger and Lindahl (2001, p. 1130) find only 'fragile' empirical evidence in favor of externalities stemming from human capital. The latter would emerge in the form of technological progress, presumably through facilitating innovation and imitation, that is, the adoption of already existing technologies.[2]

This hypothesis has received much attention in the literature. In a widely cited paper, Vandenbussche et al. (2006) show that a greater share of university-educated workers stimulates innovation but only for countries that are relatively close to the technology frontier. Ang et al. (2011) confirm this finding for both high- and medium-income countries, and also show that low-income ones do not benefit from externalities. Cerina and Manca (2016), on the contrary, argue that countries far from the technology

*For an earlier version of this chapter, see Papakonstantinou (2014). I would like to thank Wen Chen, Robert Inklaar, Bart Los, Petros Milionis, Pierre Pecher, Laurie Reijnders, Marcel Timmer and participants at the SOM PhD Conference (University of Groningen, The Netherlands, March 2014), the 33rd IARIW General Conference (Rotterdam, The Netherlands, August 2014), the 20th Spring Meeting of Young Economists (Ghent, Belgium, May 2015) and the 14th European Workshop on Efficiency and Productivity Analysis (Helsinki, Finland, June 2015) for helpful comments and suggestions.

[1] For reviews on the role of human capital for economic growth, see: Krueger and Lindahl (2001); Sianesi and van Reenen (2003); Savvides and Stengos (2009); Benos and Zotou (2014); Delgado et al. (2014); Glewwe et al. (2014).

[2] Although outside the scope of this paper, the literature has also identified other types of externalities (see, for example, Lochner (2011) on the non-production benefits of education).

frontier do benefit from a high-skilled workforce by means of technology adoption. At the industry-level, Inklaar et al. (2008) and Mason, O'Leary, and Vecchi (2012) find no compelling externalities evidence.

The externalities literature has devoted considerable attention to the construction of appropriate data on the educational attainment level of the workforce and how the quality of these data affects the education-growth relationship.[3] But much less attention has been devoted to the construction of appropriate productivity measures, even though the results could be sensitive to this as well. In order to study externalities, we need to distinguish between private and social returns to education in a growth accounting measure of productivity. The private returns should be captured by a measure of labor input that weights hours worked by their wage, also known as correcting for labor force quality. Any additional benefit from education not reflected in a higher (relative) wage, will end up in TFP which is residually measured. Thus, to properly measure externalities we require a TFP measure that accounts for inter-country differences in the educational composition of the workforce otherwise TFP will be mismeasured (Inklaar et al., 2008; Mason et al., 2012). However, Vandenbussche et al. (2006), Ang et al. (2011) and Cerina and Manca (2016) use a crude TFP measure that does not control for the above. According to Inklaar et al. (2008), any evidence of externalities of human capital disappears when an education-adjusted productivity measure is employed. Mason et al. (2012) reach a similar result.

The contribution of this paper is, thus, to use the state-of-the-art cross-country productivity measures available in the recent version of the Penn World Table (PWT)[4] to determine how widely the evidence extends in favor of externalities stemming from human capital. I focus on three types of human capital that refer to a country's share of the population with tertiary, secondary and primary educational attainment (or a country's average years of tertiary, secondary and primary schooling attained).[5] I study their impact on TFP growth by means of a panel (country-time) fixed effects regression analysis. My sample includes 106 developed and developing countries between 1970-2010. Furthermore, I allow the effect of tertiary and secondary education on TFP growth to vary with a country's distance from the world technology frontier.[6]

My analysis points to broader and more robust evidence of externalities than the

[3] See, for example, Portela, Alessie, and Teulings (2010).

[4] Specifically version 8.0 of the PWT (Feenstra, Inklaar, & Timmer, 2015) that calculates education-adjusted TFP measures. The section on TFP data below presents additional information on the construction of such residual TFP measures.

[5] Education data come from the latest version (2.0) of the Barro and Lee (2013) dataset on educational attainment.

[6] Following similar studies in the literature (e.g. Vandenbussche et al., 2006), the United States constitute the world's technology frontier.

literature so far as I find strong evidence of positive externalities from tertiary-educated workers. The results suggest positive externalities for all countries, even those far from the technology frontier. In line with Vandenbussche et al. (2006) and Ang et al. (2011), I find that university-educated workers contribute to faster productivity growth for countries close to the frontier compared to countries some distance away. At even greater distance, though, a large positive effect is found again, in line with Cerina and Manca (2016). Stated differently, the marginal effect of tertiary education on TFP growth is U-shaped: it is large for countries far from the world technology frontier, decreases as countries move closer to it and, from a point onwards, increases again. This increase, however, is relatively small in magnitude. I also find some evidence of externalities from secondary education. These are limited though to a number of middle- and/or low-income countries.

Vandenbussche et al. (2006) suggest one major shift in the growth process, from growth primarily based on imitation, facilitated by non-high-skilled workers, to innovation, which is facilitated by high-skilled, university-educated workers. The results of Ang et al. (2011) serve mostly to strengthen the evidence for this particular shift. My results point to another shift, related to Cerina and Manca (2016), where university-educated workers also significantly contribute to imitation-led growth. This finding is consistent with technology diffusion models whereby human capital enhances a country's ability for technology adoption (e.g. Nelson & Phelps, 1966; Benhabib & Spiegel, 1994, 2005).[7] Finally, I find that using a crude, rather than an education-adjusted, TFP measure does not alter the core conclusions of my analysis. The latter is still preferred though as the, conceptually, most appropriate measure when studying externalities.

My main result of broad externalities from tertiary-educated workers is robust to different measures of education (such as the average years of tertiary schooling rather than the share of university-educated workers) and age groups (people aged 15 or 25 and above and people aged 25-64), as well as to alternative estimation strategies (OLS and instrumental variables estimation). Throughout the paper, I also consider different functional forms (with or without interaction terms) and groups of countries (full sample with developed and developing economies versus restricted sample with only advanced OECD countries).

The paper proceeds as follows: The subsequent section introduces the empirical model, Section 3.3 presents the data and Section 3.4 the results. Section 3.5 concludes.

[7] Other studies that distinguish between types of human capital and also introduce the concepts of innovation and imitation are: Benhabib and Spiegel (1994, 2005); Benhabib, Perla, and Tonetti (2014); Madsen (2014); Squicciarini and Voigtländer (2015).

3.2 The Model

My baseline model to estimate the effect of human capital on TFP growth draws on the work of Vandenbussche et al. (2006). It is of a panel (country-time) form and covers 106 countries in five-year intervals over the period 1970-2010. More specifically, I will estimate the following equation:

$$g_{i,t} = \lambda_i + \mu_t + \alpha \cdot ln(P_{i,t-5}) + \beta' \cdot HC_{i,t-5} + \gamma' \cdot X_{i,t} + \epsilon_{i,t} \tag{3.1}$$

where the dependent variable $g_{i,t} = \Delta ln(rtfpna_{i,t}) = ln(rtfpna_{i,t}) - ln(rtfpna_{i,t-5})$ denotes productivity growth of country i between time $t-5$ and t. The variable $rtfpna$ stands for TFP at constant national prices and is derived from PWT 8.0 (Feenstra et al., 2015). Note that I study productivity growth in five-year intervals. This is not only due to (human capital) data availability[8], but also because research has suggested that cross-country growth estimations are more robust when five-year intervals are employed, at least compared to annual ones (Johnson, Larson, Papageorgiou, & Subramanian, 2013). The main regressors of the analysis are: (i) the logarithm of the proximity (or distance) to the TFP frontier, $ln(P_{i,t-5})$ and (ii) the human capital of country i, $HC_{i,t-5}$, both of which refer to the beginning of the period.

To calculate P, the United States act as the frontier, as commonly done in the literature (see, for example, Vandenbussche et al. (2006); Ang et al. (2011)). More specifically, the proximity variable is calculated as: $ln(P_{i,t-5}) = ln(ctfp_{i,t-5}/ctfp_{USA,t-5})$, where $ctfp$ denotes the TFP level at current PPPs and comes from PWT 8.0 (Feenstra et al., 2015).[9] Note, at this point, that I use two different TFP variables from PWT for my analysis, $rtfpna$ (for the dependent) and $ctfp$ (for the independent variable), the reason being that the former is most suited for comparisons within a country over time, whereas the latter mainly facilitates comparisons between countries at one point in time.[10] Note, also, that $ln(P_{i,t-5})$ is a negative number since I only focus on countries that have lower TFP levels than the US (I require $ln(P_{i,t-5}) \leq 0$). Hence, the larger the value of $ln(P_{i,t-5})$, the closer a country is to the frontier (stated differently, there is a relatively smaller technological distance between that country and the US). There are, however, countries in the PWT dataset which, *for some years*, have scored higher in TFP than the US. I have removed these observations from the analysis, since a story about the drivers of productivity growth makes more intuitive sense when it refers to

[8]The Barro and Lee (2013) dataset that I use for my education variables provides information for 146 countries between 1950-2010, in five-year intervals.

[9]The variable $ctfp$ is already computed relative to the US in PWT 8.0.

[10]For details, see Feenstra et al. (2015), Inklaar and Timmer (2013) and the discussion in Section 3.3.

countries that lie below the frontier and try to catch up. I have opted for the US as the world technology frontier, first, because other countries do not *consistently* (for all years) score higher in productivity and, also, because the US has commonly acted as the frontier in the literature. Furthermore, relatively small economies (e.g. Sweden, Norway) or countries with a large petroleum industry (e.g. Kuwait, Saudi Arabia) may have high(er) TFP levels but cannot adequately represent the world technology frontier for all sectors of an economy (Madsen, 2014).

Human capital ($HC_{i,t-5}$ in model 3.1) enters my empirical analysis through three alternative measures: (i) tertiary ($T\_HC_{i,t-5}$), (ii) secondary ($S\_HC_{i,t-5}$), and (iii) primary ($P\_HC_{i,t-5}$) education. Depending on the specification, these three measures (types of human capital) are either captured by a country's average years of tertiary, secondary and primary schooling or the percentage of the population with tertiary, secondary and primary education. Unless otherwise specified, the variables refer to the population aged 25 and above and come from the latest version (2.0) of the Barro and Lee (2013) dataset on educational attainment. Important to note is that, at a later stage, I augment baseline model 3.1 with interaction terms between human capital and proximity to the frontier (e.g. $ln(P_{i,t-5}) \cdot T\_HC_{i,t-5}$; $ln(P_{i,t-5}) \cdot S\_HC_{i,t-5}$). I do so in order to examine the role of education for countries at different distances from the world technological leader and, also, to identify the effects of education on TFP growth under different functional forms.

Finally, the model incorporates a set of control variables ($X_{i,t}$). Following Ang et al. (2011), this includes (i) $inflation_{i,t}$, measured by the consumer price index and defined as the annual percentage change in the cost of acquiring a basket of goods and services; (ii) $trade_{i,t}$, captured by the sum of exports and imports of goods and services as a percentage of GDP; (iii) $fdi_{i,t}$, namely the net inflows of foreign direct investment as a percentage of GDP; and (iv) $credit_{i,t}$, defined as the domestic credit to private sector, again, as a percentage of GDP.[11] All control variables come from the World Development Indicators (WDI, 2015) and are calculated as averages between time $t-5$ and t, following Ang et al. (2011). Table B.2 of the appendix provides summary statistics for all variables.

The empirical analysis is based on OLS (country) fixed effects regressions which also incorporate a set of time dummies. Country- (λ_i) and time-specific (μ_t) factors that

[11] Ang et al. (2011) also include a variable to control for a country's geographical location. As I am performing fixed effects regressions, the impact of such time-invariant variable is already accounted for. I also considered the impact of institutions on TFP growth by adding a control variable for the legal system and security of property rights from the Fraser Institute (Gwartney, Lawson, & Hall, 2014). However, this variable did not enter the regressions significantly and resulted in a great loss of observations. It was, therefore, dropped from the analysis.

influence productivity growth are, therefore, accounted for in an attempt to alleviate endogeneity concerns stemming from omitted variable bias. For robustness, I also report results from an IV regression with past values of my independent variables acting as instruments. However, this IV approach is not clearly superior according to the results of various diagnostic tests.[12] Therefore, the simple OLS estimates are preferred and used as benchmarks.

3.3 TFP Data

In this section, I describe the TFP data of my analysis and outline how a crude TFP measure compares to an education-adjusted one.

Data quality matters for identifying the effect of education on economic growth (e.g. Portela et al., 2010). In order to address measurement error concerns, various education datasets have thus been compiled and/or updated (e.g. Cohen & Soto, 2007; Lutz, Goujon, K.C., & Sanderson, 2007; Barro & Lee, 2013; Cohen & Leker, 2014; de la Fuente & Doménech, 2015). Interestingly though, the construction of TFP measures has received less attention in the externalities literature.[13] Hence, a contribution of this paper lies in the use of a state-of-the-art TFP measure from the recently revised Penn World Table (Feenstra et al., 2015, PWT 8.0).

PWT 8.0 provides yearly information on 167 countries between 1950-2011. It includes two TFP measures, called $ctfp$ (TFP level at current PPPs, where USA=1) and $rtfpna$ (TFP at constant national prices, where 2005=1), that can respectively be used to compare relative TFP levels across countries and TFP growth over time. The database improves upon the construction of TFP in three areas: (a) capital input, (b) labor shares and (c) quality of the labor force.[14]

First, capital input in PWT takes into account the differences in asset composition across countries and over time. As countries invest in assets with different life spans and thus depreciation rates, accounting for this heterogeneity is important. Furthermore, the capital stock in the beginning of the period is not estimated based on the commonly-used assumption that all countries are in a steady state when data are first observed. An alternative approach is employed that calculates capital stocks based on an assumed initial capital/output ratio. The perpetual inventory method is subse-

[12] Endogeneity does not appear to be a big problem according to post-estimation diagnostic tests and employing a system-GMM approach seems less appropriate due to post-estimation diagnostic criteria not always satisfied.

[13] Exceptions are the industry-level studies of Inklaar et al. (2008) and Mason et al. (2012), as well as the country-level analysis of Islam et al. (2014) with a focus on education quality.

[14] The discussion that follows in this subsection is based on Inklaar and Timmer (2013).

quently used to calculate capital stocks for the various asset types, countries and years. This approach results in more plausible capital stocks estimates, and particularly so for transition economies (Inklaar & Timmer, 2013).

Second, PWT constructs a measure for the share of labor income in GDP that is allowed to vary across countries and over time, and also accounts for the labor income of the self-employed. The latter constitute a large part of the workforce, especially in poorer countries. This dual adjustment has important implications as the labor shares are found to substantially vary across countries and decline over time. The explanatory power of inputs versus TFP, for example, increases when these new labor shares are introduced in a development accounting exercise (Inklaar & Timmer, 2013).

Third, and most important for my analysis, PWT takes into account the quality of the labor force by means of workers' educational attainment. Vandenbussche et al. (2006) and Cerina and Manca (2016) calculate TFP as the difference between output per adult (or per worker) and capital per adult times the capital share. Ang et al. (2011) also derive TFP as a residual of a production function that, next to physical capital, merely uses the labor force as input. The educational attainment of the labor force has largely been ignored in the construction of TFP by this stream of literature. Inklaar et al. (2008), however, find that it matters for their results. In what follows I thus outline the differences between the crude and the adjusted (for labor force quality) TFP measure. Additional information can be found in Inklaar and Timmer (2013).

The following production function is the starting point for the TFP calculations:

$$Y = A \cdot f(K, L) = A \cdot K^{\alpha} \cdot (E \cdot hc)^{1-\alpha} \tag{3.2}$$

where labor input (L), alongside its capital counterpart (K) and the respective output elasticities ($1 - \alpha$ and α), enter the production function and, with information on output (Y), TFP series (A) are generated.[15] PWT introduces a quality-adjusted labor input measure, defined as $L = E \cdot hc$ where E is the number of persons engaged in the economy (i.e. employees, as well as self-employed workers, unpaid family workers that are economically engaged, apprentices and the military) and hc their average human capital.

Human capital hc is approximated in PWT by years of schooling and an assumed private rate of return to them. More specifically, it holds that $hc = e^{\phi(s)}$ where s indicates a country's average years of schooling and $\phi(s)$ is the following piecewise linear function (following Caselli, 2005):

[15] As will be next explained, PWT uses the Törnqvist quantity index, rather than a Cobb-Douglas production function.

$$\phi(s) = \begin{cases} 0.134 \cdot s & s \leq 4 \\ 0.134 \cdot 4 + 0.101 \cdot (s-4) & 4 < s \leq 8 \\ 0.134 \cdot 4 + 0.101 \cdot 4 + 0.068 \cdot (s-8) & s > 8 \end{cases} \tag{3.3}$$

Based on Mincerian wage regressions, the slope numbers are chosen such that they correspond to private returns to education which are higher for earlier years of schooling (Psacharopoulos, 1994). Data on years of schooling are from an earlier version of Barro and Lee (2013, version 1.3) and refer to the population aged 15 and above.[16]

In order to calculate the across countries comparable TFP measure ($ctfp$), the Törnqvist quantity index of factor inputs Q^T is first used:

$$ln(Q^T_{i,USA}) = \frac{1}{2}(\alpha_i + \alpha_{USA}) ln\left(\frac{K_i}{K_{USA}}\right) + \left(1 - \frac{1}{2}(\alpha_i + \alpha_{USA})\right) ln\left(\frac{E_i \cdot hc_i}{E_{USA} \cdot hc_{USA}}\right) \tag{3.4}$$

where i denotes the country. In PWT, this measure is always calculated relative to the US, a useful feature since the US also constitutes the frontier country of my analysis. All variables are defined as above.

The across countries comparable TFP is then defined as:

$$ctfp_{i,USA} = \frac{cgdp^o_i}{cgdp^o_{USA}} \Big/ Q^T_{i,USA} \tag{3.5}$$

where $cgdp^o$ is a measure of output, specifically real GDP at current PPPs, and $Q^T_{i,USA}$ is derived from the previous equation 3.4.

Accordingly, in order to calculate a TFP measure appropriate to examine TFP growth over time ($rtfpna$), PWT uses the Törnqvist quantity index of factor inputs Q^T with respect to two periods in time t and $t-1$ as follows:

$$ln(Q^T_{t,t-1}) = \frac{1}{2}(\alpha_t + \alpha_{t-1}) ln\left(\frac{K_t}{K_{t-1}}\right) + \left(1 - \frac{1}{2}(\alpha_t + \alpha_{t-1})\right) ln\left(\frac{E_t \cdot hc_t}{E_{t-1} \cdot hc_{t-1}}\right) \tag{3.6}$$

The over-time comparable TFP is then defined according to Inklaar and Timmer (2013) as:

$$rtfpna_{t,t-1} = \frac{rgdp^{NA}_t}{rgdp^{NA}_{t-1}} \Big/ Q^T_{t,t-1} \tag{3.7}$$

[16]Although using the population aged 15-64 resulted in similar estimates.

where $rgdp^{NA}$ denotes real GDP at constant national prices and $Q^T_{t,t-1}$ is derived based on the previous equation 3.6.

Notice that in these education-adjusted TFP measures, labor L is a combination of E and hc. In a crude TFP measure, however, only the E-part would enter the calculations in equations 3.4 and 3.6. Consequently, two education-adjusted TFP measures are constructed, suitable for level and growth analyses, that carefully consider how capital stocks, labor shares and labor inputs should be computed, the latter accounting for the educational attainment of the labor force and thus allowing for a distinction between private and social returns to education. As a result, model 3.1 is suited to examine human capital externalities, namely effects of human capital on production growth beyond private returns to education.

3.4 Results

In this section, I first examine whether the composition of human capital matters, by contrasting the effects of tertiary, secondary and primary education on TFP growth. Second, I investigate to what extent these effects differ depending on a country's distance from the technology frontier. Third, I explore an alternative functional form for the education-growth relationship that allows for non-linearities. Finally, I compare the results based on a crude versus an adjusted TFP measure.

3.4.1 Composition of human capital and TFP growth

The data sources I employ allow me to examine externalities stemming from human capital in a sample of, up to, 106 countries (33 of which are current OECD members) observed every five years during the 1970-2010 period. Table B.1 of the appendix lists the countries included in the analysis.

Table 3.1 presents the results of model 3.1. All columns refer to (country) fixed effects regressions and include year dummies (not reported, due to brevity, but always jointly highly significant). Column (1) uses the average years of schooling in a country as a measure of human capital (Barro & Lee, 2013). Such measure is commonly introduced in growth regressions to control for the effect of human capital and is commonly found to be insignificant or marginally significant (Krueger & Lindahl, 2001). This is also the case in my analysis.

Being merely an average, however, this measure potentially masks different effects coming from different types of education. In order to account for this, column (2) of Table 3.1 uses the average years of *tertiary* schooling attained in a country instead. The

Table 3.1: Composition of Human Capital and TFP Growth

VARIABLES	(1: years)	(2: years)	(3: years)	(4: years)	(5: years)	(6: shares)
$ln(P_{i,t-5})$	-0.306***	-0.328***	-0.316***	-0.303***	-0.335***	-0.341***
	(0.0429)	(0.0421)	(0.0435)	(0.0443)	(0.0433)	(0.0434)
$T\_HC_{i,t-5}$		0.222***			0.196***	0.639***
		(0.0553)			(0.0604)	(0.227)
$S\_HC_{i,t-5}$	0.0169		0.0372**		0.0219	0.0348
	(0.0106)		(0.0178)		(0.0161)	(0.130)
$P\_HC_{i,t-5}$				-0.00806	-0.00573	-0.131
				(0.0150)	(0.0128)	(0.0955)
$inflation_{i,t}$	-0.0180**	-0.0170**	-0.0183***	-0.0183***	-0.0172**	-0.0170**
	(0.00693)	(0.00661)	(0.00693)	(0.00693)	(0.00663)	(0.00657)
$trade_{i,t}$	0.0643	0.0822*	0.0654	0.0752	0.0789*	0.0741
	(0.0485)	(0.0454)	(0.0465)	(0.0467)	(0.0468)	(0.0450)
$fdi_{i,t}$	0.810***	0.784***	0.777***	0.844***	0.751***	0.753***
	(0.287)	(0.260)	(0.275)	(0.292)	(0.252)	(0.252)
$credit_{i,t}$	-0.0411	-0.0759***	-0.0473*	-0.0424*	-0.0777***	-0.0782***
	(0.0249)	(0.0234)	(0.0261)	(0.0233)	(0.0236)	(0.0231)
Observations	603	603	603	603	603	603
Countries	106	106	106	106	106	106
R-squared	0.419	0.436	0.423	0.415	0.439	0.445

Notes: $g_{i,t}$, namely TFP growth of country i between time $t-5$ and t, is the dependent variable. $ln(P)$ is the logarithm of the proximity to the TFP frontier. T_HC, S_HC and P_HC denote tertiary, secondary and primary education of country i. Column (1) uses the average years of schooling as a regressor. Columns (2)-(5) use the average years of tertiary, secondary and primary schooling. Column (6) uses the share of the population aged 25 and above with tertiary, secondary and primary education. The regressors refer to the year $t-5$, apart from the variables $inflation$, $trade$, fdi, $credit$ which are calculated as averages between time $t-5$ and t. For detailed definitions of the variables, see Section 3.2. All columns present OLS-FE regressions and include time dummies. Robust standard errors, clustered by country, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

effect is positive and highly significant at the 1% level which is already an indication that the composition of human capital matters. Column (3) introduces a variable for the average years of *secondary* schooling. The effect is positive and significant at the 5% level. The variable for the average years of *primary* schooling, however, enters with a negative and insignificant sign in the regression of column (4). All three human capital measures (tertiary, secondary and primary) are simultaneously introduced in the estimation presented in column (5). Tertiary education maintains its positive and highly significant coefficient, but secondary education does not. Only tertiary education exerts a positive and significant effect on TFP growth, revealing the existence of externalities stemming from this particular type of education. Instead of years of schooling, column (6) of Table 3.1 uses the share of the population aged 25 and above with tertiary, secondary and primary education. The results are in line with those that use years of schooling. Although not reported, the results are also robust to looking at different age groups in the population (for example, people aged 15 and above or people of the 25-64 working age population). Also, similar results were attained when an alternative education database (Lutz et al., 2007) was used. Finally, an IV regression that uses past values of the independent (proximity and education) variables as instruments yielded comparable results (not reported).[17]

Among the remaining regressors, the logarithm of the proximity to the TFP frontier, $ln(P_{i,t-5})$, enters with a negative and significant coefficient, indicating TFP convergence. This is the standard catch-up effect commonly found in empirical growth analyses (e.g. Barro, 1996). Regarding the control variables, in line with the results of Ang et al. (2011), inflation ($inflation_{i,t}$) has a negative impact on productivity growth, whereas trade ($trade_{i,t}$) and FDI ($fdi_{i,t}$) a positive one. The effect of trade, however, is not always found significant at the 10% level. The domestic credit control variable ($credit_{i,t}$) enters with a negative sign.

All in all, the results suggest that the composition of human capital matters. Even though a measure of a country's average years of schooling masks the existence of externalities, there is broad and robust evidence that tertiary-educated workers significantly contribute to growth.

3.4.2 Human capital and distance to the frontier

Having identified the existence of externalities from university-educated workers, I next examine whether the effect of human capital varies with a country's distance to

[17] This is based on a 2-step GMM estimation that instruments the proximity and education regressors with their own values at time $t - 10$.

the technology frontier. To that end, I follow Vandenbussche et al. (2006) and augment my baseline model 3.1 with interactions between the human capital and proximity variables (more specifically, $ln(P_{i,t-5}) \cdot T\_HC_{i,t-5}$ and $ln(P_{i,t-5}) \cdot S\_HC_{i,t-5}$). In what follows, I only focus on tertiary and secondary education. Primary education never enters the analyses with a significant coefficient and is therefore dropped. In any case, its inclusion does not affect my results. Furthermore, I use the shares of the population aged 25 and above with tertiary and secondary education as my benchmark human capital variables.

Table 3.2 presents the one-way-interactions results using (country) fixed effects regressions. Again, all estimations include year dummies (not reported, due to brevity, but always jointly highly significant). Column (1) of Table 3.2 refers to the whole sample of countries listed in Table B.1 of the appendix. The proximity variable, $ln(P_{i,t-5})$, enters again with a negative and significant coefficient and the control variables behave in a similar manner as before. The level effect of tertiary education ($T\_HC_{i,t-5}$) maintains its positive and significant impact on TFP growth, whereas that of secondary schooling ($S\_HC_{i,t-5}$) is negative and insignificant. The coefficients of these level variables indicate the magnitude of the marginal effect when $ln(P_{i,t-5}) = 0$, in other words at the frontier. The coefficients of the interaction terms suggest that the effect of education decreases as countries move closer to the world technology frontier, significantly for the case of secondary and insignificantly for that of tertiary education. For a better inspection of the results, the upper (lower) panel of Figure 3.1 plots the marginal effect of tertiary (secondary) human capital on TFP growth (solid black and red line respectively), conditional on a country's distance to the frontier. The dashed black (or red) lines show the 95% confidence intervals.

The upper panel of Figure 3.1 clearly indicates that tertiary education has a positive and significant impact on TFP growth for *all* countries, irrespective of their distance to the frontier: the marginal effect, alongside the confidence interval lines, lie above the horizontal zero threshold. The impact of secondary education on TFP growth is less broad: it is positive and (marginally) significant for countries far from the frontier (at the left end of the horizontal axis), and its effect decreases and turns negative and insignificant for those close to it.[18] Consequently, there is evidence of externalities stemming from tertiary human capital and referring to all countries. Secondary education also positively affects TFP growth but its impact is smaller

[18]The lower panel of Figure 3.1 does not allow a clear visual inspection of the confidence interval lines due to scaling. However, for $ln(P) \leq -1$, both the lower and upper 95% confidence interval lines lie above the horizontal zero threshold indicating a significant effect of secondary education on TFP growth. Countries for which $ln(P) \leq -1$ are primarily low- and lower-middle-income ones.

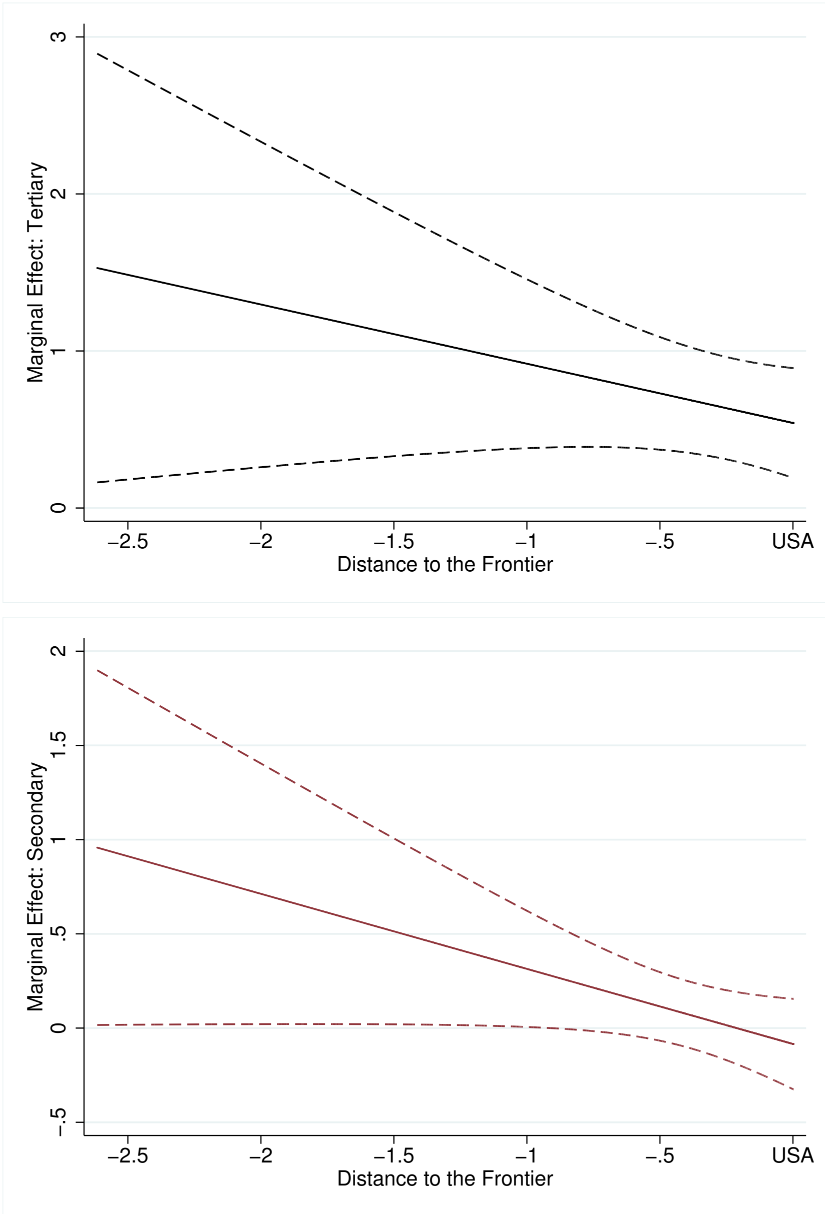
Table 3.2: Human Capital and Distance to the Frontier

VARIABLES	(1: Full Sample)	(2: Advanced OECD Countries)	(3: Remaining Countries)
$ln(P_{i,t-5})$	-0.178***	-0.119	-0.172***
	(0.0548)	(0.144)	(0.0646)
$T\_HC_{i,t-5}$	0.541***	0.482**	0.348
	(0.178)	(0.189)	(0.316)
$S\_HC_{i,t-5}$	-0.0842	-0.0312	-0.0951
	(0.122)	(0.102)	(0.222)
$ln(P_{i,t-5}) \cdot T\_HC_{i,t-5}$	-0.377	0.154	-0.559*
	(0.284)	(0.440)	(0.313)
$ln(P_{i,t-5}) \cdot S\_HC_{i,t-5}$	-0.398*	-0.295	-0.405
	(0.212)	(0.364)	(0.258)
$inflation_{i,t}$	-0.0145**	-0.161	-0.0137**
	(0.00581)	(0.151)	(0.00567)
$trade_{i,t}$	0.0534	0.154*	0.0541
	(0.0458)	(0.0859)	(0.0472)
$fdi_{i,t}$	0.675***	0.0407	0.756**
	(0.255)	(0.331)	(0.301)
$credit_{i,t}$	-0.0592**	-0.0318	-0.0853**
	(0.0252)	(0.0191)	(0.0390)
Observations	603	144	459
Countries	106	22	84
R-squared	0.475	0.503	0.495

Notes: $g_{i,t}$, namely TFP growth of country i between time $t-5$ and t, is the dependent variable. $ln(P)$ is the logarithm of the proximity to the TFP frontier. T_HC (S_HC) is the tertiary (secondary) human capital of country i. All columns use the share of the population aged 25 and above with tertiary and secondary education. The regressors refer to the year $t-5$, apart from the variables $inflation$, $trade$, fdi, $credit$ which are calculated as averages between time $t-5$ and t. For detailed definitions of the variables, see Section 3.2. Column (1) refers to the full sample. Column (2) incorporates only advanced OECD countries and column (3) all the rest. All columns present OLS-FE regressions and include time dummies. Robust standard errors, clustered by country, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

and significant only for countries far from the world technology frontier (low- and lower-middle-income, in particular).

Figure 3.1: Marginal Effect of Tertiary and Secondary Education on TFP Growth



Notes: The solid black (red) line shows the marginal effect of tertiary (secondary) education on TFP growth, conditional on the distance to the frontier (upper and lower panel respectively). The dashed black and red lines show the respective 95% confidence intervals. The marginal effects are calculated based on column (1) of Table 3.2.

Interesting to note is that, at a first instance, I do not find evidence for the effect of tertiary education to increase with proximity to the frontier. On the contrary, the effect appears, if anything, decreasing. This suggests that a highly-educated workforce is particularly important for countries far from the technology frontier by facilitating technology adoption. However, Vandenbussche et al. (2006) have argued that a high-skilled workforce is all the more important as countries approach the world's technological leader and turn to innovation to grow. This finding is empirically confirmed by Ang et al. (2011) for high- and medium-income countries. To examine if there is any evidence for the Vandenbussche et al. (2006) argument, I split the countries of my sample in two groups: one that consists of advanced OECD economies and another that incorporates all the rest.[19] This follows Vandenbussche et al. (2006) who examine the relationship between human capital and growth among high-income OECD countries but, also, Ang et al. (2011) who split their sample on the basis of income classification. Column (2) of Table 3.2 refers to the advanced OECD countries and column (3) to the remaining ones.

An interesting difference between columns (2) and (3) is the sign of the $ln(P_{i,t-5}) \cdot T\_HC_{i,t-5}$ interaction term: positive and insignificant for the advanced OECD countries and negative and significant for the remaining ones. The latter is in line with Cerina and Manca (2016) and points to evidence of externalities from a university-educated workforce in countries far from the frontier. However, this is in contrast to Ang et al. (2011) who fail to find externalities evidence for this group of countries. The positive but insignificant coefficient of the interaction provides some, yet not strong, support for the Vandenbussche et al. (2006) hypothesis. These differences in results could potentially be attributed to the superior TFP measure I adopt (compared to Vandenbussche et al. (2006); Ang et al. (2011); Cerina and Manca (2016)), the different education data I use (compared to Cerina and Manca (2016) who use the Cohen and Soto (2007) dataset) or the estimation technique I employ. Regarding the latter, Ang et al. (2011) and Cerina and Manca (2016) use the system-GMM estimator. The sensitivity of this estimator is, however, already reflected in the different results these two studies obtain.[20]

My results so far suggest that, as my sample is quite diverse and consists of countries at very different stages of development, there might be non-linear effects that need to be taken into account. This is further investigated in the next sub-section.

[19] An asterisk marks the countries that belong in the former group in Table B.1 of the appendix. These countries are advanced economies (Barro & Lee, 2013) and also OECD members. With the exception of Germany, Iceland and Japan, these are also the countries studied by Vandenbussche et al. (2006). Removing these three from the sample produced similar results.

[20] I have also tried using the system-GMM estimator but its post-estimation diagnostic tests not always satisfied the required statistical criteria.

3.4.3 An alternative functional form

I have so far demonstrated the existence of externalities stemming primarily from tertiary education. I have also found some evidence that these effects vary with a country's distance to the technology frontier and that a simple two-way interaction term might not be able to capture non-linear effects in my, quite diverse, sample. The natural next step to take is, thus, to explore non-linearities related to a country's distance to the frontier.

To that end, I employ a functional form that includes, the logarithm of the proximity to the TFP frontier squared, $(ln(P_{i,t-5}))^2$, as well as its interaction with tertiary and secondary human capital, alongside the level-variables of tertiary and secondary education and their linear interactions with proximity, as before. Table 3.3 presents the results based on this new, augmented functional form for the full sample of countries.

According to the results of column (1), which refers to the simple OLS-FE estimation, the negative and significant effect of the proximity variable is maintained. The level effect of tertiary education is positive and significant, indicating the magnitude of the marginal effect at the frontier. The remaining education-variables enter insignificantly, likely due to their correlations, but the tertiary-education-related ones ($T\_HC_{i,t-5}$; $ln(P_{i,t-5}) \cdot T\_HC_{i,t-5}$; $(ln(P_{i,t-5}))^2 \cdot T\_HC_{i,t-5}$) are found to be jointly significant.[21] This is not, however, the case for the secondary-education-related variables ($S\_HC_{i,t-5}$; $ln(P_{i,t-5}) \cdot S\_HC_{i,t-5}$; $(ln(P_{i,t-5}))^2 \cdot S\_HC_{i,t-5}$).[22]

For a better inspection of the results, the upper panel of Figure 3.2 plots the marginal effect of tertiary (solid black line) and secondary (solid red line) human capital on TFP growth, conditional on a country's distance to the frontier. Figure 3.2 is plotted based on column (1) of Table 3.3. To facilitate inspection, I do not plot here the confidence intervals but, if I do, the effect of tertiary education is significantly different from zero for all observed $ln(P)$'s, whereas that of secondary education only for those countries with $-1.4 < ln(P) < -1.1$ (at the 5% level). Countries such as India, Kenya and Sri Lanka fall within this range. The marginal effect of tertiary education is calculated as $\partial g/\partial T\_HC = \beta_{T\_HC} + \beta_{ln(P)\cdot T\_HC} \cdot ln(P) + \beta_{(ln(P))^2\cdot T\_HC} \cdot (ln(P))^2$, and that of secondary education as $\partial g/\partial S\_HC = \beta_{S\_HC} + \beta_{ln(P)\cdot S\_HC} \cdot ln(P) + \beta_{(ln(P))^2\cdot S\_HC} \cdot (ln(P))^2$.[23]

Two key findings emerge: first, the marginal effect of tertiary human capital is

[21] A test of joint significance of these variables resulted in a p-value of 0.0011.
[22] A test of joint significance resulted in a p-value of 0.2409.
[23] Note that the subscripts of the β's indicate the variable in Table 3.3 each β-coefficient refers to.

Table 3.3: An Alternative Functional Form

VARIABLES	(1: OLS-FE) Adjusted TFP	(2: IV-FE) Adjusted TFP	(3: OLS-FE) Crude TFP
$ln(P_{i,t-5})$	-0.230**	-0.186**	-0.264***
	(0.0878)	(0.0872)	(0.0900)
$T\_HC_{i,t-5}$	0.616***	0.878***	0.566***
	(0.196)	(0.168)	(0.189)
$S\_HC_{i,t-5}$	-0.0199	0.0861	-0.0295
	(0.107)	(0.0774)	(0.113)
$ln(P_{i,t-5}) \cdot T\_HC_{i,t-5}$	0.234	0.724	0.309
	(0.722)	(0.579)	(0.696)
$ln(P_{i,t-5}) \cdot S\_HC_{i,t-5}$	-0.235	-0.0350	-0.199
	(0.343)	(0.262)	(0.322)
$(ln(P_{i,t-5}))^2$	-0.0255	0.00199	-0.0225
	(0.0390)	(0.0344)	(0.0303)
$(ln(P_{i,t-5}))^2 \cdot T\_HC_{i,t-5}$	0.423	0.609	0.413
	(0.460)	(0.555)	(0.403)
$(ln(P_{i,t-5}))^2 \cdot S\_HC_{i,t-5}$	0.0721	-0.0736	0.0458
	(0.239)	(0.187)	(0.183)
$inflation_{i,t}$	-0.0139**	-0.00528***	-0.0140**
	(0.00567)	(0.00129)	(0.00574)
$trade_{i,t}$	0.0498	0.0604*	0.0568
	(0.0428)	(0.0323)	(0.0434)
$fdi_{i,t}$	0.674***	0.362**	0.709***
	(0.256)	(0.174)	(0.261)
$credit_{i,t}$	-0.0655***	-0.127***	-0.0642***
	(0.0236)	(0.0178)	(0.0224)
Observations	603	407	603
Countries	106	73	106
R-squared	0.480	0.342	0.474
Kleibergen-Paap (p-value)		0.0165	
Hansen J (p-value)		0.1562	
Endogeneity test (p-value)		0.2894	

Notes: $g_{i,t}$, namely TFP growth of country i between time $t-5$ and t, is the dependent variable. $ln(P)$ is the logarithm of the proximity to the TFP frontier. T_HC (S_HC) is the tertiary (secondary) human capital of country i. All columns use the share of the population aged 25 and above with tertiary and secondary education. The regressors refer to the year $t-5$, apart from the variables $inflation$, $trade$, fdi, $credit$ which are calculated as averages between time $t-5$ and t. For detailed definitions of the variables, see Section 3.2. Columns (1) and (3) present OLS-FE regressions. Column (2) presents IV-FE regressions using past values (at time $t-10$, $t-15$ and $t-20$) as instruments. Columns (1) and (2) use the adjusted TFP measure. Column (3) uses the crude one. All regressions refer to the full sample and include time dummies. Robust standard errors, clustered by country, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

larger than that of secondary and, second, there is some evidence for a U-shaped relationship between tertiary human capital and TFP growth, but the same does not hold for secondary education. More specifically, as the distance to the frontier decreases and we move further to the right of the horizontal axis, the positive and decreasing effect of tertiary education levels off and, from a point onwards, starts increasing again. As suggested in the previous sub-section, this provides some, yet not strong, support for the argument of Vandenbussche et al. (2006) that tertiary education complements the innovation process in countries close to the frontier. However, it is the decreasing effect that dominates the education-growth relationship. Secondary education, on the contrary, lacks any complementarity to innovation, as its effect is overall decreasing for the countries of my sample.

In the lower panel of Figure 3.2, I plot again the marginal effect of tertiary education but zoom in on countries relatively close to the frontier for a better inspection of the results. The marginal effect reaches a minimum at $ln(P) = -0.27$ and the upward sloping part of the curve mainly refers to proximity levels of high-income economies, such as Australia, Austria, Denmark, Iceland, Ireland, Israel, Japan, The Netherlands, Singapore, Spain, Sweden, and the US.[24] The fact that the marginal effect of education reaches a minimum is consistent with the notion that maintaining imitation strategies as a country approaches the frontier, may result in non-convergence traps (Aghion & Howitt, 2009), in order to escape from which a country should turn to innovation to grow. Consequently, there is some evidence that a high-skilled workforce is required for the innovation process in technologically advanced countries and there is even stronger evidence with respect to needed human capital facilitating the adoption of technologies and the diffusion of knowledge in less technologically advanced countries that grow primarily via imitation (as the marginal effects are higher for countries the furthest away).

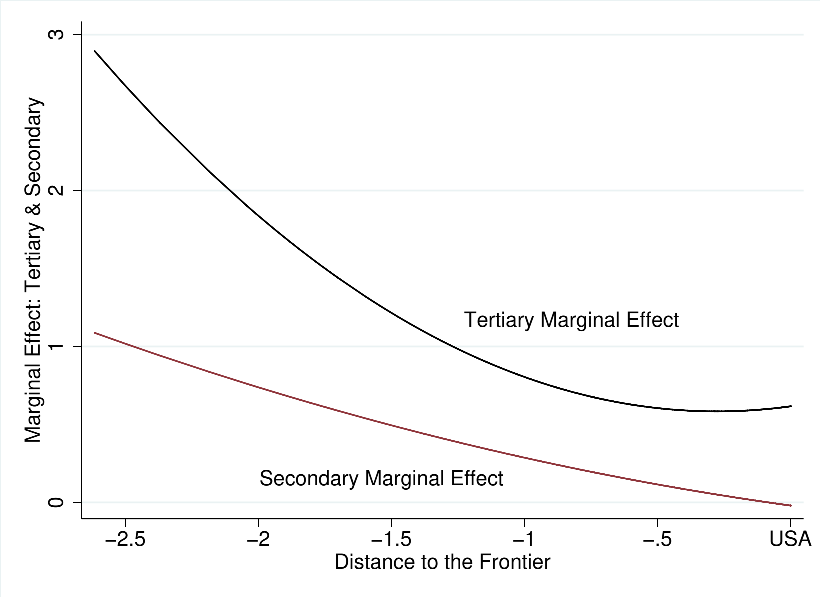
To get a better idea of the magnitude of the marginal effects of tertiary and secondary education, Table 3.4 below presents them, alongside the 95% confidence intervals, for countries at different distances from the frontier.

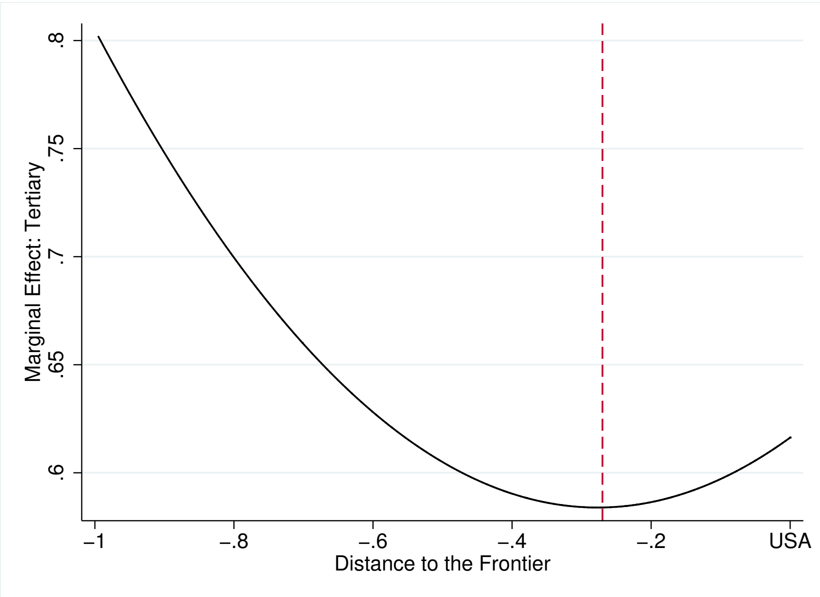
All tertiary marginal effects are positive and significant at the 5% level. The same does not hold, however, for the secondary marginal effects which are overall decreasing and insignificant at the 5% level.[25] The tertiary marginal effect is large for Cameroon, a lower-middle income country at the first quartile of the distance distribution. The

[24]Most of them are also countries that formed the sample of the regression presented in column (2) of Table 3.2.

[25]There are some countries for which the secondary marginal effect is significant at the 5% level (see the discussion in the text) but these lie before the first quartile of the distance distribution.

Figure 3.2: Marginal Effect of Tertiary and Secondary Human Capital on TFP Growth (Quadratic Interactions)





Notes: The solid black (red) line shows the marginal effect of tertiary (secondary) human capital on TFP growth, conditional on a country's distance to the frontier. The upper panel shows the marginal effects for the whole sample, whereas the lower one zooms in on the tertiary marginal effect for countries close to the frontier. The turning point of the curve is at $ln(P) = -0.27$ (lower panel, dashed red line). The marginal effects are calculated based on column (1) of Table 3.3.

Table 3.4: Marginal Effects for Countries at Different Distances from the Frontier

	25%	50%	Lowest Point	75%	Frontier
ME:	0.744	0.594	0.584	0.587	0.616
Tertiary	[0.184, 1.305]	[0.165, 1.022]	[0.218, 0.950]	[0.246, 0.928]	[0.233, 0.999]
ME:	0.247	0.094	0.051	0.027	-0.019
Secondary	[-0.024, 0.519]	[-0.104, 0.292]	[-0.128, 0.230]	[-0.149, 0.202]	[-0.230, 0.190]
Example	Cameroon (1980)	Costa Rica (2000)	Japan (1975)	New Zealand (2000)	US (all years)

Notes: The marginal effects (ME) are calculated based on column (1) of Table 3.3. The 95% confidence intervals are presented in brackets below the marginal effects. The lowest point refers to the minimum of the U-shaped curve of Figure 3.2 (lower panel). The minimum is at $ln(P) = -0.27$.

effect decreases as we approach the country at the second quartile (an upper-middle income country, Costa Rica) and takes its minimum value for Japan, a country between the second and third quartile. After that, the marginal effect slowly starts to increase, as we see from its magnitude for New Zealand, the high-income economy at the third quartile of the distribution, and subsequently the US, the frontier country. Notice, however, that despite the U-shaped pattern of the tertiary marginal effect shown in Figure 3.2, the change in its magnitude is rather small as we move from Costa Rica (second quartile), to Japan (lowest point), New Zealand (third quartile) and finally the frontier.

To facilitate the robustness of these results, column (2) of Table 3.3 presents the equivalent of column (1) using instrumental variables (IV). For this, the regressors $ln(P)$, T_HC, S_HC and all their interactions have been instrumented with their own values at time $t-10$, $t-15$ and $t-20$.[26] The reason I use these particular instruments stems, on the one hand, from the literature and, on the other, from a number of IV diagnostic tests. Vandenbussche et al. (2006), for example, use their regressors lagged twice as instruments. Mason et al. (2012) use one extra lag, whereas Ang et al. (2011) employ all lagged levels and first differences of their regressors as instruments in a system-GMM estimation. As no consensus has been reached, I opt for a number of instruments that satisfies a number of IV diagnostic tests. The latter are presented at the bottom of Table 3.3 and point to the relevance and validity of the instruments.[27] More specifically, the Kleibergen and Paap under-identification

[26]The control variables are not taken to be endogenous and are therefore not instrumented.

[27]Column (2) refers to the 2-step GMM estimation. Following Vandenbussche et al. (2006) and Ang et al. (2011), I also tried using lagged public expenditures on education as an external instrument, but this variable proved not to be a strong predictor for human capital and, also, resulted in a large loss of observations.

test rejects the null hypothesis that the equation is under-identified. According to the Hansen J statistic, the instruments are valid. However, based on the endogeneity test, I cannot reject the null hypothesis that the specified endogenous regressors can actually be treated as exogenous in which case the OLS-FE estimates should be preferred.[28] For completeness, I present in Table 3.3 the results based on both estimation methods.[29]

To sum up, using different functional forms to identify the relationship between human capital and TFP growth, I have found robust evidence for externalities. Tertiary education, in particular, entails an overall positive effect on TFP growth which decreases as countries move closer to the frontier and, from a point onwards, increases again yet to a smaller extent. The decreasing impact is more dominant in my sample and suggests a fundamental role of tertiary education for less developed economies, whereby high-skilled workers facilitate the adoption of technologies developed at the frontier and promote growth. In these countries, tertiary human capital can also raise the productivity of the unskilled labor force, via "a *higher* incidence of learning from others" (Sianesi & van Reenen, 2003, p. 160). The increasing effect as countries become more technologically advanced can be attributed to the fact that innovation, which requires a high-skilled labor force to materialize, is more pronounced, than imitation, in countries close to the TFP frontier. Secondary education also results in externalities, but smaller ones and significant only for a number of middle- and/or low-income countries. Its effect does not increase when countries come closer to the frontier.

3.4.4 Adjusted versus crude TFP

My results so far are based on what I call an adjusted TFP measure taken from PWT. As a final step, I would like to contrast these results with those based on a crude productivity measure, namely one that does not take into account the quality (educational attainment) of the labor force. In this way, I will be able to conclude whether my results are sensitive to the use of a TFP measure similar to that of Vandenbussche et al. (2006), Ang et al. (2011) and Cerina and Manca (2016). In order to do so, I re-calculate the variables for TFP level and growth from PWT without adjusting for human capital, and re-do the analysis. The labor input into the production function is now merely the number of persons engaged in the economy. This implies that equations 3.4 and 3.6 do not include the hc- but only the E-part of the labor input measure L.

[28]Note that the OLS-FE results were preferred over the IV ones in the specifications I estimated and that held regardless of the functional form.

[29]Note that under the IV specification, observations drop and secondary education loses its significance among low- and lower-middle-income countries.

Column (3) of Table 3.3 presents OLS-FE results based on the crude TFP measure. These can be directly compared to column (1) of the same table which uses the adjusted measure instead. Simply eyeballing the regression coefficients suggests that there is not much difference between the two. The regressors carry the same sign and are of similar magnitude. A test of the hypothesis that the coefficients of the two regressions are equal, against the alternative that they are not, resulted in the rejection of the latter.

Consequently, using an adjusted, instead of a crude, TFP measure does not alter the core conclusions of my analysis. However, the former measure still has its merits for two reasons: first, conceptually, it is a better suited measure to use in the context of externalities, as it allows for a distinction between private and social returns to education. Second, the TFP measures I adopt from the PWT allow for asset heterogeneity and labor shares to vary across countries and over time, which constitute important improvements in the construction of productivity data.

3.5 Conclusion

Human capital, commonly captured in empirical research by the level of education, holds a prominent role in academic and policy-related debates. In this paper, I have examined the relationship between different types of human capital and productivity growth for countries at different distances from the technology frontier, a topic which has produced mixed results in the literature. Motivated by the seminal work of Krueger and Lindahl (2001) who found limited evidence of externalities, Vandenbussche et al. (2006) identified the importance of human capital composition and argued that a university-educated workforce is all the more important for innovating countries, close to the technology frontier. Ang et al. (2011) confirmed this finding for high- and middle-income countries but failed to find any externalities evidence for imitating countries, far from the technology frontier. In contrast to Vandenbussche et al. (2006) and using industry- rather than country-level analyses, Inklaar et al. (2008) and Mason et al. (2012) found no compelling externalities evidence. In contrast to Ang et al. (2011), Cerina and Manca (2016) pointed to the importance of high-skilled workers for developing countries.

In this paper, I have employed different functional forms and used state-of-the-art TFP measures to examine the link between education and growth. My analysis has discovered evidence of externalities that extends to all countries of my sample. The composition of human capital matters greatly as it is primarily the tertiary-educated workers that contribute to growth. There is also evidence that the marginal effect of tertiary education on TFP growth is U-shaped: large for countries far from the technology frontier and decreasing as we move closer to it, in line with Cerina and Manca (2016), but increasing as we further approach the frontier, in line with Vandenbussche et al. (2006). It is worth noting, however, that the decreasing effect dominates and that tertiary education is found to play a fundamental role for growth, particularly for less technologically advanced economies. The increase in the marginal effect for countries close to the frontier is relatively small in magnitude. All in all, investing in higher education appears to generate social returns in all countries, poor and rich.

APPENDIX B

Appendix Chapter 3

Table B.1: Countries List

Armenia, Australia*, Austria*, Bahrain, Barbados, Belgium*, Benin, Bolivia, Botswana, Brazil, Bulgaria, Burundi, Cameroon, Canada*, Central African Republic, Chile, China, Colombia, Costa Rica, Cote d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark*, Dominican Republic, Ecuador, Egypt, Estonia, Fiji, Finland*, France*, Gabon, Germany*, Greece*, Guatemala, Honduras, Hungary, Iceland*, India, Indonesia, Iran, Iraq, Ireland*, Israel, Italy*, Jamaica, Japan*, Jordan, Kazakhstan, Kenya, Korea (Republic of), Kuwait, Kyrgyzstan, Latvia, Lesotho, Lithuania, Macao, Malaysia, Malta, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Netherlands*, New Zealand*, Niger, Norway*, Panama, Paraguay, Peru, Philippines, Poland, Portugal*, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Serbia, Sierra Leone, Singapore, Slovak Republic, Slovenia, South Africa, Spain*, Sri Lanka, Swaziland, Sweden*, Switzerland*, Tajikistan, Tanzania, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, Ukraine, United Kingdom*, United States*, Uruguay, Venezuela, Zimbabwe.

Notes: Table B.1 lists the countries used in the analysis. An asterisk marks the countries that belong to the group of advanced (Barro & Lee, 2013) OECD members, as described in Section 3.4.2.

Table B.2: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
g	603	0.014	0.136	-0.923	0.618
$ln(P)$	603	-0.602	0.532	-2.615	0
T_HC (shares)	603	0.101	0.094	0	0.555
S_HC (shares)	603	0.311	0.200	0.002	0.875
P_HC (shares)	603	0.347	0.179	0.001	0.871
T_HC (years)	603	0.330	0.301	0.001	1.618
S_HC (years)	603	2.098	1.464	0.019	6.893
P_HC (years)	603	4.073	1.746	0.277	8.989
AVG_HC (years)	603	6.500	3.151	0.405	13.126
$inflation$	603	0.383	2.071	-0.026	22.516
$trade$	603	0.760	0.462	0.090	4.039
fdi	603	0.025	0.030	-0.036	0.259
$credit$	603	0.475	0.405	0.014	2.480

Notes: Summary statistics refer to a sample of 106 countries between 1970-2010. g stands for TFP growth, calculated in five-year intervals; $ln(P)$ is the logarithm of the proximity to the frontier; T_HC (shares) refers to the percentage of tertiary schooling attained in population; S_HC (shares) to the percentage of secondary schooling attained in population; P_HC (shares) to the percentage of primary schooling attained in population; T_HC (years) refers to the average years of tertiary schooling attained; S_HC (years) to the average years of secondary schooling attained; P_HC (years) to the average years of primary schooling attained; AVG_HC (years) to the average years of schooling attained (this is the variable used in column 1 of Table 3.1); $inflation$ is defined as the annual percentage change in the cost of acquiring a basket of goods and services; $trade$ is the sum of exports and imports of goods and services as a percentage of GDP; fdi denotes the net inflows of foreign direct investment as a percentage of GDP; and $credit$ the domestic credit to private sector, again, as a percentage of GDP. For details, see Section 3.2.

CHAPTER 4

Brain Drain or Gain? The Structure of Production, Emigration and Growth*

4.1 Introduction

High-skilled people tend to emigrate from poorer countries in greater numbers than the low-skilled, raising the specter of a 'brain drain' that would leave these countries with less human capital and worse prospects for development.[1] Docquier and Rapoport (2012, p. 682), for example, report that high-skilled migration from developing to developed economies increased faster compared to that of overall migration towards OECD countries.[2] However, the opportunity to migrate increases the expected returns to education, thus improving the incentives for human capital formation and opening up the possibility of a 'brain gain'.

To determine which of these effects is more important, the existing literature on migration and human capital has typically tested whether larger high-skilled (i.e. university-educated) emigration leads to an increase in the number of high-skilled people, and found qualified support for this.[3] More specifically, this direct approach implies examining the effect high-skilled emigration rates have on human capital accumulation, captured by the growth in the proportion of high-skilled people in the native population. One important drawback of this direct approach, though, is

*For an earlier version of this chapter, see: Papakonstantinou and Inklaar (2014). We would like to thank Viola Angelini, Sorin Krammer, Marcel Timmer and seminar participants at the University of Groningen for helpful comments and suggestions.

[1]See Bhagwati and Hamada (1974) for early discussions and Docquier and Rapoport (2012) for a recent overview of this topic. This paper focuses on the migration-human-capital relationship, but migration has a broader range of effects on a country than just on the available amount of human capital.

[2]With high-skilled migrants, the authors mean tertiary-educated ones.

[3]See e.g. Beine, Docquier, and Rapoport (2001); Beine et al. (2008); Beine, Docquier, and Rapoport (2010); Beine et al. (2011) and Di Maria and Lazarova (2012).

that it ignores the impact on medium-skill levels,[4] while these can also be important for increasing a country's human capital. Another drawback is that positive effects that are farther removed in time are not attributed to the initial spur of migration. For instance, skill-biased technical change (SBTC) may increase demand for human capital after the initial 'brain gain'.

The contribution of our paper is to use a more indirect approach to test the relationship between migration and human capital, so that we need not specify precisely which types of migration lead to which type of human capital improvement and how fast.[5] We start from the empirical approach of Ciccone and Papaioannou (2009), who find that a large initial human capital endowment leads to specialization in human-capital-intensive industries.[6] We call this the education effect. After controlling for it, we find that countries with higher emigration rates also specialize in human-capital-intensive industries. We take this as evidence that countries with higher emigration rates increase their endowment of human capital at a faster rate than countries with lower emigration rates. This migration effect is also economically important as it is about one- to two-thirds as large as the education effect of Ciccone and Papaioannou (2009). Further analysis shows that the set of countries with the lowest initial levels of human capital benefits even more from migration, a finding that is supportive of our hypothesis and in line with the broader migration-human-capital literature. We also show that our findings for total migration can be traced to the migration of the high- *and* medium-skilled, with no positive effect from low-skilled migration. This means that our effect is not driven by the emigration of low-skilled people, which would also have raised average human capital levels, but instead points to the importance of improved incentives for human capital formation, i.e. a 'brain gain'.

Our sample covers up to 68 countries and 28 manufacturing industries and we analyze growth over the period 1980-2000. We employ a country-industry panel set-up, where we explain industry growth in value added or employment with an interaction of a country's emigration rate with an industry's knowledge intensity.[7] An important advantage of this approach is that reverse causality is less likely to be a problem, since we identify the net migration effect from the variation in growth across

[4]People that finish upper-secondary but not tertiary education.
[5]That indirectness is also a drawback, since those detailed links of the causal chain are important to establish which aspects of the relationship are important, when and where. We feel this is a price worth paying in that our indirect approach opens up new avenues for research.
[6]Romalis (2004) has shown similar results in the context of trade specialization.
[7]As well as country and industry fixed effects and a range of control variables.

industries within countries.[8] In contrast, most of the empirical studies on 'brain drain' have relied on cross-sectional samples, which limits the ability to draw "conclusive inferences regarding causality" (Di Maria & Lazarova, 2012, p. 942).

Our findings are robust to using value added or employment growth as dependent variables; to different measures of industries' knowledge intensity; to the use of different migration databases; and to measurement error in the migration data. We also show that our findings do not simply reflect that more open economies specialize in more knowledge-intensive activities. When we include alternative indicators of openness, such as openness to migratory inflows, trade and foreign direct investment (FDI), the effect of emigration on growth of knowledge-intensive industries is very similar.

Our paper proceeds as follows: Section 4.2 discusses the related literature. Section 4.3 introduces the empirical model, Section 4.4 presents the data and Section 4.5 the results. Section 4.6 puts forward points for discussion and Section 4.7 concludes.

4.2 Related Literature

Determining the effect of emigration on human capital is very relevant in view of human capital as a key determinant of economic growth. In this section we briefly discuss the literature, though we refer the reader to Docquier and Rapoport (2012) for a more extensive review of the 'brain drain/gain' debate.

International migration entails welfare implications and affects the economic performance of the sending country (Chen, 2009). More specifically, high-skilled emigration has a direct negative effect on the level of human capital as it deprives the home country of its high-skilled workforce, i.e. a 'brain drain' occurs. The economy not only loses workers that could be employed in the domestic production, but, partly, also its capacity to innovate and/or adopt new technologies (Marchiori, Shen, & Docquier, 2013). However, the literature identifies various feedback mechanisms through which (high-skilled) emigration could lead to increases in human capital, potentially benefiting the source economy and giving rise to a 'brain gain'. These feedback channels include remittances (Faini, 2007; Adams & Cuecuecha, 2013), return migration (Borjas, 1989; Faini, 2003) and technology diffusion via scientific networks formed by migrants (Kerr, 2008).

Furthermore, emigration improves the incentives to acquire (or upgrade one's)

[8]See also Rajan and Zingales (1998) on the relationship between financial development and growth. Using international patent citations, Kerr (2008) employs a similar approach to show how ethnic research communities in the US affect technology diffusion.

skills: if the opportunity to migrate improves the expected returns to education, the incentives to actually get an education improve, potentially leading to a 'brain gain'. Given that only part of a country's residents will eventually emigrate, the level of human capital need not decrease but could even increase with greater emigration. Mountford (1997) and Stark et al. (1997, 1998) were the first to theoretically establish the 'brain gain' argument based on the idea that "expectations about future migration opportunities affect education decisions" (Docquier & Rapoport, 2012, p. 701).

The greater availability of migration data has also triggered empirical research, at the macro-level (Beine et al., 2001; Faini, 2003; Beine et al., 2008; Docquier et al., 2008; Beine et al., 2010, 2011; Di Maria & Lazarova, 2012) and the micro-level (Gibson & McKenzie, 2011; Batista et al., 2012), to establish whether there is indeed an incentive effect, i.e. whether greater emigration opportunities lead to more schooling.[9] Although there is growing evidence in favor of the 'brain gain', there are still contradictory findings in the literature and the debate is far from settled. In the next sections, we turn to our approach to study the 'brain drain/gain'.

4.3 The Model

Our model to estimate the effect of emigration on growth of knowledge-intensive industries draws on the work of Ciccone and Papaioannou (2009) and takes the following form:

$$g_{s,i} = \beta_1 \cdot (M_s/P_s) \cdot KI_i + \beta_2 \cdot HC_s \cdot KI_i + \beta_3 \cdot X_i' \cdot Z_s + \beta_4 \cdot S_{s,i} + \lambda_s + \mu_i + \epsilon_{s,i} \quad (4.1)$$

where the dependent variable is the annual growth rate g of value added or employment in country of origin s in industry i during the 1980-2000 period; M_s/P_s is the ratio of the number of people that lived abroad to a country's population in 1980; KI_i is the knowledge intensity of industry i; HC_s is an indicator of the level of human capital in 1980 in country s and $S_{s,i}$ denotes the share of industry i in manufacturing value added or employment of country s in the beginning of the period. The inclusion of this variable allows us to control for initial differences in the size of various industries. We also control for other determinants of industry growth (physical capital, property rights and financial development) by interacting a country level variable (Z_s) with an industry level variable (X_i). Finally, λ_s and μ_i are country-

[9]This stream of (empirical macro) research is discussed in more detail in Section 4.6 where we compare our findings to those of the existing literature.

and industry-specific effects and residual growth is captured by $\epsilon_{s,i}$. The inclusion of country and industry effects means that we are comparing differential industry growth patterns within countries.

Compared with Ciccone and Papaioannou (2009), our model adds the migration term, $(M_s/P_s) \cdot KI_i$. Ciccone and Papaioannou (2009) find that β_2 is positive: a higher initial endowment of human capital leads to faster growth of knowledge-intensive industries. We focus on β_1, so whether migration has an effect on the growth of knowledge-intensive industries after the effect of the initial endowment of human capital has been accounted for. If there is a significant and positive effect, we take this as evidence that high-migration countries have increased their human capital at a faster rate than low-migration countries. This would correspond to a net 'brain gain', while a negative β_1 would imply a net 'brain drain'.

The model we use is an indirect method of identifying the effect of migration on human capital: we interpret a relationship between migration and the growth of knowledge-intensive industries as being driven by changes in human capital. An advantage of this indirect approach is that we do not need to precisely identify each link of the causal chain -from emigration of certain types of workers, to improved incentives for others to increase their human capital, to a particular net effect on total human capital. Instead, we simply note that to explain the observed growth pattern in high-emigration countries, human capital has to have changed in a particular direction. That does require carefully controlling for the initial human capital level, which we do following Ciccone and Papaioannou (2009). It also requires ascertaining that the emigration rate is not a proxy for a more general type of openness: if the economy is more open, it might more easily attract foreign investment and technology, stimulating growth in precisely the knowledge-intensive industries. We also do this in our analysis.

One other concern could be that we analyze the effect of total migration, rather than migration by skill type. This means that, say, a positive β_1 could be the result of predominantly skilled emigration leading to stronger incentives to get an education (i.e. the 'brain gain' argument) but it could also be the result of unskilled emigration that directly raises the average level of human capital of the origin country. Given the importance of skilled emigration, the 'brain gain' argument seems the most relevant one a priori, but to explicitly distinguish between these explanations we also split overall emigration into emigration by skill type.

4.4 Data

4.4.1 Industry growth

The dependent variable of our model ($g_{s,i}$) is the compound annual growth rate of value added or employment and refers to the country of origin s and the industry i over the 1980-2000 period.[10] Data on both value added and employment are obtained from the Industrial Statistics of the United Nations Industrial Development Organization (UNIDO, 2006). The 2006 edition of the INDSTAT3 database reports value added and employment data for 181 countries and 28 manufacturing industries (as well as for total manufacturing) for the period 1963 to 2004, organized at the three-digit International Standard Industrial Classification (ISIC) revision 2 level.

For a country to be included in our study, we first require that the UNIDO (2006) dataset has value added (or employment) information for it for at least ten years. We set 1980 as the first and 2000 as the last year to derive data for our analysis. We do so, as the knowledge intensity variable we use (KI_i) refers to the year 1980 and also, in order to allow for long-term effects of emigration on industry growth. If, however, the country-industry-specific value added (or employment) data are missing in 1980 and/or 2000 (or are zero or negative -the latter occurs in value added data but not often), we respectively use the value of the first available year after 1980 and/or before 2000 instead. We do so to allow for a broader sample of countries and industries in our analysis, as the country-industry coverage in UNIDO (2006) varies over the years (for example, more information is available for the 1980s compared to the 1990s). The number of years between the first and last observation is taken into account through the compound annual growth rate calculation. Furthermore, we require a difference of at least ten years between the first and the last observation, again in order to examine relatively long-term effects. Following Ciccone and Papaioannou (2009), for a country-industry observation to be included in the analysis, it should refer to a year (between 1980 and 2000) that has (non-missing) observations for at least ten industries. The data to construct our initial share ($S_{s,i}$) variable are also derived from UNIDO (2006). This variable is the ratio of value added (or employment) of a particular country and industry, in the first year for which data are available, to the

[10]Growth is computed as the compound annual growth rate (CAGR): $(Y_T/Y_t)^{1/T-t} - 1$ where Y_T is value added or employment in year T (the year for which value added or employment is last observed, but not after 2000) and Y_t is value added or employment in year t (the year for which value added or employment is first observed, but not before 1980). Y refers to country-industry-specific observations. We allow for a difference $(T - t)$ of no less than ten (and a maximum of twenty) in order to capture relatively long-term effects. See the main text for a detailed discussion of the variables construction.

total manufacturing value added (or employment) of the country in that same year.

Important to note at this point is that, in the UNIDO (2006) dataset, value added is expressed in current US dollars.[11] In order to appropriately deflate value added, one would need a country-industry-specific deflator, which is however largely unavailable for all countries and industries included in our analysis. Deflating the data using for example the US producer price index would still not take into account the country-industry specific inflation effect, controlling for which is rather unclear if and to what extent and direction would affect our results. For that reason, we also conduct the analysis using employment data, following Ciccone and Papaioannou (2009).

Our data are limited to the manufacturing sector of the economy, primarily for reasons of data availability. Furthermore, manufacturing industries may be driven more strongly by country-level supply-side factors (e.g. the endowment of human capital) than by country-level demand factors. Since manufacturing industries tend to sell their products not only domestically but also abroad, country-specific demand factors favoring one set of industries over another are less likely to play a dominant role. Since we are interested in identifying the effect of human capital, a supply-side factor, our manufacturing data can be helpful. In addition, manufacturing industries are not qualitatively different from other industries in terms of knowledge intensity. Both manufacturing and non-manufacturing industries can have a low knowledge intensity (e.g. wood products and construction) or a high knowledge intensity (e.g. electronics and financial services).

Following the literature that employs country-industry specifications (for example, Rajan & Zingales, 1998; Ciccone & Papaioannou, 2009), we exclude the United States from the sample since it acts as our benchmark country. A maximum of 66 countries is included in our regressions using value added and 68 in our employment specifications. A list of all countries included in the analysis can be found in Table C.1 of the appendix.

4.4.2 Knowledge intensity

Our empirical specification requires data on the knowledge intensity of manufacturing industries. Since information at the industry level is rather limited, we follow the literature that employs country-industry models (Rajan & Zingales, 1998; Ciccone & Papaioannou, 2009) and rely on data from a benchmark country to proxy global industry characteristics. The United States has been suggested as a natural

[11] As stated in the data documentation file, "data are originally stored in national currency values at current prices. The system allows conversion of currency data from national currency into current US dollars, using the average period exchange rates" (UNIDO, 2006).

choice, partly because US data are detailed, reliable and widely available, but also because US labor markets are less regulated (Ciccone & Papaioannou, 2009, p. 70). Therefore, inter-industry knowledge intensity differences are likely to better capture inter-industry technological differences. Since there is a technological reason why some industries have higher levels of knowledge intensity than others, we expect inter-industry technological differences to persist across countries. We are therefore confident that using the US as a benchmark yields good proxies for global industry characteristics. We are not claiming here that it is necessary for industries to experience the same *absolute* level of knowledge intensity across all countries as there are large differences in the magnitude of knowledge intensity across countries. Instead, we require a statement of the following type to hold: "If petroleum refineries require a larger level of knowledge intensity than leather products in the United States, it will also require a larger knowledge intensity level in India" (compare Rajan and Zingales (1998, p. 563)).

Data on the knowledge intensity of industries are from Ciccone and Papaioannou (2009). The authors compute three knowledge intensity measures for 28 US manufacturing industries in 1980: (i) the average years of schooling of employees (we call this variable $schooling_i$), (ii) the ratio of hours worked by employees with at least twelve ($secondary_i$) and (iii) at least sixteen ($college_i$) years of schooling to total hours worked by all employees. We use all three of them in the empirical analysis. The most knowledge-intensive industries are petroleum refineries, printing and publishing and industrial and other chemicals, while the least knowledge-intensive are leather products, wearing apparel, footwear and textiles.

4.4.3 Country data

The main variable of interest in our empirical specification is migration. We measure migration as the number of people living away from their home country relative to the sending country's population (M_s/P_s), both in 1980. This variable is interacted with the industry level knowledge intensity variable ($schooling_i$, $secondary_i$ or $college_i$) to form the main regressor of our analysis, the migration interaction, $(M_s/P_s) \cdot KI_i$. Migration data are from the Global Bilateral Migration Database (GBMD) (Özden, Parsons, & Schiff, 2011) and population data from the World Development Indicators (WDI, 2012). The GBMD provides information on bilateral migrant stocks for 226 countries. The figures are decennial and cover the period 1960-2000.[12] We focus on the

[12]The figures come from censuses (therefore they are decennial) but, when observations are missing, they are generated either by interpolation or by applying propensity measures (see, Özden et al. (2011)).

year 1980, which constitutes the beginning of the period under examination and, since the data are in a bilateral set-up, we sum them by country of origin over all receiving countries. Note that we thus use information on the stock of migrants. This is a measure that is consistent with our analysis since it not only includes individuals who leave the home country in 1980 but also those that left in earlier years. Data for total migration (based on Özden et al. (2011)) and total population (based on WDI (2012)) are presented in Table C.1 of the appendix (columns (2) and (6) respectively). The ratio of the two, which is the variable that, interacted with knowledge intensity, enters the regressions, reveals that the countries included in our benchmark specification have on average 5.8% of their population living abroad. The smallest share is that of Brazil (0.25%), while Jordan has the largest ratio of migration to population among our set of countries (28.8%).

We use the GBMD (Özden et al., 2011) for our analysis because, first, it includes information for the year 1980, the beginning of the period under examination, and, second, because it captures migration towards the whole world, rather than only towards OECD (Organisation for Economic Co-operation and Development) countries as the bulk of studies on 'brain drain' (Beine et al., 2001, 2008, 2010, 2011; Di Maria & Lazarova, 2012). However, to facilitate the robustness of our results, we later also use alternative migration databases (Dumont, Spielvogel, & Widmaier, 2010; United Nations Department of Economic and Social Affairs, 2012; Brücker, Capuano, & Marfouk, 2013). Our findings are broadly similar (see, Section 4.5.3).

We are also interested in controlling for the direct effect of human capital on growth of knowledge-intensive industries, to capture the effect that Ciccone and Papaioannou (2009) focus on. We use three different measures of human capital in 1980, taken from the Barro and Lee dataset on educational attainment (Barro & Lee, 2013, version 1.2): (i) average years of schooling (yr_sch_s in Barro and Lee (2013)), (ii) percentage of complete secondary (lsc_s) and (iii) percentage of complete tertiary (lhc_s) schooling attained in a country's population. We interact the industry level variable $schooling_i$ with the country level variable yr_sch_s, $secondary_i$ with lsc_s and $college_i$ with lhc_s and these form the human capital interaction variable.

Following the approach of Ciccone and Papaioannou (2009), we include other variables that may affect the specialization patterns of countries. These variables also take the form of industry characteristics interacted with country characteristics. Again, industry level variables refer to our benchmark country, namely the US.

We use industry capital intensity (k_i) interacted with country capital levels (K_s/Y_s) to control for the effect that a greater endowment of capital could lead to a specialization in more capital-intensive industries (following Romalis (2004)). We also interact an industry's contract intensity (c_i) with a country's property rights index (P_s), an approach also followed by Nunn (2007) and Chor (2010). In our specifications, P_s interacted with c_i shows whether countries with good property rights specialize in contract-intensive industries. Finally, we interact an industry's dependence on external finance (ed_i) with a country's level of financial development (FD_s). With this interaction, we are able to control for the Rajan and Zingales' (1998) argument that external finance dependent industries experience faster growth in countries with a higher level of financial development.

To ensure that the migration effect not only reflects a general impact of openness on industrial specialization, we also consider a number of control variables that capture different aspects of openness. Specifically, we consider the number of immigrants to the total population (IM_s/P_s), the ratio of exports to GDP (X_s), the ratio of exports plus imports to GDP (XM_s) and the ratio of FDI to GDP (FDI_s). Each of these variables is also interacted with industry knowledge intensity (KI_i) to establish whether openness leads to faster growth in knowledge-intensive industries. If the (e)migration variable only measures the general degree of openness of the economy, we would expect its coefficient to fall substantially as other measures of openness are included. If instead the coefficient on migration captures an additional effect, i.e. the incentive effect found elsewhere in the literature, the coefficient would not be much affected by the inclusion of alternative openness measures. Table C.2 of the appendix summarizes the full definition and sources for all variables used in the analysis.

4.5 Results

In this section, we first explore whether countries that have higher emigration subsequently experience faster growth in knowledge-intensive industries. Second, we consider whether the effect differs across countries. Third, we decompose migrants by their skill/education level and, fourth, we put our analysis through a number of robustness tests.

4.5.1 Initial migration shares and subsequent industry growth

Table 4.1 presents our results when growth in value added (columns (1), (2), (3)) and growth in employment (columns (4), (5), (6)) serve as the dependent variable of our model. The first row (Total Migration $\cdot KI_i$) reports the effect of initial migration on growth of knowledge-intensive industries (the β_1-coefficient). All specifications incorporate the control variables for the level of human capital, physical capital, property rights, financial development and the initial share of each industry in total manufacturing. Columns (1) and (4) use the industry level variable $schooling$ to measure industry knowledge intensity, columns (2) and (5) use $secondary$ and columns (3) and (6) use $college$.

We see that the coefficient for the migration interaction is positive and statistically significant at the 5% or 1% level across all specifications, with the exception of column (4) of Table 4.1 where it turns marginally insignificant (p=0.108).[13] In other words, countries with higher emigration rates show faster subsequent growth in knowledge-intensive manufacturing industries. This implies that better emigration prospects improve the level of human capital. Given the importance of skilled migration this could well be evidence for the 'brain gain' argument, where better opportunities to emigrate improve the incentives to get an education. This improvement in incentives would then outweigh the actual 'brain drain' from skilled workers leaving the country. Our results remain robust when we use both value added and employment growth, as well as to the inclusion of control variables and different measures of industries' knowledge intensity.

From the table we see that the human capital interaction also shows positive and statistically significant coefficients across all specifications, in line with Ciccone and Papaioannou (2009). This implies that the effect of migration on industry growth operates in addition to the effect of initial human capital. This in turn implies that higher emigration would lead to increases in human capital from a given initial level.

To get a sense of the size of the estimates, consider an industry with a high knowledge intensity (e.g. transport equipment) and one with a low knowledge intensity (e.g. pottery); a country with a high emigration share (e.g. Mauritius) and one with a low emigration share (e.g. Philippines) and also a country with high human capital levels (e.g. Denmark) and one with low human capital levels (e.g. Zimbabwe). When we examine growth in value added, our findings for the migration effect imply that the transport equipment industry grows 0.28 to 0.32 percentage points faster (on average per year) than the pottery industry when comparing growth in Mauritius to the Philippines. In comparison, the education effect shows that transport equipment grows 0.46 to 0.73 percentage points faster in Denmark than in Zimbabwe. The estimated employment regressions imply similar effects, with a migration effect of 0.22 to 0.27 percentage points and an education effect of 0.47 to 0.94 percentage points.[14]

Note further that the physical capital interaction variable is always positive but

[13] Note that when we use past values of migration as an instrument to alleviate measurement error, migration becomes significant, at the 5% level (see also Table 4.5 and the discussion below).

[14] These calculations are based on the results of all columns of Table 4.1.

Table 4.1: The Effect of Migration on Growth of Value Added and Employment

VARIABLES	Value Added			Employment		
	(1: *sch.*)	(2: *sec.*)	(3: *coll.*)	(4: *sch.*)	(5: *sec.*)	(6: *coll.*)
Total Migration $\cdot KI_i$	0.0575**	0.449**	1.049***	0.0436	0.417**	0.737**
	(0.0217)	(0.171)	(0.311)	(0.0268)	(0.202)	(0.369)
Human Capital $\cdot KI_i$	0.00175**	0.348**	1.586***	0.00222**	0.465**	1.807***
	(0.000817)	(0.154)	(0.573)	(0.000907)	(0.190)	(0.641)
Physical Capital $\cdot k_i$	0.00264	0.00262	0.00350	0.00288	0.00276	0.00405
	(0.00466)	(0.00468)	(0.00462)	(0.00422)	(0.00430)	(0.00424)
Property Rights $\cdot c_i$	-0.00567	-0.00581	-0.00562	-0.00613	-0.00631	-0.00610
	(0.00593)	(0.00597)	(0.00589)	(0.00454)	(0.00459)	(0.00452)
Financial Development $\cdot ed_i$	0.0369**	0.0367*	0.0405**	0.0344**	0.0338**	0.0392**
	(0.0182)	(0.0185)	(0.0184)	(0.0153)	(0.0155)	(0.0160)
Initial Share	-0.216***	-0.213***	-0.210***	-0.174***	-0.171***	-0.163***
	(0.0540)	(0.0540)	(0.0539)	(0.0397)	(0.0406)	(0.0386)
Observations	1,668	1,668	1,668	1,733	1,733	1,733
Countries	66	66	66	68	68	68
R-squared	0.134	0.132	0.134	0.135	0.133	0.132

Notes: Table 4.1 presents the results with growth in value added (columns (1)-(3)) and employment (columns (4)-(6)). Migration data are from the GBMD (Özden et al., 2011). Columns (1) and (4) use the industry level variable *schooling* to measure industry knowledge intensity, columns (2) and (5) the variable *secondary* and columns (3) and (6) the *college* one. See Table C.2 for variable definitions. All specifications include country and industry fixed effects. Robust standard errors, clustered by country, in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

never statistically significant, in line with the estimates of Ciccone and Papaioannou (2009). Second, the property rights interaction enters with a negative sign, although always insignificant. Intuitively, we would expect to find a positive coefficient for this variable, since literature suggests that countries with better institutions specialize in the more complex industries (Costinot, 2009). However, the exclusion of this variable did not alter our results. Furthermore, using other data sources (for example, the International Country Risk Guide Project and the Freedom House) to measure property rights did not affect our estimates. We opted for data from the Fraser Institute (Gwartney, Lawson, & Hall, 2012) since they cover the largest possible number of countries and the data are publicly available and widely used. Additionally, the country level variable we derive from Fraser Institute reflects the legal system and security of property rights and we believe that it matches better with contract intensity, the respective industry level variable, than, for example, a variable that measures civil liberties or political rights. Third, the finance interaction always enters with a positive and statistically significant sign (at the 10% or 5% level), in line with the results of Rajan and Zingales (1998). Finally, as was to be expected, the variable that controls for initial differences in the size of various industries (Initial Share, $S_{s,i}$) always has a negative and highly statistically significant coefficient.

4.5.2 Heterogeneity across countries

As a next step, we want to explore whether the 'brain gain' effect that we find is more pronounced in some countries rather than others. We find evidence that the countries with the lowest levels of human capital benefit the most from emigration, based on the following equation:

$$\begin{aligned} g_{s,i} = \beta_1 \cdot (M_s/P_s) \cdot KI_i + \beta_5 \cdot (M_s/P_s) \cdot KI_i \cdot \bar{H}_s + \beta_2 \cdot HC_s \cdot KI_i + \\ \beta_3 \cdot X_i' \cdot Z_s + \beta_4 \cdot S_{s,i} + \lambda_s + \mu_i + \epsilon_{s,i} \end{aligned} \tag{4.2}$$

In this equation we include an extra term, where the migration interaction is further interacted with the dummy variable $\bar{H}_s$. This dummy variable equals one for countries in the bottom quartile of the world human-capital distribution ($lhc_s < 0.0074$) as identified from all countries included in Barro and Lee (2013).[15] Coefficient β_1 now gives the effect of migration on growth of knowledge-intensive industries in countries in the top three quartiles of the human-capital distribution, while β_5 shows

[15]We experimented with alternative cut-off points and continuous interactions. These did not reveal clear patterns.

Table 4.2: The Effect of Migration and the Initial Level of Human Capital

VARIABLES	Value Added (1)	Employment (2)
Total Migration $\cdot KI_i$	1.206***	0.891**
	(0.301)	(0.354)
Total Migration $\cdot KI_i \cdot \bar{H}_s$	7.827**	7.802**
	(3.402)	(3.572)
Human Capital $\cdot KI_i$	2.340***	2.563***
	(0.605)	(0.695)
Observations	1,668	1,733
Countries	66	68
R-squared	0.139	0.139

Notes: Table 4.2 presents the results with growth in value added (column (1)) and employment (column (2)). Migration data are from the GBMD (Özden et al., 2011). In both cases, the industry level variable $college$ is used. The human capital dummy ($\bar{H}_s$) is equal to one for countries in the bottom quartile of the world human-capital distribution. See Table C.2 for variable definitions. All specifications include country and industry fixed effects, and also control for physical capital, property rights, financial development and the initial share (coefficients not reported). Robust standard errors, clustered by country, in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

the additional impact of migration in countries in the bottom quartile.

The results in Table 4.2 show that the low human capital countries experience a greater shift in specialization towards more knowledge-intensive industries, compared to countries with initially high levels of human capital. This can be explained from the idea that the lower quartile group of countries would more easily be able to increase its human capital level from the initially low base. However, the countries with higher levels of human capital still show significantly faster growth in knowledge-intensive industries, so in the analysis that follows, we use the results from Table 4.1 as our baseline.[16] The results are only shown for the $college$ measure, but are broadly similar for the other knowledge-intensity measures.[17] Note also that the specifications of Table 4.2 incorporate all control variables (physical capital, property rights, financial development, initial share). The coefficients are not reported here, due to brevity, but are similar in magnitude and statistical significance to those reported in Table 4.1.

[16]Note that the coefficients from equation 4.2 are both larger than the migration effect in Table 4.1 based on equation 4.1. This seems related to the inclusion of both country and industry dummies and the resulting smaller within-country variation of the migration-human-capital interaction variable. Multicollinearity can then push up both coefficients.

[17]Due to brevity, in the rest of the paper, we only present the results with the knowledge intensity variable $college$.

4.5.3 Skill-decomposition of migrants

The purpose of this subsection is twofold: first, we want to test the robustness of our findings to the use of an alternative migration database. Second, we want to examine which skill-groups of migrants drive our results. So far, we have studied the effect of total migration on industrial specialization and found that it leads to faster growth of knowledge-intensive industries. However, this effect could be systematically related to skilled emigration and improved incentives for human capital formation (i.e. 'brain gain') or to unskilled emigration, which directly raises the average level of human capital in a country. Distinguishing between these explanations requires a distinction between the skilled and the unskilled migration rate.

Table 4.3 presents the results using the migration database of Brücker et al. (2013). Data refer to migration towards 20 OECD destination countries in the year 1980 (while the GBMD covers migration to all countries).[18] One important advantage of this dataset is that, particularly for the year 1980, information is not based on imputations but almost entirely directly from censuses or population registers of the destination countries.[19] Columns (1) and (3) of Table 4.3 show the value added and employment regression respectively. Both columns refer to the total stock of migrants (Brücker et al., 2013) divided by the origin country's population in 1980 (WDI, 2012) and to the $college$ variable to capture industry knowledge intensity. These columns show that our earlier results, based on the GBMD (Özden et al., 2011), also hold with this alternative database.[20]

The main benefit of the Brücker et al. (2013) data is information on the skill composition of migrants. In columns (2) and (4) of Table 4.3, we separate the total migration rate into two groups, high- and medium-skilled migrants and low-skilled migrants. We combine the high- and medium-skilled in a single group, because migration of the two skill groups is so highly correlated (about 0.96) that separate effects cannot be

[18]The Brücker et al. (2013) dataset covers migration in the period 1980-2010 in five-years intervals and refers to the total number of foreign-born individuals aged 25 and over living in each of the following 20 OECD destination countries: Australia, Austria, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and the United States.

[19]The Netherlands is the only exception.

[20]We have also performed our analysis using data from Dumont et al. (2010) and the United Nations Department of Economic and Social Affairs (2012). The migration variable was positive and significant at the 5% or 10% level for the case of value added and positive but insignificant for the case of employment using these datasets. We present the results using the Brücker et al. (2013) dataset since it refers to the year 1980, the beginning of the period under examination. Data from Dumont et al. (2010) and the United Nations Department of Economic and Social Affairs (2012) refer to later years (1990 and 2000).

Table 4.3: Skill-decomposition of Migrants

VARIABLES	Value Added (1)	(2)	Employment (3)	(4)
Total Migration $\cdot KI_i$	1.265***		0.925*	
	(0.384)		(0.496)	
High- and Medium-skilled Migration $\cdot KI_i$		3.589***		2.316*
		(0.901)		(1.359)
Low-skilled Migration $\cdot KI_i$		-1.223		-0.581
		(0.948)		(1.312)
Human Capital $\cdot KI_i$	1.546**	1.420**	1.768***	1.696**
	(0.585)	(0.579)	(0.644)	(0.655)
Observations	1,668	1,668	1,733	1,733
Countries	66	66	68	68
R-squared	0.133	0.134	0.131	0.132

Notes: Table 4.3 presents the results with growth in value added (columns (1) and (2)) and employment (columns (3) and (4)). Migration data are from Brücker et al. (2013). In all cases, the industry level variable $college$ is used. See Table C.2 for variable definitions. All specifications include country and industry fixed effects, and also control for physical capital, property rights, financial development and the initial share (coefficients not reported). Robust standard errors, clustered by country, in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

identified.[21]

The group of high-skilled migrants have finished tertiary education, medium-skilled have secondary education and hold a high-school certificate and low-skilled are those with lower-secondary, primary and no schooling attainment. We simultaneously introduce in the regressions two variables: one that captures the share of high- and medium-skilled migrants (Brücker et al., 2013) to a country's population (WDI, 2012) in 1980 and one that refers to the ratio of low-skilled migrants (Brücker et al., 2013) to population (WDI, 2012) in that same year. In this way, we can contrast the coefficients of these variables and determine whether the 'brain gain' argument holds or whether our results are due to unskilled migration.

Table 4.3 shows the results for value added (column (2)) and employment growth (column (4)). The coefficient of high- and medium-skilled migration is positive and significant, whereas that of low-skilled migration is insignificant. This supports the 'brain gain' argument and shows that the high- *and* medium-skilled migrants drive the growth in human-capital-intensive industries. This suggests that migration

[21]Note that if we perform separate regressions, one for the high- and one for the medium-skilled migration, we still conclude that these two groups positively and significantly affect the growth of knowledge-intensive industries. However, such a strategy does not facilitate comparison between the different skill-groups of migrants and potentially suffers from omitted-variable bias.

opportunities for medium-skilled workers also have the type of incentive effects that migration opportunities for high-skilled workers do. Although not reported, the specifications of Table 4.3 incorporate all control variables (physical capital, property rights, financial development, initial share). Again, the coefficients are similar to those presented in Table 4.1.

4.5.4 Robustness analysis

We have shown that high-emigration countries experience faster growth in knowledge-intensive manufacturing industries. As a first step to determine the robustness of this finding, we test whether the migration effect might be due to openness in general, rather than due to the specific effect of emigration on human capital formation. In the following analysis, we use total migration from the GBMD (Özden et al., 2011).[22]

Table 4.4 shows the results using growth in value added (columns (1)-(4)) and employment (columns (5)-(8)) after the inclusion of various openness measures. We first, in columns (1) and (5) of Table 4.4, include an interaction term between industry knowledge intensity (KI_i) and the share of immigrants (the stock of foreign-born people) in a country's population (IM_s/P_s). High-emigration countries continue to experience higher growth in their knowledge-intensive manufacturing industries, as our positive and statistically significant β_1-coefficient demonstrates - though the significance of the effect on employment growth is reduced.

Alongside emigration, immigration also seems to be positively affecting the growth of human-capital-intensive industries. Note, however, that this effect disappears when the additional openness measures are introduced in the regressions (compare to columns (4) and (8) of Table 4.4). A positive and significant effect is to be expected if we assume that immigration increases the variety of skills and ideas in an economy and, thus, positively impacts productivity and income per capita (Ortega & Peri, 2012) and if highly-educated immigrants get employed in knowledge-intensive industries where they can put their skills into productive use. However, the latter is not always the case. There is often a mis-match between immigrants' skills and the type of job they get in the host country. Often, immigrants are over-qualified for the tasks they are asked to perform, for example due to language barriers, leading to a 'brain waste'.

[22]Using the Brücker et al. (2013) data produced broadly similar results. Including all openness controls, the β_1-coefficient is positive and significant at the 1% for the case of value added and at the 10% for the case of employment (compare to columns (4) and (8) of Table 4.4 respectively). The decomposition of migrants into high- and medium- versus low-skilled still reveals that it is the former group that drives the outcome. The coefficient for high- and medium-skilled migration is positive and highly statistically significant (1%) for the case of value added, and positive but insignificant for the case of employment.

Table 4.4: The Effect of Migration on Growth of Value Added and Employment: Robustness Analysis

VARIABLES	Value Added				Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Total Migration $\cdot KI_i$	0.962***	0.903***	0.862***	0.820***	0.657*	0.563*	0.571	0.509
	(0.315)	(0.287)	(0.306)	(0.295)	(0.372)	(0.333)	(0.353)	(0.333)
*Im*migration $\cdot KI_i$	0.725*			0.103	0.707*			-0.0466
	(0.416)			(0.300)	(0.421)			(0.344)
Total Trade $\cdot KI_i$		0.123***		0.0638		0.144***		0.114**
		(0.0418)		(0.0447)		(0.0406)		(0.0519)
FDI $\cdot KI_i$			3.921***	2.736*			3.561***	1.707
			(0.879)	(1.425)			(1.017)	(1.469)
Human Capital $\cdot KI_i$	0.904	1.566***	1.605**	1.472**	1.174	1.768***	1.833**	1.808**
	(0.713)	(0.530)	(0.613)	(0.730)	(0.781)	(0.584)	(0.695)	(0.767)
Observations	1,668	1,668	1,573	1,573	1,733	1,733	1,638	1,638
Countries	66	66	62	62	68	68	64	64
R-squared	0.135	0.138	0.134	0.134	0.133	0.139	0.133	0.136

Notes: Table 4.4 presents the robustness analysis results with growth in value added (columns (1)-(4)) and employment (columns (5)-(8)) as dependent variable. Migration data are from the GBMD (Özden et al., 2011). In all cases, the industry level variable *college* is used. See Table C.2 for variable definitions. All specifications include country and industry fixed effects, and also control for physical capital, property rights, financial development and the initial share (coefficients not reported). Robust standard errors, clustered by country, in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

This could explain an insignificant or negative effect of immigration on the growth of knowledge-intensive industries.

Second, we include in the regressions an interaction term between the share of total trade (exports and imports of goods and services) to a country's GDP (XM_s) and the knowledge intensity of industries (KI_i). Columns (2) and (6) of Table 4.4 present the results for value added and employment respectively. Total trade has a positive and significant impact on the growth of knowledge-intensive industries, a finding that is in line with Romalis (2004), who demonstrates a similar effect of trade on international specialization. Even so, our migration variable continues to enter the regressions with a positive and significant sign. A similar result was also reached when, instead of total trade, we interacted the share of exports (of goods and services) to a country's GDP (X_s) and the knowledge intensity of industries (KI_i). Columns (3) and (7) add FDI (FDI_s) as an alternative openness variable and although its interaction with industry knowledge intensity also influences specialization patterns, the migration effect remains very significant for growth in value added, but drops for growth in employment (p=0.110).

Finally, columns (4) and (8) of Table 4.4 include immigration, trade and FDI simultaneously. Not all openness variables are individually significant, likely due to their high correlations, but the migration effect remains very significant for value added growth. The significance of the effect on employment growth drops again, though (p=0.131).[23] This could indicate that part of the specialization in skill-intensive manufacturing industries is related to faster labor productivity growth. We also included the openness variables in the regressions from Table 4.2, and the finding that the migration effect is stronger in countries with initially low human capital levels is also robust to the inclusion of these additional variables.

Finally, we performed a number of additional robustness tests. We used the 1960 migration to population ratio as an instrument for the 1980 ratio. This follows a similar analysis in Ciccone and Papaioannou (2009) for human capital and aims to alleviate measurement error in 1980 migration levels.[24] Data were again derived from the GBMD (Özden et al., 2011) and the WDI (2012). The first stage regression revealed that this is a relevant instrument to use. The F-values (between 21.55 and 23.11) indicated that there is no weak identification problem. Table 4.5 presents the results with value added (column (1)) and employment (column (2)), and the indus-

[23] This is not the case with the Brücker et al. (2013) data, where the β_1-coefficient is positive and significant at the 10% for the case of employment.

[24] An alternative in the same spirit is to use the migration variable from the Brücker et al. (2013) database as an instrument for the variable from the GBMD (Özden et al., 2011) database. The results were very similar to those shown in Table 4.5.

Table 4.5: Instrumental Variable (IV) Regressions

VARIABLES	Value Added (1)	Employment (2)
Total Migration $\cdot KI_i$	1.072***	0.854**
	(0.370)	(0.411)
*Im*migration $\cdot KI_i$	0.0745	-0.0854
	(0.298)	(0.342)
Total Trade $\cdot KI_i$	0.0618	0.111**
	(0.0421)	(0.0484)
FDI $\cdot KI_i$	2.676*	1.634
	(1.383)	(1.403)
Human Capital $\cdot KI_i$	1.484**	1.828**
	(0.718)	(0.764)
Observations	1,573	1,638
Countries	62	64
R-squared	0.134	0.135
First Stage F-value	21.55	23.11

Notes: Table 4.5 presents the IV regressions results. Column (1) refers to the value added and column (2) to the employment regression. Migration data are from the GBMD (Özden et al., 2011). In all cases, the industry level variable $college$ is used. See Table C.2 for variable definitions. All specifications include country and industry fixed effects, and also control for physical capital, property rights, financial development and the initial share (coefficients not reported). Robust standard errors, clustered by country, in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

try level variable $college$. The conclusion that we reach also after the instrumental variable (IV) regression is that high-emigration countries experience higher growth in their knowledge-intensive industries. Note, furthermore, that by alleviating measurement error through the IV regressions, migration has again turned significant for employment growth.

As an additional robustness test, we also excluded every country and industry one-by-one. This had no effect on the overall results though for a few combinations of omitted countries, industries and knowledge intensity measures, significance would drop.[25] The specification where we allow for a differential effect in low human capital countries remained unaffected to the exclusion of each and every country or industry.

[25] Value added regressions using the $college$ variable remained robust throughout.

4.6 Discussion

Analyzing the effects of migration on industrial specialization, we conclude that industries that rely heavily on human capital grow faster in high-emigration countries and that this relationship is driven by high- and medium-skilled migrants. Our study differs from the existing empirical 'brain drain/gain' literature (e.g. Beine et al., 2001, 2008; Docquier et al., 2008; Beine et al., 2010, 2011; Di Maria & Lazarova, 2012) in that we infer an effect on country human capital from observing specialization in knowledge-intensive industries rather than directly testing for the effect of migration on human capital formation. Our conclusions are also different, in part. In contrast to most studies we find that, although stronger among low-human-capital countries, a 'brain gain' effect dominates all countries. We argue that there are two complementary explanations for this: the broader view on human capital we adopt and the self-reinforcing effects of SBTC.

Overall, the recent empirical macro-literature provides some evidence for the 'brain gain'. However, the number of origin countries that gain (or lose) from emigration and the magnitude of these gains (or losses) vary. Examining 37 developing countries, Beine et al. (2001) find a positive and significant impact of gross emigration on human capital, particularly for low-GDP countries. In a larger sample of countries (127) and using tertiary (rather than total) emigration, Beine et al. (2008) also find evidence for a 'brain gain'. It is the countries with low levels of human capital and low emigration rates that gain the most from high-skilled emigration (e.g. China, India, Indonesia, Brazil, Egypt, Bangladesh) but, since the absolute gains outweigh the absolute losses, the developing world benefits as a whole. On the contrary, Docquier et al. (2008) reach more pessimistic conclusions, as they find that high-skilled emigration negatively impacts the post-secondary-educated population in the developing world. Studying the effect of migration on the level and the composition of human capital, Di Maria and Lazarova (2012) also conclude that emigration has potentially detrimental impacts on economic growth, depending on a country's level of technological sophistication. Finally, in a panel set-up, Beine et al. (2011) provide evidence for a 'brain gain', particularly for low-income countries.

We find that the positive effects of emigration on industrial specialization accrue to all countries. One explanation relates to the definition of human capital we adopt. To begin with, we do not equate 'brain drain' with high-skilled emigration. We rather focus on all migrants and show that it is not only the high- but also the medium-skilled ones that trigger the growth in knowledge-intensive industries. This distinguishes our paper from the recent literature (e.g. Beine et al., 2011) and is more in line with the argument of Beine et al. (2001) that 'brain drain' implies migrants with above-average skills rather than "engineers, physicians, scientists or other very highly skilled professional" (p. 276).

By the same token, specialization in human-capital-intensive industries relates to increases in the broader human capital rather than only in the tertiary-educated population. If, for example, a population changes from one where primary education is most prevalent to one where secondary education is dominant, this qualifies, by all accounts, as an increase in the stock of human capital of the economy. Those secondary-schooled workers may not be "sufficiently skilled" for a knowledge-intensive industry in a country close to the technological frontier, but they may well be qualified in less-advanced economies. As a result of this increase in human capital endowments, relatively knowledge-intensive industries will grow faster. Focusing solely on tertiary education, by looking at high-skilled emigration and how it affects high-skilled human capital at home, leaves out any changes occurring at lower levels, underestimating the full extent of skill upgrading that is taking place.

The typical model in the 'brain drain/gain' literature uses a fairly stylized production sector, which is then used to inform the likely effects of migration. Furthermore, the typical direct empirical test of the link between greater emigration and increases in schooling is unlikely to capture any indirect effects. The work of Acemoglu (1998, 1999, 2002) suggests that modeling a skill-intensive and a labor-intensive sector will often lead to SBTC. Under SBTC, any increases in human capital will lead to greater demand for skilled workers and provide the incentives for further increases in the supply of human capital. A single-sector model will not give rise to such dynamics. Furthermore, a direct test of the effect of emigration on human capital may relate to the first round of human capital increases, but if there is SBTC, there is a plausible argument that the further endogenous increases in demand for and supply of human capital can also be related to greater initial emigration. Our approach attributes the full effect to emigration since we look at the end result of human capital increases and sectoral specialization after, a maximum of, two decades.

4.7 Concluding Remarks

International migration is a major aspect of globalization, central in both academic and policy-related debates. In this paper, we have studied the impact of emigration on the human capital of sending countries by analyzing industry growth patterns and have relied on a dataset that covers up to 68 countries and 28 manufacturing industries over the period 1980-2000.

Our results show a 'brain gain', whereby high-emigration countries see faster growth in knowledge-intensive manufacturing industries. This specialization effect is only to be expected if the *net* effect of migration on human capital is positive. The size of this effect is considerable, at about one- to two-thirds as large as the effect of initial human capital levels on specialization, the education channel of Ciccone and Papaioannou (2009). Both high- and medium-skilled migration drive the growth of knowledge-intensive industries. Furthermore, countries with initially low levels of human capital benefit substantially more. Our results are not driven by general economic openness, as controlling for immigration, trade and FDI does not alter our conclusions. The source of migration data that is used does not drive our results either. Compared with the existing literature, we find that a broader group of countries benefits, in part (we argue) because we do not solely focus on tertiary-educated migrants and human capital and because our approach would also capture the effects of SBTC.

Important to note is also how the changes in the production structure that we find relate to economic growth. Hausmann, Hwang, and Rodrik (2007) have shown that the type of goods a country specializes in matters for its economic performance. Specialization in goods that rich countries export induces faster growth than specialization in other goods. From their analysis, we can thus infer a connection between the production of more sophisticated goods and economic growth. Our analysis also relates to these broader consequences for the economy, as it shows how migration affects the production structure and shifts specialization towards sophisticated industries, which in turn can have favorable implications for economic development.

The limitations of our study also need to be addressed. To begin with, we analyze industry growth patterns rather than directly linking (high-skilled) migration to increases in the number of high-skilled people. The benefits of this strategy have already been outlined, but there is also a limitation to it. The lack of specificity on the precise links along the causal chain from emigration to specialization also means that it may be some other variable that is driving or moderating the effect. Furthermore, high-skilled emigration impacts areas which our study does not cover. Bhargava et al. (2011), for example, examine how human development indicators (e.g. health outcomes) are affected by physician emigration in developing countries and do not find compelling evidence for a 'brain gain'.

Important to clarify at this point is that our study finds an average positive effect of emigration on industry growth, *for the countries that form our sample*. This is not to say, however, that an indefinite outflow of high-skilled people won't entail detrimental effects, as it is hard to imagine how a country that is completely drained from its high-skilled workforce will manage to benefit from it. Although we were not able to detect it in our sample, there might still be a non-linear effect with respect to the size of emigration and a respective threshold beyond which emigration increases no longer have positive growth effects. What matters is the speed at which high-skilled people emigrate compared to that at which new high-skilled people are "generated". The latter is naturally affected by the access to and quality of a country's educational system which can facilitate the creation of new skills and talents.

There are also extensions that could be applied to our paper. One could, for example, incorporate the role of the informal sector in the framework. The informal sector accounts for a large share of the labor force, particularly in developing countries (Goldberg & Pavcnik, 2004), and figures prominently in recent economic debates. Our focus is currently on the formal manufacturing sector but we would expect emigration, which induces growth of knowledge-intensive industries, to lead to a shift from the informal to the formal sector. Since unskilled workers are more likely to participate in the informal sector, as migration facilitates the accumulation of human capital, the formal sector would expand to the detriment of the informal. Accordingly, the services sector could also provide an avenue for future research.

Overall, our findings have important implications for both the developing and the developed world. Bhagwati and Dellalfar (1973) have suggested that a "tax on brains" could be imposed on the higher income earned by the migrant in the host country. Sending countries would receive this tax as a compensation for the negative externalities of (high-skilled) emigration (Docquier & Rapoport, 2012). However, a "tax on brains" would, likely, act as a counter-incentive for migration and our analysis implies that restricting international mobility might prevent sending countries from reaping the maximum of emigration's benefits. Furthermore, it is often claimed that higher-education expenditures in traditional emigration countries should be reduced since migrants are educated at the expense of their government before they leave the country. Even so, we have shown that emigration generates changes in the production structure that could result in favorable implications for economic development. Such a finding is very relevant for both migration- and education-related policies.

APPENDIX C

Appendix Chapter 4

Table C.1: List of Countries Included in the Analysis and Key Figures

Country	Migration: total GBMD	Migration: total Brücker et al. (2013)	Migration: high- and medium-skilled Brücker et al. (2013)	Migration: low-skilled Brücker et al. (2013)	Population: total WDI (2012)
Argentina	315269	104681	62213	42468	28131040
Australia	222632	116553	65888	50665	14692000
Austria	618810	475561	303756	171805	7549433
Bangladesh	5047223	33023	18820	14203	80624423
Barbados	68467	53860	31955	21905	248796
Belgium	414680	212693	87101	125592	9859242
Bolivia	166734	15689	10250	5439	5352649
Botswana	79600	557	148	409	996211
Brazil	302935	60836	32373	28463	121711864
Cameroon	138279	8683	4558	4125	9109727
Canada	1211849	765558	475352	290206	24593000
Central African Republic	37732	1000	600	400	2273630
Chile	401856	69173	47292	21881	11178817
China	4174988	353506	190792	162714	981235000
Colombia	719142	105073	64755	40318	26874906
Costa Rica	51792	20198	12262	7936	2343345
Cyprus	154456	95406	58402	37004	685510
Denmark	249239	146827	80552	66275	5123027

Ecuador	148834	63212	34951	28261	7957811
Egypt	1030182	135219	94170	41049	44952497
El Salvador	159304	58670	24136	34534	4656263
Finland	344332	272761	118829	153932	4779535
France	1423049	394504	246033	148471	55166046
Ghana	380565	35998	21794	14204	10922708
Greece	1183275	696743	208807	487936	9642505
Guatemala	97580	39994	17038	22956	7036484
Honduras	81455	24671	12772	11899	3627640
Iceland	19147	9275	5043	4232	228138
India	7582096	647840	401425	246415	700058589
Indonesia	489804	137875	59543	78332	150820044
Iran	529305	138787	103530	35257	38576541
Ireland	911750	865101	440364	424737	3412800
Israel	379720	69949	49611	20338	3878000
Italy	4510364	2870494	645551	2224943	56433883
Jamaica	426824	319424	183263	136161	2133000
Japan	602467	210892	159699	51193	116782000
Jordan	628401	28722	18612	10110	2181000
Kenya	318867	67241	38585	28656	16267558
Malawi	263950	4114	1806	2308	6239898
Malaysia	409630	53213	38310	14903	13832586
Mauritius	66983	37380	17955	19425	966000
Mexico	2579330	1302092	282826	1019266	68776411
Netherlands	726627	510463	313483	196980	14149800
New Zealand	236982	129900	90572	39328	3113000
Norway	167770	128230	56513	71717	4085620
Pakistan	3970210	196355	82955	113400	80492664
Panama	108197	42371	31332	11039	1953029
Peru	134083	51247	37745	13502	17286832
Philippines	980831	438896	327956	110940	47063923
Portugal	1872021	878851	93776	785075	9766312
Republic of Korea	1089819	196121	149829	46292	38124000
Senegal	213314	23123	3085	20038	5414070
Singapore	150803	24465	15349	9116	2414000
South Africa	249121	87010	56809	30201	27576000
Spain	1900957	831694	142968	688726	37439035

Sri Lanka	397135	43315	27114	16201	14747000
Sweden	221174	139396	72038	67358	8310531
Switzerland	326381	136915	84242	52673	6319408
Syria	306846	41791	22688	19103	8906543
Thailand	134235	39150	27259	11891	47482643
Trinidad and Tobago	112085	84284	57049	27235	1078200
Tunisia	511902	196448	28992	167456	6384000
Turkey	2392038	1550173	310006	1240167	44105216
United Kingdom	4154492	2658721	1454055	1204666	56314216
Uruguay	180508	20760	11509	9251	2914683
Venezuela	158428	24460	18270	6190	15036273
Zambia	141306	4736	3765	971	5775165
Zimbabwe	222094	13065	7059	6006	7289463

Notes: Table C.1 presents the countries included in the analysis (column 1), as well as absolute numbers for: total migration based on the GBMD (Özden et al., 2011) (column 2); total migration based on Brücker et al. (2013) (column 3); high- and medium-skilled migration based on Brücker et al. (2013) (column 4); low-skilled migration based on Brücker et al. (2013) (column 5); as well as total population from the WDI (2012) (column 6). Column (3) is the sum of columns (4) and (5). Figures refer to the maximum number of countries that enters our specifications.

Table C.2: Summary of the Variables, their Names, Definitions and Sources

Variable	Acronym	Definition	Source
Country-Industry Level Variables			
Growth of Value Added (Employment)	$g_{s,i}$	Annual growth rate of value added (or employment) in country s and industry i over 1980-2000.	UNIDO (2006)
Initial Share	$S_{s,i}$	The share of industry i in manufacturing value added (or employment) of country s in the beginning of the period.	UNIDO (2006)
Industry Level Variables			
Knowledge Intensity (KI_i)	$schooling_i$	Average years of schooling of employees in the US in 1980.	Ciccone and Papaioannou (2009)

	$secondary_i$	Ratio of hours worked by employees with at least 12 years of schooling to total hours worked by all employees in the US in 1980.	Ciccone and Papaioannou (2009)
	$college_i$	Ratio of hours worked by employees with at least 16 years of schooling to total hours worked by all employees in the US in 1980.	Ciccone and Papaioannou (2009)
Capital Intensity	k_i	Share of real capital stock to total value added in the US in 1980.	Bartelsman and Gray (1996); Ciccone and Papaioannou (2009)
Contract Intensity	c_i	The cost-weighted proportion of an industry's inputs that are highly differentiated and can therefore be expected to require relationship-specific investments in the production process in the US in 1997.	Nunn (2007); Ciccone and Papaioannou (2009, p. 71)
External Finance Dependence	ed_i	The fraction of capital expenditures not financed with cash flows from operations in the US for the period 1980-1989.	Kroszner, Laeven, and Klingebiel (2007, p. 200)
Country Level Variables			
Total Migration	M_s/P_s	Ratio of the number of people that in 1980 lived abroad to a country's population.	GBMD (Özden et al., 2011); WDI (2012); Brücker et al. (2013)
High- and Medium-Skilled Migration	$(H\_M_s + M\_M_s)/P_s$	Ratio of high- and medium-skilled migrants to population in 1980.	WDI (2012); Brücker et al. (2013)
Low-Skilled Migration	L_M_s/P_s	Ratio of low-skilled migrants to population in 1980.	WDI (2012); Brücker et al. (2013)
Human Capital	yr_sch_s	Average years of schooling in 1980.	Barro and Lee (2013, version 1.2)

	lsc_s	Percentage of complete secondary schooling attained in a country's population in 1980.	Barro and Lee (2013, version 1.2)
	lhc_s	Percentage of complete tertiary schooling attained in a country's population in 1980.	Barro and Lee (2013, version 1.2)
Physical Capital	K_s/Y_s	Capital-output ratio in 1980.	Klenow and Rodríguez-Clare (2005)
Property Rights	P_s	Index for the legal system and security of property rights in 1985.	Gwartney et al. (2012)
Financial Development	FD_s	The domestic credit to private sector relative to GDP in the year 1980.	WDI (2012)
Immigration	IM_s/P_s	Share of immigrants (the stock of foreign-born people) in a country's population in 1980.	GBMD (Özden et al., 2011); WDI (2012)
Exports	X_s	Exports of goods and services as a share to GDP in 1980.	Heston, Summers, and Aten (2012); United Nations Statistics Division (2012)
Total Trade	XM_s	Exports and imports of goods and services as a share to GDP in 1980.	Heston et al. (2012); United Nations Statistics Division (2012)
Foreign Direct Investment	FDI_s	Net inflows of FDI to GDP in 1980.	WDI (2012)
Human Capital Dummy	$\bar{H}_s$	Dummy variable equal to one for countries in the bottom quartile of the world human-capital distribution ($lhc_s < 0.0074$), zero otherwise. The quartile is identified based on all countries included in Barro and Lee (2013, version 1.2) and refers to the year 1980.	Barro and Lee (2013, version 1.2)

CHAPTER 5

Samenvatting (Dutch Summary)

Er is veel consensus in de literatuur met betrekking tot het belang van onderwijs, dat wil zeggen menselijk kapitaal. Zowel voor de economie als voor de maatschappij als geheel heeft onderwijs grote waarde: het genereert geldelijke omzet, maar ook sociaal rendement, zoals effecten op misdaadcijfers, volksgezondheid, sterftecijfers, vruchtbaarheid, politieke participatie (bv. Moretti, 2005; Lochner, 2011). Daarom speelt onderwijs zo'n centrale rol in het economische en politieke debat.

Dit proefschrift onderzoekt het belang van onderwijs, en dus menselijk kapitaal, voor het faciliteren van snellere economische groei. Het heeft een plaats binnen een brede, recente opleving van literatuur waarin gezocht wordt naar een beter begrip van menselijk kapitaal en de effecten ervan op groei (bv. Fraumeni, 2015; Lucas, 2015). Er bestaan verschillende theorieën met betrekking tot de manieren waarop menselijk kapitaal economische groei beïnvloedt (bv. Nelson & Phelps, 1966; Mankiw et al., 1992). In empirisch onderzoek wordt gewoonlijk naar deze relatie gekeken door middel van omvangrijke datasets, empirische opstellingen en methodologieën.

Elk hoofdstuk van dit proefschrift beantwoordt een specifieke vraag met betrekking tot de effecten van menselijk kapitaal op economische groei.

Een standaard uitgangspunt bij groei- of ontwikkelingsrekening is de aanname van constante arbeidsdiensten per gewerkt uur. Deze aanname kan echter ongeldig blijken wegens vintage effecten: pas afgestudeerden wijken van eerdere cohorten af met betrekking tot de arbeidsdiensten per gewerkt uur die zij leveren. Dit kan bijvoorbeeld het gevolg zijn van betere scholing of 'on-the-job training'. Bowlus en Robinson (2012) hebben aangetoond dat vintage effecten in de Verenigde Staten aanzienlijk zijn (zo zijn bijvoorbeeld de arbeidsdiensten per gewerkt uur van hooggeschoolde werknemers in de loop van de tijd toegenomen). Daardoor wordt de groei van menselijk kapitaal onderschat en die van de totale factor productiviteit (TFP) overschat.

In **Hoofdstuk 2** volg ik de aanpak van Bowlus en Robinson (2012) en gebruik ik een nieuwe maatstaf voor menselijk kapitaal waarin rekening wordt gehouden met vintage effecten. Op deze manier laat ik de veronderstelling los dat een jaar op school een constante hoeveelheid menselijk kapitaal oplevert. De introductie van deze vintage effecten bij het berekenen van de groei verhoogt de arbeidsdiensten van hooggeschoolde werknemers in de Verenigde Staten en het Verenigd Koninkrijk vergeleken met de standaard groeirekening. Daarentegen is de bijdrage van menselijk kapitaal aan groei in continentale Europese landen (Frankrijk, Duitsland, Italië, Nederland en Spanje) tussen 1995 en 2005 gedaald. In die periode speelden vintage effecten van menselijk kapitaal een grote rol in de verklaring van het verschil in de trans-Atlantische productiviteitsgroei.

Het beschrijven van groei en ontwikkeling mag een belangrijk diagnostisch middel zijn, het negeert alle indirecte bijdragen van menselijk kapitaal. Deze methodieken houden geen rekening met interacties tussen efficiëntie en fysieke als ook menselijke kapitaalopbouw (Caselli, 2005; Barro & Lee, 2015). Als gevolg hiervan wordt de rol van menselijk kapitaal niet volledig meegewogen. Deze indirecte kanalen impliceren dat er externaliteiten bestaan.

Externaliteiten van menselijk kapitaal komen tot uiting als de maatschappelijke rendementen van onderwijs hoger zijn dan de persoonlijke rendementen (bv. Krueger & Lindahl, 2001). Dit betekent dat de voordelen van menselijk kapitaal niet beperkt blijven tot de persoon die onderwijs krijgt, maar dat ze ook merkbaar zijn voor medewerkers, de gemeenschap, het land en zelfs andere landen. Als alleen het persoonlijke rendement van onderwijs wordt meegenomen, zou dat dus tot een onderwaardering van het belang van menselijk kapitaal leiden. Dat kan weer een verkeerde invloed hebben op overheidsbeleid ten aanzien van onderwijsvoorzieningen.

Het bestaan van externaliteiten komt op twee manieren in de literatuur tot uitdrukking: de eerste heeft te maken met de “spill-over” van menselijk kapitaal die de productiviteit van anderen kan verhogen (bv. Lucas, 1988) en de tweede koppelt menselijk kapitaal aan technologische vooruitgang en adoptie van nieuwe technologie (bv. Nelson & Phelps, 1966; Romer, 1990). Onderwijs maakt werknemers meer innovatief en daardoor bepaalt het menselijk kapitaal het niveau van technologische vooruitgang. Bovendien zijn minder geavanceerde economieën afhankelijk van de adoptie (imitatie) van nieuwe en meer productieve technologieën om bij te blijven. Menselijk kapitaal is dus instrumenteel in dit proces (Nelson & Phelps, 1966; Benhabib & Spiegel, 1994, 2005).

In **Hoofdstuk 3** kijk ik opnieuw naar het vermogen van menselijk kapitaal om externaliteiten te genereren door middel van technologische vooruitgang en adoptie van technologie. Ik wijk van de veronderstelling af, dat de bijdrage van menselijk kapitaal kan worden gemeten aan de persoonlijke opbrengst die tot uitdrukking komt in het loonstrookje. Om potentiële externaliteiten op te sporen, gebruik ik een econometrische methode die menselijk kapitaal met de totale factor productiviteit (TFP) verbindt. Empirisch onderzoek over dit onderwerp heeft gemengde resultaten opgeleverd (bv. Vandenbussche et al., 2006; Inklaar et al., 2008). De bijdrage van hoofdstuk 3 ligt in het gebruik van state-of-the-art TFP-data, waar het privé-rendement van scholing uit is gehaald. Dat maakt het mogelijk om conclusies te trekken over het bestaan van externaliteiten.

Uit mijn analyse komt een ruimer bestaan van externaliteiten naar voren dan uit de literatuur tot nu toe. Externaliteiten worden gegenereerd door tertiair opgeleide mensen en hangen in hoge mate af van het niveau van de technologische ontwikkeling van een land. Ik vind ook bewijs dat niet alle soorten/niveaus van onderwijs (tertiair, secundair, primair) dezelfde invloed hebben op de TFP-groei. De samenstelling van menselijk kapitaal is belangrijk.

Handel, FDI en migratie vormen de globaliseringskrachten/-kanalen waardoor technologie wordt verspreid over verschillende landen. Menselijk kapitaal faciliteert deze verspreiding door zijn effect op de absorptiecapaciteit van de economie (bv. Keller, 2004). In het geval van migratie ligt het ingewikkeld: als mensen landsgrenzen oversteken, wordt het niveau van menselijk kapitaal van zowel het thuis- als het gastland beïnvloed. De richting waarin het menselijk kapitaal van het thuisland wordt beïnvloed, is a priori onbekend. Er zijn zowel negatieve als positieve krachten: aan de ene kant wordt het menselijk kapitaal negatief beïnvloed als hooggeschoolden migreren ('brain drain'). Aan de andere kant is er steeds meer bewijs dat emigratie de vorming van menselijk kapitaal in het thuisland bevordert via feedback mechanismen zoals terugkerende migranten, overgemaakt geld, netwerken en stimulerende effecten ('brain gain'). Gezien de centrale rol van menselijk kapitaal voor economische groei, is het van groot belang om uit te zoeken hoe migratie de richting daarvan beïnvloedt.

Uiteindelijk ligt er dus een empirische vraag: wat is het effect van emigratie op het menselijk kapitaal van het thuisland? Emigratie kan de prikkels verbeteren om vaardigheden te verwerven of te verbeteren: als de mogelijkheid om te migreren de verwachte opbrengsten aan onderwijs verbetert, worden de prikkels om een opleiding te krijgen sterker en dat leidt tot een toename van het menselijk kapitaal in het thuisland. Mountford (1997) en Stark et al. (1997, 1998) hebben als eersten het idee ontwikkeld dat "verwachtingen over toekomstige migratiekansen invloed hebben op onderwijsbeslissingen" (Docquier & Rapoport, 2012, p. 701).

In **Hoofdstuk 4** onderzoek ik potentiële *internationale* "spill-overs" van menselijk kapitaal. Ik analyseer de impact van migratie op het menselijk kapitaal van het thuisland en kom tot de conclusie dat landen met een hogere emigratie van vakbekwame werknemers een snellere groei in hun kennisintensieve industrieën laten zien. Mijn bevindingen over de totale migratie laten zich met name herleiden tot de migratie van zowel hoog- als middelhoogopgeleide werknemers, maar tonen geen positief effect van de migratie van laaggeschoolden. Dit suggereert, wellicht verrassend, een 'brain gain' in plaats van 'brain drain'.

Samenvattend kunnen we zeggen dat we veel weten over de mogelijke voordelen -monetair en niet-monetair- van onderwijs op zowel individueel als nationaal en zelfs internationaal niveau. Verder onderzoek kan individuen en de samenleving als geheel helpen om de voordelen en de kosten beter tegen elkaar af te wegen en beleidsmakers een richtlijn in handen te geven.

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