Agglomeration, globalization and regional labor markets

Micro evidence for the Netherlands

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Agglomeration, globalization and regional labor markets

Micro evidence for the Netherlands

ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad Doctor aan
de Vrije Universiteit Amsterdam,
op gezag van de rector magnificus
prof.dr. L.M. Bouter,
in het openbaar te verdedigen
ten overstaan van de promotiecommissie
van de Faculteit der Economische Wetenschappen en Bedrijfskunde
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in het auditorium van de universiteit,
De Boelelaan 1105

door

Stefan Pieter Theodorus Groot

geboren te Enkhuizen

promotoren: prof.dr. H.L.F. de Groot
prof.dr. P. Rietveld

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PREFACE

Many PhD theses revolve around a single concept. This one is about two. The original idea was that the topic would be the labor market effects of globalization. However, while being stationed at a spatial economics department, it soon turned out that many of my colleagues were quite thrilled about the regional dimension of economic phenomena. Furthermore, the first three years of the four-year project were marked by an abundant availability of micro data on agglomeration, while far less data related to globalization were available. The end result is that this thesis is as much about agglomeration as it is about globalization, or maybe even more. However, the two topics are not as distinct as it may seem on first sight: both are strongly related to the division of labor, and both share that their evolution has been – to a considerable extent – shaped by technological progress. Most of the data used in this thesis cover 2000–2008, a time of turbulent change in international trade, and almost exploding use of computers and the internet.

Not only the contents of the thesis have ended somewhat different from what I expected, the same holds for the writing process. When I started the project, I had expected to spend my time on reading papers about one narrow topic, writing papers about one narrow topic, and then hopefully after four years there would be enough material to fill a book. What followed – to my great pleasure and relief – was a heterogeneous mix of activities, together with colleagues at VU University, the Netherlands Bureau for Economic Policy Analysis (CPB) and sometimes Statistics Netherlands (CBS). In addition to working on scientific research, I enjoyed my involvement in teaching and performing some contract research. Though the lack of focus sometimes worried me, the end result has positively surprised me in the sense that the different chapters seem to fit together rather well. And it is the end result that counts. Furthermore, I have always considered myself a generalist, and have very much liked the opportunity to expand my knowledge on a diverse range of topics.

One of the most enjoyable elements of working as a scientist has been working together with so many different people. Scientific work is not done in isolation, but rather as a process of cooperation. The many discussions with colleagues about economics and other intellectual matters – whether it was in the

Mensa or while working on a project – always interested me. I therefore like to sincerely thank the many colleagues I have worked with during the past years, or who have commented on my work. I would like to thank Platform31 and the Netherlands Bureau for Economic Policy Analysis for financial and material support, and Statistics Netherlands for making available the micro data. Without the involvement of these three institutions, this thesis would not have been possible. But most of all, I would like to thank my supervisor, Henri de Groot, for his many motivating and inspiring ideas, and his always constructively critical comments.

Even though economists have recognized the value of the domestic and international division of labor since well over two centuries ago, opposing the free movement of people across space as well as international trade has remained fairly common. My findings add to the evidence that agglomeration and globalization result in higher productivity, without causing notable negative transitional effects. I hope that my findings will lead to better policy, which helps to maximize the benefits of specialization and efficient allocation of resources.

Apeldoorn, January 2013, Stefan Groot

1 INTRODUCTION

Much of the dynamics in the global economy take place within the vicinity of cities. Because of their harbors, airports and other transportation facilities, they are major hubs to the rest of the world and thriving centers of economic activity. Trading cities and the type of externalities that can be found in cities play an important role in driving economic growth (see, for example, Jacobs, 1984 and Simmie, 2001). Recent trends in globalization have further enhanced the importance of cities as the command centers of activities that are dispersed around the globe (Jones, 2005).

1.1 Central Topics in the Thesis

Agglomeration

From the very fact of their existence, it can be observed that clustering together in towns and cities must bring advantages to its population. Without some sort of economies of scale, agglomeration economies, or other local advantages, people would have been distributed more or less randomly across space (see the spatial impossibility theorem by Starrett, 1978). Firms and workers are much more productive in close proximity of other firms and workers than they would be in relative isolation, as an extensive literature – dating back to as far as the founding fathers of economics – has shown.

One of the advantages of living in cities in the past – that is, until the end of the *ancient regimes* in the early 1800s – was the relative safety offered by city walls. Within a densely populated area the costs of facilities with high fixed costs, such as city walls, water supply, hospitals and schools, can be covered by a large number of people. However, the advantages of cities go much further than that. In the classical works by Adam Smith (1776) and Alfred Marshall (1890), the success of cities is explained by allowing for increased specialization, the availability of large pools of labor, closer linkages between intermediate suppliers, and by easing the diffusion of knowledge. The concentration of people together with a great variety of activities in close vicinity is thus precisely what makes this crowding attractive in the first place.

The famous pin factory example by Adam Smith (1776) is one of the first economic discussions of the concept of the division of labor, and the advantages of fragmentation of production processes that is made possible by agglomeration (that is, the clustering together of firms and people). In the view of Smith, agglomeration results in higher productivity because it allows for increased specialization. Smith provides three arguments in support of his reasoning. First, the division of labor within the pin factory enables each worker to spend more time on a narrower set of tasks (for example, he describes that 18 different steps are required to manufacture a pin), thereby improving the ability to perform these tasks. Second, by not having to switch between the multiple tasks that need to be performed to produce a pin, switching costs such as changing tools can be avoided. Third, Smith argues that more simplistic tasks make the application of technology less complicated, which may result in higher innovation. In the pin factory, therefore, each increase in the division of labor results in increased output per worker. Specialization is not possible beyond the point where a worker is no longer fully occupied with his set of tasks, or to put it in the words of Adam Smith (1776, p. 17): “the division of labor is limited by the extent of the market” (see also Stigler, 1951). Therefore, the productive advantages of *cities* are to some extent defined by the size of accessible markets.

Transportation and transaction costs have played a central role in shaping the history of cities. The evolution of the size of cities throughout history is mostly driven by the available modes of transport. The ‘extent of the market’ is not only defined by distance, but also by the speed at which distance can be traveled. In ancient Rome, a population of around one million lived in an area with a radius of only a few kilometers (Morley, 1996); the distance that could be traveled by foot. At the time of the 1869 census[1] Amsterdam’s 265 thousand citizens lived within an area of just 14 square kilometers, more or less the same area it occupied at the end of the golden age. Commuting longer distances was simply not feasible until low cost mass transportation became available in the late 19th century. Between

[1] Comparable and detailed historical census data for the Netherlands is available for each decade since 1849, and is available through http://www.volkstelling.nl.

the end of the 18th century and the early 1960s, the area of Amsterdam increased tenfold, while its population only tripled. The introduction of trains, trams and other transport improvements reduced transportation costs and allowed people to live further from their jobs. The course of history has thus resulted in *less* rather than *more* crowding of cities.

The geography and economic structure of cities started to change even more when cars became affordable to the general public (Glaeser and Kahn, 2004), which was in the 1960s in the Netherlands and somewhat earlier in the US. In just a few decades, suburbanization diffused urban populations over large areas. In 2010, the Amsterdam metropolitan area had a population of 2.3 million and an area of 1,600 square kilometers. Even outside the metropolitan area, there are many towns from which ten to twenty percent of the labor force commutes to Amsterdam on a daily basis. As advancements in transportation have decreased distance in terms of time, the geographical size of cities has increased, and commuting between the suburbs and the productivity centers became one of the central features of agglomeration processes. This allowed ever larger numbers of people to benefit from the productivity advantages of cities.

Globalization

The effects of transportation costs are far from limited to transaction costs within the boundaries of the city. As cities depend on continuous imports of food to feed its population, and export the produced surplus of goods to distant markets, access to water has been crucial to their success. Even nowadays, transportation of goods over water remains to be far cheaper than transport over land (or by air, for that matter). Prior to the invention of motorized land transport, sailing ships were the only available mode of transport that could transfer goods economically over longer distances. It should therefore come as no surprise that most cities were built close to waterways. Their harbors expanded effective markets to more distant locations, thereby allowing even more specialization.

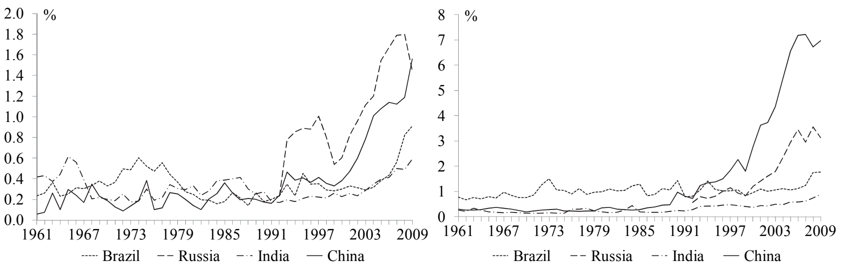
International trade caught the attention of David Ricardo (1817). As he explains in his classical work, when countries specialize according to comparative cost advantages, this increases productivity even further. Just as advancements in transportation changed the shape of cities by increasing the geographical size of markets for labor, goods and services, decreasing prices of transportation and communication have allowed for increased international division of labor. Consequently, productivity increased even further. As John Stuart Mill (1848, p. 130) explains, “The increase of the general riches of the world, when accompanied with freedom of commercial intercourse, improvements in navigation, and inland communication by roads, canals or railways, tends to give increased productiveness to the labour of every nation […] by enabling each locality to supply with its special products so much larger a market, that a great extension of the division of labour in their production is an ordinary consequence.”

The outer limit of markets – or, at least, some markets – is nothing less than the globe. The acceleration of this process of markets becoming increasingly global, which followed the invention of information and telecommunication technologies, caused some economists to sense a “death of distance” (Cairncross, 1997). Paradoxically, trends in agglomeration suggest a rather opposite view, and the importance of agglomeration seems to have increased. The process of increased globalization that started at the end of the 20th century has enhanced the role of cities, which have gained importance as the command centers of activities that are dispersed around the globe (Jones, 2005). For example, while the population of the city of Amsterdam fell from 880 thousand in 1960 to 670 thousand in 1985, it had recovered to 780 thousand by 2010 (De Groot et al., 2010). It is thus clear that proximity is more important than ever in shaping our economic and geographical landscape, and – in strong contrast to the work of Cairncross (1997) – distance is more alive than ever. The relevant question is thus not what would happen if the world were flat, or if distance were dead, but rather what would happen if transaction costs would decrease. The answer to this question depends on the size of agglomeration economies, transportation costs, and consumer preferences (Leamer, 2007; Garretsen, 2007).

Technological advancements in transportation as well as information and telecommunication have resulted in increasingly complex and global production systems. As Figure 1.1 shows, international trade with emerging markets has increased at a fascinating speed during the last two decades. Between 2000 and 2008 (the years for which we have micro data available in later chapters), the share of imports from the BRIC countries in total Dutch imports increased from just 5 percent to 13 percent. The share of the BRIC countries in Dutch exports increased from 1½ to over 4 percent. As the differences in economic structure between the Netherlands and the BRIC countries are much larger than the differences between the Netherlands and other advanced economies, the possibilities for specialization are relatively large.

Following the founding fathers of economics – Smith, Ricardo and Mill – there has been little discussion among economists about the positive long-term effects of this trend: higher productivity allowing for a higher standard of living. The advantages of trade with the BRIC countries is, for example, reflected in lower prices of imported goods (Groot et al., 2011a). However, it is also clear that international integration – not just with the BRIC countries – has resulted in some changes in people's lives and the way business is done. One of the central topics that this thesis addresses is the labor market implications of these changes.

Figure 1.1. Dutch export (left) and import (right) shares to and from the BRIC countries



Source: Groot et al. (2011a, p. 28).

As Scott (2006) notes, even the early economists had attention for the potential negative side effects of increased specialization. In the fifth part of *The Wealth of Nations*, Smith (1776) expresses his concern about the effects that high levels of specialization could have on the dignity of work. The work of Smith prompted Jean-Baptiste Say (1803) to comment bitterly about the presumed need to spend ones' career on the manufacturing of one 18th of a pin (Scott, 2006). Another point of concern has been that the simplification of work through specialization has made it easier to replace workers by machines or by other workers. It has often been feared that this could result in a race to be bottom in payment or other working conditions. However, this line of thought is mostly based on the fallacy that the amount of work within the economy is somehow fixed, such that if a job is lost – for example, due to mechanization or someone abroad doing it cheaper – unemployment goes up. In reality, the division of labor is far from a zero sum game. Unemployment is mostly the outcome of a complex interplay between supply and demand on the labor market, whereby employers continue to hire employees as long as their marginal productivity exceeds the labor costs.

Therefore, if labor becomes more productive – regardless whether it is due to mechanization, increased specialization, or increased international trade – the long-term consequence will be higher wages rather than higher unemployment. However, the short-term effects are less trivial. The fact that the size of the total pie goes up, does not exclude the possibility that some individuals end up with a smaller piece of the pie than they had before. There might be transition effects: if *you* happen to be the one to be fired, this is likely to result in at least a temporary loss of employment and income. Furthermore, the increased domestic and international division of labor may make the skills of some workers more valuable, while reducing the value of those of others.

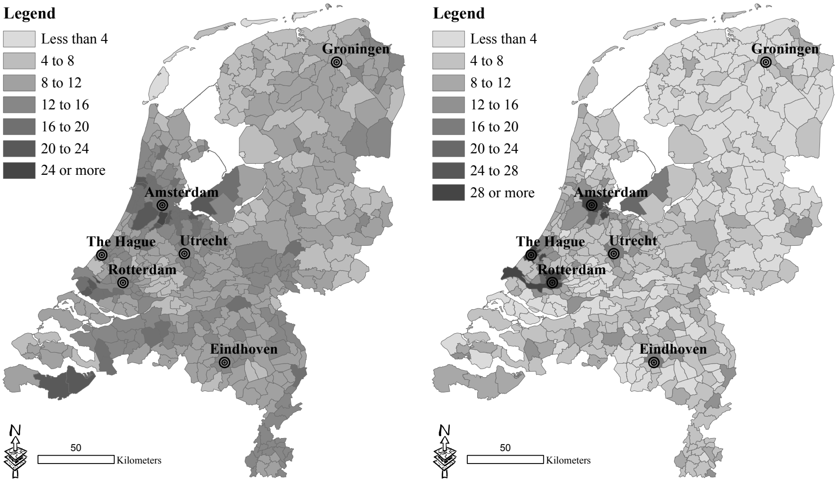
Regional labor markets

Rather than analyzing the effects of agglomeration and globalization on the aggregate Dutch labor market, we focus in this thesis on regional labor market effects. Regions differ in economic density, economic structure, as well as the composition of their work force. Therefore, trends in regional wages and productivity, and commuting patterns, are likely to be heterogeneous across regions. Furthermore, due to the location of harbors (Rotterdam, Amsterdam) and airports (Schiphol) there are substantial differences between regions in their international accessibility. As Figure 1.2 shows, there is also substantial heterogeneity in the distribution of foreign owned firms and foreign-born employees across space. A novel feature of this thesis is that we take this heterogeneity explicitly into account.

A natural spatial level of aggregation for analyzing regional differences in wages and productivity as well as unemployment, is that of the local labor market (Briant et al., 2010). For example, large wage differences and differences in unemployment *within* local labor markets are unlikely to exist, because labor is relatively mobile within short distance. NUTS-3 regions are a reasonable approximation for local labor markets in the Netherlands (see Appendix A, p.

177). In contrast, because commuting takes place mostly *within* local labor markets, we analyze commuting patterns on the level of municipalities.

Figure 1.2. Share of labor force employed at foreign owned firms (left) and share of foreign-born employees in the labor force (right), 2008



Source: Own calculations based on CBS micro data.

1.2 Micro data

Traditionally, economic analyses of phenomena such as agglomeration and globalization have relied mostly on aggregate data. This literature has shown a substantial positive effect on productivity of the increased division of labor that is made possible by agglomeration and globalization (see, for example, Frankel and Romer, 1999, for the relation between trade and GDP, and Ciccone and Hall, 1996, for the relation between economic density and productivity). Much less attention, however, was devoted to the potential negative effects that such trends could have for individual groups of workers. Furthermore, the use of aggregated data may result in conclusions that are inaccurate. For example, Combes et al. (2008a) have shown that a part of the correlation between agglomeration and aggregate productivity is explained by differences in labor market composition rather than a positive relation between density and productivity. Correlations between aggregated variables may even disappear almost completely when micro data are used, as Chapter 5 will show regarding the negative relation between education and unemployment risk.

During the last few decades, both the theoretical and the empirical literature have shifted towards a microeconomic approach, that stresses the importance of heterogeneity across workers and firms (see Melitz, 2003, for the theoretical underpinnings of the importance of firm heterogeneity, and Bernard et al., 2007, for an overview of the empirical literature). Increased availability of micro data to the scientific community – particularly since the 2000s – has played an important role in this process.

Van Bergeijk et al. (2011) provide a discussion of the transition from this traditionally macro towards a more micro approach in studying globalization and agglomeration. An important lesson that has been learned is that insights in heterogeneity across regions, firms, and workers are essential to fully grasp the complexity of economic problems. From a policy perspective, this implies that one-size-fits-all policies are the exception rather than the norm. For example, authors such as Autor et al. (1998 and 2006), argue that technological progress and globalization are skill biased, such that their impact on wages and employment are positive for some groups of workers while negative for others. Micro data are essential to test the empirical implications of such hypotheses, as it allows to explicitly analyze worker and firm heterogeneity. More generally, micro data allow us to reduce heterogeneity that remains unobserved at a more aggregate level. Previous studies have shown that these effects may be substantial (Duranton, 2010; Melo et al., 2009).

In the Netherlands, the availability of micro data that allows to address topics such as globalization has improved substantially during the last ten years (see also CBS, 2010). However, the empirical literature that uses micro data is still in an early phase, partly because there remain substantial limitations to the accessibility of micro data (Van Bergeijk et al., 2011). Even if micro data are available within statistics offices, it is not always made available to researchers because of privacy considerations. Another problem is the fragmentation of data. For example, to analyze patterns in location behavior of workers and firms, and the resulting commuting patterns, linked data are required that include variables related to the location of the firm where an employee works, data related to residence location, data on his or her commute, and data on individual characteristics such as education and occupation. Similarly, when analyzing the labor market effects of globalization, data that include both firm level indicators such as exports, imports, and foreign ownership, *and* individual worker characteristics, wages, and unemployment, remain scarce.

The micro data that are used in this thesis allow to go one step further, and analyze what happens with individual employees and firms in conjunction with relevant variables that are related to agglomeration and globalization. It is also precisely the availability of this micro data that enables us to offer some unique insights into the underlying mechanisms that determine labor market outcomes on a spatially disaggregated level.

1.3 Research questions

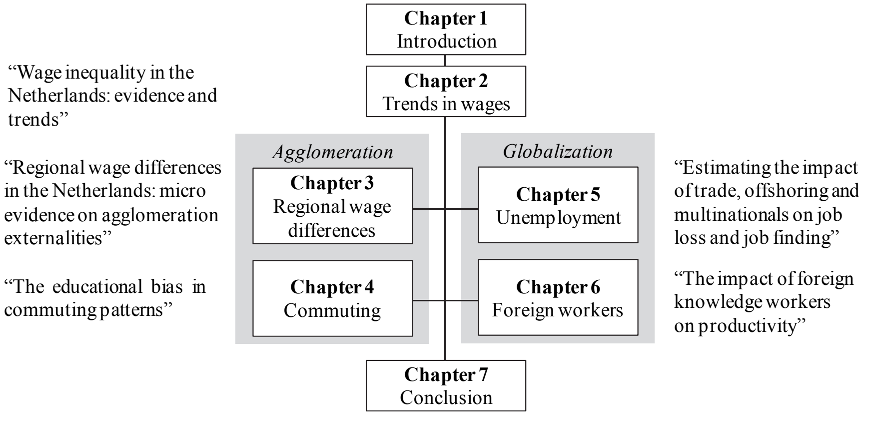
From the previous sections, a number of questions emerge. It is clear that recent trends in agglomeration and globalization are substantial, and that these trends could have potentially large effects for employees in terms of wages and unemployment. Furthermore, it has become clear that these effects could be asymmetric for different types of workers, and across regions. This thesis therefore addresses a number of – mostly empirical – questions for the specific case of the Netherlands based on unique micro data at the individual level of firms and workers:

- How did (regional) wage inequality change between 2000 and 2008, and what patterns are found for different groups of workers?
- What is the contribution of agglomeration economies to variations in productivity of firms as measured by wages paid to workers?
- How are commuting patterns related to production and agglomeration externalities, and to amenities, and does this relation depend on individual worker characteristics, such as level of education?
- What is the relation between trade, offshoring and foreign owned firms on job loss and job finding?
- What is the relation between the presence of highly educated foreign workers and productivity of Dutch firms as measured by wages paid to workers?

1.4 Structure of the thesis

This thesis consists of seven chapters. Besides the introduction and the conclusion, there are five self-contained studies: one general chapter about recent trends in wage inequality, two chapters that are related to agglomeration, and two that are related to different dimensions of globalization. Figure 1.3 presents a schematic outline of the relation between the different chapters.

Figure 1.3. Schematic outline of the thesis



Wage inequality; a decomposition approach

As a logical step to start the quest for the effects of agglomeration and globalization on the labor market, Chapter 2 will explore recent trends in wage inequality. If changes in the division of labor have different effects on people with different characteristics, this should become visible by analyzing the wage distribution. Authors such as Autor et al. (1998 and 2006), have argued that technological progress and globalization are skill biased. The tasks performed by lower educated workers are often more routine, which makes it easier to either replace their labor by machines or by offshoring it abroad.

In Chapter 2, we explore and decompose trends in Dutch wage inequality into different components, such as gender, age, and level of education. This chapter contributes to the literature by providing detailed decompositions that are made possible by the available micro data and an extension to the framework of Juhn et al. (1993), and the fact that we provide empirical evidence on trends in Dutch wage inequality during the last decade (expanding on Ter Weel, 2003).

Agglomeration economies and regional wage differences

In Chapter 3, we shift our attention to explaining *regional* wage differences. As agglomerations allow for more specialization, lower transaction costs, and because close proximity of people and firms eases the diffusion of knowledge, it is to be expected that productivity is higher in cities. In a competitive labor market, this will be reflected in higher wages. Spatial wage disparities may reflect several other forces, most particularly sorting processes of both individuals and firms with different characteristics. As we show in this chapter, higher skilled workers are more attracted to working in areas with a high employment density than less skilled workers. However, even after correcting for regional heterogeneity in both worker characteristics and sectoral structure, doubling the employment density of a region is associated with a 4.8 percent increase in wages. Besides economic density, Chapter 3 looks at various other sources of agglomeration economies, such as specialization within industries, competition, and diversity of the regional economy.

This chapter adds to the current literature on agglomeration economies (for example, the work of Combes et al., 2008a) by using more detailed data on individual worker characteristics, such as level of education, and by providing estimates of agglomeration economies that are both relevant for Dutch policy makers and for an international comparison of estimated agglomeration economies.

Commuting and agglomeration

After finding that skilled workers are more likely to work in agglomerated areas than lower skilled workers, Chapter 4 will analyze whether such a bias also can be found in commuting patterns. We will not only devote attention to agglomeration driven by productivity, but also discuss amenities, as skill differences can strongly influence both job and home location.

Even though studies related to commuting have often included education as a control variable, we are one of the first to explicitly address this relationship. Furthermore, we take into account both the attractiveness of a location as a place to work and the attractiveness as a place to live as determinants of location decisions and thus commuting patterns.

As employment in cities is more specialized relative to the countryside, the benefits of commuting are likely to be higher for skilled workers. Furthermore, because of a more complex matching process for more specialized workers, the high skilled may be less likely to find a job close to home. At the same time, high skilled high paid workers might have a higher willingness to pay for housing close to agglomeration centers, such that they can reduce commuting time and benefit from urban amenities. Results show that highly educated commuters travel further, both in distance and time. Furthermore, they are more likely to commute towards relatively productive places and they are more likely to live in and commute from areas with higher land rents.

Unemployment, trade, offshoring and multinationals

Chapter 5 shifts attention to the international division of labor, and estimates the impact of several dimensions of globalization on job loss and job finding. It thus focuses on the earlier mentioned short term (transitional) effects of globalization. Together with worker characteristics such as age, gender and education, we analyze whether working for a foreign owned firm or an exporting firm, as well as the offshorability of the occupation of a worker, are related to the probability of unemployment. Once a worker has become unemployed, we analyze the relation between the same characteristics of the worker and last known job on the probability of finding a new job.

This chapter employs a rather unique dataset, in which our employer-employee database is linked to data on unemployment benefits. We can thus observe the entire life cycle of unemployment – from the previous job to unemployment and from unemployment back to a new job – in one unified framework. It will be one of the first studies that analyzes both the transition from a job to unemployment and the transition from unemployment back to a new job in an integrated manner. In addition, besides using a number of existing offshorability indicators, we develop our own indicator that explicitly takes the importance of proximity for occupations into account. Besides providing interesting and novel stylized facts on the nature of unemployment by level of education, by occupation, and by industry, we show that unemployment and globalization are mostly unrelated.

Foreign workers and firm productivity

In Chapter 6, we analyze the effects of the presence of highly educated foreign workers on the productivity of firms and regions. Cities have a long history of attracting high shares of foreign workers. In the 17th century, a large share of the French Huguenots and Portuguese Jews that migrated to the Netherlands choose Amsterdam as their residence. According to the 1849 census, 4.6 percent of Amsterdam's population was foreign born, whereas this figure was 3.0 percent for other Dutch cities and only 1.9 percent for the countryside. Nowadays an even larger share of the population is born outside the Netherlands, and these are even more concentrated in the larger agglomerations (see Figure 1.2).

Particularly, the presence of *skilled* foreign workers may bring benefits to productivity, as their knowledge may be transferrable and complementary to that of natives. The presence of a diverse workforce in cities may thus (to some extent) explain higher productivity. However, causality could also go in the other direction, as foreign workers might be attracted by high productivity and wages. As interpersonal relations that allow for the exchange of relevant professional knowledge are particularly dense within firms, a logical starting point to look for productivity advantages is within firms. Chapter 6 compares the wages of high skilled foreign workers to the wages of comparable natives, and estimates the effects of the presence of high skilled foreign workers from advanced countries on the wages on other workers within the same firm. We find that foreign knowledge workers earn slightly less than comparable native colleagues do, and that their presence is positively related to the wages of other workers in the firm. This chapter contributes to the literature by its firm level approach. This does not only allow to test whether the observed relation between the presence of foreign workers and wages on the regional level also exists on the firm level, it also enables us to better control for endogeneity and omitted variable bias on the level of regions.

2 WAGE INEQUALITY IN THE NETHERLANDS: EVIDENCE AND TRENDS

"Measuring the growth of incomes or the inequality of incomes is a little like Olympic figure skating – full of dangerous leaps and twirls and not nearly as easy as it looks."

Alan Reynolds (2006)

2.1 Introduction[2]

Rising wage inequality in the US and other OECD countries has provoked debates on the severity of this phenomenon, its causes, and its potential remedies. Up to now, however, the size of changes in the income distribution and especially its causes, have remained controversial. During the 1980s and 1990s, wages of some groups on the US labor market – especially blue collar workers – have fallen in real terms, whereas the wages of workers in the higher percentiles of the wage distribution have grown substantially (Lawrence, 2008).

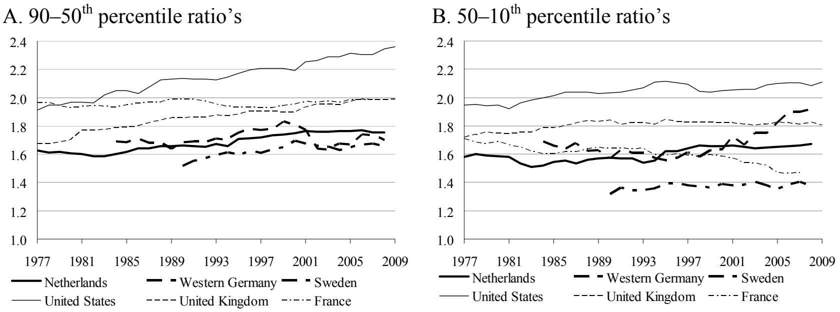
The Netherlands is often considered an exception to this general picture (Burniaux et al., 2006; Förster and Mira d'Ercole, 2005). This chapter contributes to the existing literature on wage inequality in several ways. We are the first to use micro data to decompose trends in Dutch wage inequality after 2000. Furthermore, we develop an extension to the Juhn et al. (1993) framework that enables us to separately analyze how changes in the supply of different worker characteristics as well as the prices of those characteristics changed the wage distribution. Even though the provided decompositions do not truly explain trends in wage inequality, they provide useful insights in the underlying characteristics of trends in wage inequality.

Changes in Dutch wage inequality have been mild, both when compared to the substantial increase in US wage inequality and when compared to trends in most other European countries. Figure 2.1 shows standardized percentile ratio's for the 90–50th and 50–10th (pre-tax) gross wage differentials of six OECD

[2] This chapter is based on Groot and De Groot (2011).

countries. Wage inequality has increased substantially in the US throughout the entire 1977–2009 period (albeit the change was notably higher at the upper half of the distribution). The Netherlands, in contrast, was consistently among the countries characterized by relatively low wage inequality, with relatively moderate change of wage inequality during the entire period. Ter Weel (2003) shows that the Dutch 90–10th percentile wage differential increased by less than two percent between 1992 and 1998, after having increased by eight percent between 1986 and 1992. Similarly, Atkinson and Salverda (2005) have shown that inequality in the Netherlands has remained fairly stable during most of the 1977–1999 period.

Figure 2.1. Trends in inequality of gross annual wages of full-time working employees in six OECD countries, 1977–2009



Source: OECD Statistics on international wage inequality.

The literature on Dutch wage inequality in recent years is limited, despite several important trends such as globalization and the advent of information and telecommunication technologies, that may have impacted the wage distribution in the past decade. This chapter describes and decomposes trends in the Dutch wage distribution during the 2000–2008 period, using detailed micro data on wages and employee characteristics. We show that the best-paid workers have gained more during this period than workers in the middle of the distribution have. Workers at the lower percentiles, however, have gained as well relative to the median worker. The 99–90th wage differential of male (female) workers has increased by 4.2 (1.1) percent, and the 90–50th differential by 2.4 (1.6) percent. At the bottom of the wage distribution, inequality remained constant for males, while inequality of wages of women decreased substantially as the 50–10th differential decreased by

2.2 percent. The net effect of these changes on aggregate inequality measures such as the Theil and Gini coefficients boils down to only a very moderate increase in inequality.

An important advantage of using micro data instead of macro data is that the former can provide insights in how changes observed in the aggregate wage distribution are related to changes in (implicit) prices and volumes of individual worker characteristics. This allows us to show that changes in aggregate wage inequality have no single explanation, but are the net effect of diverse and complex interactions on the labor market. More specifically, we will describe levels and trends of Dutch wage inequality, and apply the framework of Juhn et al. (1993) to distinguish three types of effects: (i) quantity changes of observable worker characteristics – e.g. the effect of changes in labor market composition; (ii) changes in the implicit prices of worker characteristics; and (iii) residual changes that are related to unobservable worker characteristics.

Additionally, we extend this method to identify trends in prices and quantities of isolated components of human capital, like education and age. The method developed in Juhn et al. (1993) can only do this for all components combined. Because there are likely to be substantial differences between trends in the supply of labor of females versus males (both in terms of quality and quantity), we perform separate wage regressions and decompositions for males and females. Well-paid jobs are not uniformly distributed across professions and regions. We will therefore present results not only for the economy as a whole, but also for different regions. This shows that after correcting for observed human capital, wages in the four largest agglomerations of the Netherlands (Amsterdam, Rotterdam, The Hague and Utrecht) pay a premium of 8.9 (8.3) percent in 2008 (2000).

Skill-biased technological progress is generally considered the most plausible explanation for increasing wage inequality in the US (Autor et al., 1998 and 2006; Katz and Murphy, 1992). Other potential causes are globalization, reduced supply of skilled labor, and labor market institutions (see, for example, Nahuis and De Groot, 2003). The theories result in very similar testable hypotheses: rising skill and experience premiums. The mechanisms through which they operate are, however, very different. In the first case, technological progress increases relative demand for skills. For example, the advent of information and communication technology might be in favor of especially the high skilled (Autor et al., 1998 and 2006; Katz and Murphy, 1992). In the case of globalization it is increased competition with countries housing large pools of unskilled workers that reduces the relative demand for low-skilled labor and thus increases the skill premium (i.e. wages of higher skilled workers increase relative to the wages of lower skilled). The third case emphasizes the fact that access to higher education is no longer increasing as it did during the 1970s and 1980s, reducing the (growth of) the supply of high skilled labor (or alternatively that the quality of high skilled is deteriorating). It has proven difficult to empirically separate these different forces, and the debate is far from settled.

Nahuis and De Groot (2003) and Ter Weel (2003) argue that the relative stability of the Dutch wage distribution is explained by the fact that educational attainment has continued to grow for a relatively long period in time. Between 2000 and 2008, the number of students graduating from higher tertiary education continued to increase. Increased demand for skilled labor (possibly caused by skill biased technological progress or globalization) has thus been balanced by increased supply of skilled workers, such that the resulting price of skills showed little change. In countries where supply of skilled labor remained constant during recent decades (as was the case in the US), it resulted in a higher skill premium and thereby higher wage inequality. Nowadays, the number of highly educated workers is increasing at a much lower rate, albeit it is still increasing. In the Netherlands, the skill premium of male (female) workers has increased by 15 (35) percent between 2000 and 2008, which suggests that demand for high skilled labor has been increasing faster than supply.

Finally, the effects of labor market institutions on the wage distribution can be substantial (Alderson and Nielsen, 2002; Suyker and De Groot, 2006; Gottschalk and Smeeding, 1997). Changes in the way wages are negotiated, minimum wages, unemployment benefits, unionization, and other labor market institutions are known to be important determinants of wage inequality (Teulings and Hartog, 1998).

The remainder of this chapter is organized as follows. The next section will present the micro data used in this chapter. Section 2.3 presents descriptive statistics on (trends in) Dutch wage inequality between 2000 and 2008. Section 2.4 discusses the methodology that we have used to decompose trends in inequality in different components, and present the results of this exercise. Section 2.5 focuses on the regional dimension of wage inequality. Section 2.6 concludes.

2.2 Data

We use employee micro data from Statistics Netherlands (CBS). Data on worker characteristics are drawn from nine consecutive cross-sections of the annual labor force survey (*EBB, Enquête Beroeps Bevolking*), covering the period 2000–2008.[3] For wages, we rely on tax data reported by employers, available through the CBS social statistics database (SSB*, Sociaal Statistisch Bestand*). For workers with multiple jobs, we include each job as a separate observation. We have used the CBS consumer prices deflator (CPI*, Consumenten Prijs Index*) to deflate annual earnings. Throughout most of our analyses, we rely on log hourly wages, defined as the natural logarithm of the deflated pre-tax wage (the so-called fiscal wage, which is employer reported) divided by the number of hours worked. The latter is calculated by multiplying the sum of standardized[4] monthly contractual hours and over hours (available through SSB) by the number of months the employee worked during a year, which is based on the start and end date of the job. The derivation by CBS of hours worked, as well as start and end dates of jobs, are based on employer reported data.

To make sure that only workers with a sufficiently strong attachment to the labor market are included, we have imposed the following restrictions. First, workers must be older than 18 on January 1st and younger than 65 on December 31st of each year, and must work for at least 12 hours per week.[5] Second, the hourly wage should exceed the minimum wage in 2008 (adjusted for inflation), which was 7.83 euro per hour in prices of 2008. Third, wages should not exceed 10 times the median wage to avoid an excess impact of extremely high incomes. We use age as a proxy for experience, which captures different sources of human

[3] Due to methodological changes in the labor force survey, there is a discontinuity in our dataset between 2005 and 2006. The effects of this change have been filtered out by keeping the wage distribution constant between 2005 and 2006. Our methodology compares (log) wages at each percentile of the wage distribution, thus considering the wage distribution as a continuum. For the years 2000 to 2005, we subtract the change between 2005 and 2006 at each percentile.

[4] In this context, standardization implies a correction for differences in paid leave (including illness).

[5] Statistics Netherlands defines workers with a working week of at least 12 hours as employed. Workers with a working week of at least 36 hours are considered full-time employees. Jobs occupied by teenagers are often sideline jobs, that would be outliers in our dataset.

capital, including – but not limited to – present and previous occupations. We measure education as the nominal number of years of schooling that is needed to achieve the (self-reported) highest level of education that a worker has successfully achieved. Other worker characteristics that are included are country of birth – a binary variable that indicates whether a worker is born in the Netherlands or not – and gender (all from census data), and whether a worker is employed part-time (less than 36 hours[6] per week) or full-time (36 hours or more). The resulting dataset of nine cross-sections contains 436,734 observations, an average of 48,526 per year. Sample size increased substantially over time by Statistics Netherlands, with only around 20,000 observations in our dataset in the first years and over 80,000 in the last. Even though we are – to some extent – able to follow individuals over time, creating a (balanced) panel would substantially reduce the number of observations. Therefore, we use the data as pooled cross-sections.

Table 2.1 presents some descriptive statistics on the key variables of interest. It must be kept in mind that all figures reflect our sample rather than the total Dutch working population, and thus may not be fully representative. Pre-tax real wages have increased by 8.0 percent between 2000 and 2008. Even though the period of observation is limited, some pronounced changes have occurred. Workers in 2008 are 0.63 years older. The average years of education and share of women remained rather constant, while the share of part-time jobs in our sample increased substantially.[7] As part-time workers and females are overrepresented at the lower percentiles of the wage distribution, and older workers feature most prominently at the higher percentiles, this could have resulted in increased wage inequality. If, however, changes in worker characteristics are evenly distributed (if the higher average age is, for example, not the result of increased labor market participation of older workers, but only a level effect), inequality would have

[6] Weekly hours worked are calculated by dividing standardized monthly working hours (both contractual hours and over hours) by 4.333, which is the quotient of 52 (weeks) and 12 (months).

[7] The latter is partly due to a methodological revision by Statistics Netherlands between 2005 and 2006. It can be observed that part-time workers have a higher probability to be included in the labor force survey after the revision. Though we correct for this in the results presented in the remainder of this chapter, the descriptive statistics in Table 2.1 refer to the uncorrected data.

remained unchanged. The use of micro data gives the possibility to determine what driving forces are dominant, and how they interact.

Table 2.1. Descriptive statistics, 2000–2008

	2000	2002	2004	2006	2008
# Observations	17,829	22,953	45,553	82,676	82,089
Log real hourly wage	2.896	2.922	2.937	2.955	2.976
	(0.373)	(0.371)	(0.375)	(0.425)	(0.426)
Age	41.95	42.42	43.10	42.19	42.58
	(9.80)	(9.95)	(10.05)	(10.68)	(11.00)
Education (years)	14.89	14.96	15.22	14.83	14.90
	(3.175)	(3.160)	(3.142)	(3.119)	(3.116)
Female	0.432	0.465	0.487	0.420	0.431
	(0.495)	(0.499)	(0.500)	(0.494)	(0.495)
Part-time	0.384	0.403	0.430	0.582	0.566
	(0.486)	(0.491)	(0.495)	(0.493)	(0.496)
Foreign born	0.068	0.071	0.068	0.074	0.080
	(0.252)	(0.258)	(0.251)	(0.262)	(0.271)

Note: Standard deviations are in parentheses.

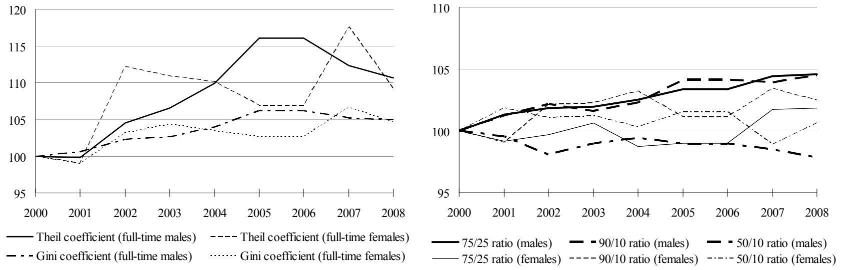
2.3 Trends in inequality

Before we start exploring the characteristics of both levels and trends in the distribution of wages, we first look in somewhat greater detail at trends in wage inequality in the Netherlands. Figure 2.2 shows how the distribution of pre-tax real hourly wages of employees in the Netherlands changed during the last decade. Wage inequality among full-time working male employees increased somewhat, even though change at the 90–50th percentile was very small (see panel A). However, when we look at female employees, there is almost no change visible. While the Gini coefficient increased only moderately for both male and female full-time workers, the Theil index shows substantial change (see panel B). Because the Theil coefficient is relatively more sensitive in the tails of the wage distribution, whereas the Gini index is more sensitive in the middle, this finding is consistent with evidence showing that inequality increased mostly at the top of the distribution, which is presented later in this chapter.

Figure 2.2. Trends in wage inequality of full-time working males and females, 2000–2008

A. Standardized Gini and Theil coefficients workers

B. Standardized percentile ratios of full-time



The finding that changes in wage inequality are moderate is consistent with previous studies on wage inequality in the Netherlands (Suyker and De Groot, 2006; Irrgang and Hoeberichts, 2006; SCP, 2007; Ter Weel, 2003; Van den Brakel-Hofmans, 2007). Comparative research into wage inequality in advanced countries indicates that, during the past two decades, wage inequality increased in most OECD countries (Gottschalk and Smeeding, 1997; OECD, 2007). The Netherlands thus appears to be one of the few exceptions to the general trend. There is some variety in studies that rank countries based on wage inequality, but the Netherlands is generally viewed as a country with a relatively egalitarian distribution and only a slight increase in inequality (see, for instance, Burniaux et al., 2006; Förster and Mira d'Ercole, 2005).[8] Notwithstanding these results, recent findings of Straathof et al. (2010) indicate that also in the Netherlands top wage inequality has started to increase somewhat, following the international trend.

As the Theil index is an entropy based measure, it is relatively straightforward to decompose inequality into different components (Theil, 1979). Authors like Bourguignon (1979) and Shorrocks (1980) have developed a simple methodology to decompose inequality into a within-group component and a between-group component. Inequality within each subgroup g is given by:

$$T_g = \sum_{i=1}^{l_g} \frac{w_{g,i}}{w_g} \ln\left(\frac{w_{g,i}}{w_g}\right) \quad , \tag{2.1}$$

[8] The OECD (2007) reports the same for disposable income, but reports a clear increase in wage dispersion measured as the 90th to 10th percentile ratio.

where l_g is the number of workers in group g, $w_{g,i}$ the wage of each worker and w_g the average wage of the workers in the group. Inequality between these subgroups is then given by:

$$T_{between} = \sum_{g=1}^{N} \frac{l_g}{L} \frac{w_g}{\overline{w}} \ln\left(\frac{w_g}{\overline{w}}\right) \quad , \tag{2.2}$$

where N equals the number of groups that are defined, L the total labor force, and $\overline{w}$ the average wage across all workers. When inequality within each subgroup has been calculated using equation (2.1) and between-group inequality using equation (2.2), total inequality is equal to the sum of average within-group inequality T_g in each of the N subgroups that were distinguished (weighted by their economic weight), and between group inequality:

$$T = \sum_{g=1}^{N} \frac{l_g}{L} \frac{w_g}{\overline{w}} T_g + T_{between} \quad . \tag{2.3}$$

The Theil index thus provides the possibility of an exact decomposition of inequality, where different components are meaningful and can be added by simple mathematical manipulations. A disadvantage of the Theil index – which is equal to the mean product of income and its own logarithm (Theil, 1972, p. 100) – is that its interpretation has no clear economic logic. The popularity of the Theil coefficient in the economic literature is thus largely based on its suitability for estimating the contribution of different groups to total inequality (Fields, 1979).[9]

The Theil coefficient can also be used to further decompose total between group inequality into the specific contribution of each type of between group inequality (e.g., education, experience, gender and part-time versus full-time in our case), by a more sophisticated extension of the Theil model that was introduced by Fishlow (1972).

[9] In this respect, the Gini coefficient is the exact opposite of the Theil coefficient. The Gini coefficient is often used for its clear economic interpretation, which originates in the Lorenz curve. Gini decomposition procedures have been developed by, among others, Rao (1969) and Fei and Ranis (1974). These methods are not based on weighting different inequality components, since ranking of subgroups on each of this different inequality is required, but on more complex calculation methods (Fields, 1979).

The contribution of one type of between group inequality can be written as:

$$T_{between-education} = \sum_{edu=1}^{7} \frac{l_{edu}}{L} \frac{w_{edu}}{\overline{w}} \ln\left(\frac{w_{edu}}{\overline{w}}\right) \quad , \tag{2.4}$$

where the average wage in each industry is:

$$w_{edu} = \sum_{edu=1}^{7} \sum_{age=1}^{11} \sum_{gen=1}^{2} \sum_{part=1}^{2} \frac{l_{edu,age,gen,part,i}}{l_{edu}} w_{edu,age,gen,part,i} \quad . \tag{2.5}$$

Similar equations yield the contribution of gender and experience to total inequality between groups. Total between-group inequality is given by the sum of the different components, and a remaining part with random effects and interactions. Formally:

$$\begin{aligned} T_{between} = {} & T_{between-education} + T_{between-experience} + T_{between-gender} \\ & + T_{between-part-time} + T_{between-interactions} \, . \end{aligned} \tag{2.6}$$

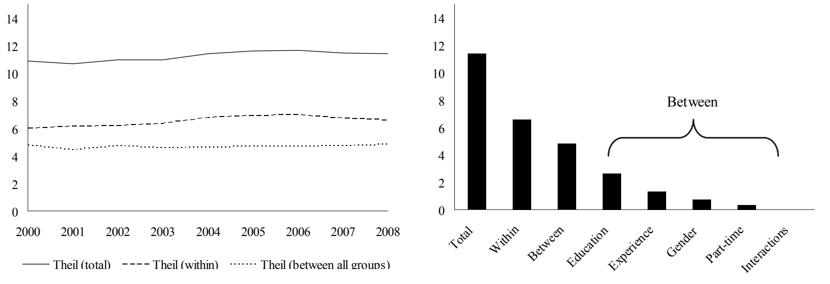
We use this equation to determine how much of total between-group inequality is associated with variation among education, gender, and experience wage averages. The difference between equation (2.2) and equation (2.6) stems from the exclusion of variation in income classes, and is equal to the within-group variation.

The left panel of Figure 2.3 shows the development over time of total, within and between-group inequality, as computed by the method described in equations (2.1)–(2.3). It reveals a marginal increase of total wage inequality. About 40% of inequality is due to between-group differences, and it appears that the share of between-group inequality has remained fairly constant. The right panel of Figure 2.3 and Table 2.2 show the results of a further decomposition of inequality between groups with the method described in equations (2.4)–(2.6). The most important source of between-group inequality is between workers with different levels of education, followed by differences between workers that differ by age. A relatively small effect is attributed to differences between gender or differences between part-time and full-time workers.

Figure 2.3. Trends in wage inequality of real hourly wages, 2000–2008

Theil coefficients of within and between

Additional decompositions for 2008 inequality*



* Number of subgroups: 9 for education, 9 for age, 2 for gender, 2 for part-time.

Looking at the trends in Table 2.2, it becomes clear that there is a relatively high variation over time in the different components that sum up to the more constant overall inequality. Inequality between education groups increased by 14 percent, but this was overcompensated by steep decreases in inequality between workers with different experience levels (–34 percent). Even though we cannot fully explain the large shifts in inequality between experience groups between 2000 and 2004, the dynamics in the composition of the labor market in terms of age have been rather large. For example, the participation rate of workers between 55 and 65 increased from 33.6 percent to 46.3 percent. The gender gap remained constant, while the amount of inequality associated with differences between part-time and full-time workers has more than doubled.

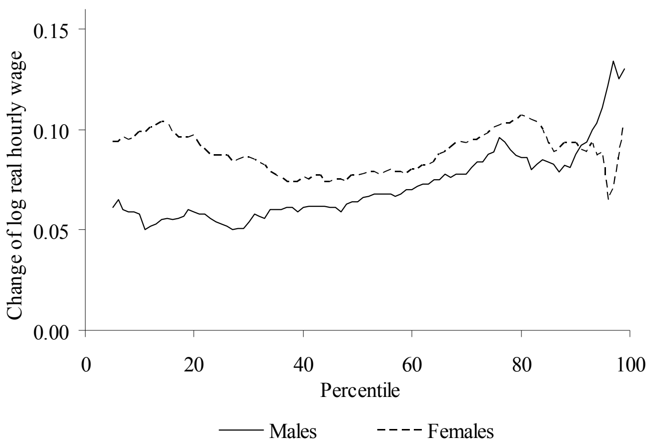
Table 2.2. Theil decomposition pre-tax wage inequality of real hourly wages

	2000	**2002**	**2004**	**2006**	**2008**
Total	10.88	10.98	11.40	11.66	11.39
Within groups	5.98	6.19	6.76	6.98	6.58
Between groups:	4.80	4.71	4.62	4.67	4.81
Education	2.31	2.51	2.44	2.52	2.63
Experience	2.03	1.62	1.40	1.31	1.32
Gender	0.72	0.64	0.74	0.70	0.72
Part–time	0.12	0.18	0.21	0.26	0.36
Interactions	–0.09	–0.10	–0.12	–0.12	–0.22

Note: Number of subgroups: 9 for education, 9 for age, 2 for gender, 2 for part-time.

As the Gini and Theil indices are aggregate measures for inequality, they are not very informative about where in the wage distribution changes have occurred. An observed change in the coefficients can be consistent with many different underlying processes. Figure 2.4 shows recent trends in Dutch wage inequality among male and female workers, as measured by percentile changes of log hourly wages between 2000 and 2008, for each percentile of the wage distribution. The median wage of male workers has increased by 6.4 percent, the median wage of females by 7.7 percent. Though we do not have a clear explanation for the higher wage growth of female workers compared to males, it is not explained by a change in composition.[10]

Figure 2.4. Trends in male and female wage inequality, 2000–2008



The negative slope for the bottom half of the wage distribution implies that wages have become somewhat more equal for the lower incomes. For wages above the median, the pattern is diverged, though most of the higher percentiles experienced above median wage growth. At the highest percentiles, there has been some diversion. While female workers at the top five percentiles have gained 8.3 percent on average, which is very close to wage growth of the median female worker, their male counterparts gained as much as 12.4 percent which was far above median. It seems thus that when looking at males, “the rich” have gained

[10] For example, when gender fixed effects together with a large number of variables related to worker characteristics (including education and industry) are included when estimating one wage regression per year, the estimation results show a substantial reduction in the male-female wage differential, by almost 2 percentage points between 2000 and 2008.

the most, while for females this is not the case. It is important to note that wages in Figure 2.4 have not been corrected for a changing composition of the labor market. It could be that the people who are rich in 2008 have different characteristics than those in 2000.

The six panels in Figure 2.5 compare wage changes by percentiles for different subgroups on the labor market. Differences in average wage growth are related to between group inequality (e.g. if one curve is above another on average, average wage growth was higher in that group), while differences in the shape of the distributions are the result of changing within group inequality. Similar to Figure 2.4, the panels in Figure 2.5 compare aggregated change in real log wages between 2000 and 2008.

The panels A (males) and B (females) compare workers with different levels of education. We start by discussing level effects. Wages of male workers with only primary education have decreased by 1.2 percent on average in real terms, while this figure increased by 0.1 percent for females. Wages of male (female) workers with secondary education increased by 3.9 (5.9) percent and wages of workers with tertiary education by 5.6 (8.4) percent. Between group inequality has thus increased (as the highest growth rate was experienced by the group with the highest average wage in 2000), which is consistent with the results of the Theil decomposition. This increasing skill differential can be observed consistently for male and female employees, and implies increasing rewards to skills.

For male workers with only primary education, wages around the median and at the higher percentiles (except for the top decile of the distribution) have decreased substantially in real terms, while wages at the lower percentiles have remained constant. For workers with secondary education, wages have increased slightly faster at both the highest and the lowest percentiles, thus increasing within group inequality at the top of the distribution, while decreasing it at the bottom. Compensation of workers with tertiary education has increased more at the higher percentiles than at the rest of the distribution, resulting in higher inequality.

Panel C (males) and panel D (females) compare wages of workers of different age. Age groups mainly differ in the level of growth. Wages of male (female) workers in their thirties and early forties have increased by 7.6 (8.6) percent, wages of younger workers by 6.5 (8.9) percent, and wages of older workers by 3.3 (5.5) percent on average. This reduced inequality between groups of older and younger females. For males, inequality between groups increased somewhat because wages of workers between 31 and 45 increased faster than wages of younger workers, but inequality decreased because older workers experienced the slowest average wage growth among all groups.

The most likely explanation for the relatively low growth rate of wages of older workers is a changing skill composition within this group. Well paid and higher educated workers are far more likely to continue working when they are old than less educated workers, but during the last decade policies targeted at increasing labor market participation of elderly workers have been implemented. As less educated workers are now also more likely to work in their fifties and sixties, the average level of education has decreased. This results in relatively low aggregate growth of wages for this group of workers. An alternative explanation is also related to changing institutions. Even though workers are generally thought to reach the top of their productivity between their forties and fifties, older workers have the highest wages for institutional and historical reasons. As the economy has become more competitive, inequality between older workers and workers of middle age could have decreased because of a weaker institutional link between tenure and wage. Differences between trends in the distribution of wages within the different groups are relatively small. All ages show a similar above average growth of wages at the highest percentiles for males, while the distribution remained constant within all age groups for females.

Panel E (males) and F (females) compare wages of full-time workers with wages of part-time workers. Wages of male (female) full-time workers increased by 9.6 (13.0) percent, substantially faster than wages of part-time workers, which increased by 4.4 (7.4) percent. The fact that growth of full-time worker wages outpaced aggregate wage growth is the result of an increased share of part-time jobs (that earn lower hourly wages). The fact that wages of full-time workers wages increased faster than wages of part-time workers could be explained by reduced supply of full-time labor.

Figure 2.5. Trends in wage inequality by subgroup, 2000–2008

Payment of part-time jobs of females has become slightly more equal, which is consistent with a decreasing importance of cohort effects. The increased share of part-time jobs is closely related to increased female labor market participation. Euwals et al. (2007) show that the participation rate of women (at a given age) increases as they are member of younger age cohorts, but find that this effect is now declining. Because of this, an increasing share of the part-time jobs is occupied by older workers (that have higher average wages). This results in a shift in percentiles.

We have thus far seen that composition effects explain a large part of observed trends in the wage structure. The Mincerian wage regression (Mincer, 1974) is an often-used tool to analyze the structure of wages, as it separates variation in wages due to observed worker characteristics from a residual wage component (e.g. the distribution of the error term). We have estimated a wage regression for each year separately:

$$w_{it} = X_{it}\beta_t + \varepsilon_{it} \ , \tag{2.7}$$

which explains log wages w_i as a function of a constant and worker characteristics X_i, and a remainder ε_i that is attributed to unobserved differences between workers. We include education (years of educational attainment), age (as a proxy for experience), whether a person works part-time or not, and whether a person is foreign born or not. The results are presented in Table 2.3.

The skill premium (e.g. the monetary value of having attended one additional year of school) ranges from 5.4 percent to 6.2 percent for males and from 4.8 percent to 6.5 percent for females, and is moderately increasing over time for males, and substantially increasing for females. The returns to age or experience are concave, with an estimated top in 2000 (2008) at 56 (52) for males, and 52 (51) for females. The career premium, measured as the expected *ceteris paribus* wage difference between an 18 year old male (female) worker and a worker at the career top ranges from 82 (47) percent in 2000 to 83 (54) percent in 2008. Experience is thus considerably more rewarded for males compared to females. Full-time workers earn more than part-time workers, and native born workers earn more than foreign born. The latter is most likely at least partially the result of omitted variables, like social skills (for example language proficiency).

The distribution of the unexplained wage component ε_i can be interpreted as inequality within groups on the labor market with narrowly defined worker characteristics, which is conceptually similar to the within group inequality from the previous section. Sorting all workers in our sample by this residual wage gives the distribution of wages independent from observed human capital.

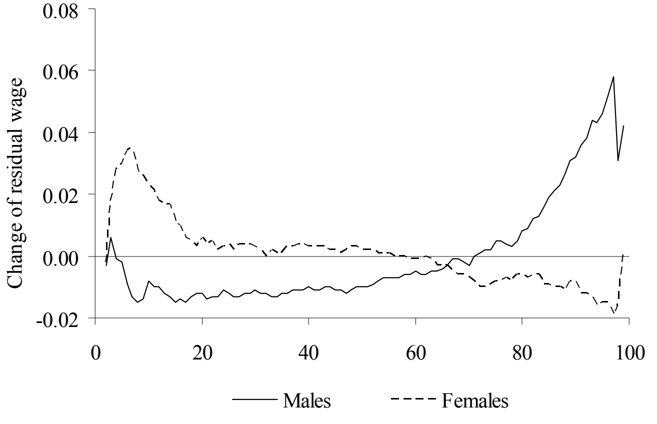
Table 2.3. Estimation results of wage regressions, 2000–2008

	2000		**2004**		**2008**	
	Males	*Females*	*Males*	*Females*	*Males*	*Females*
# Observations	10,133	7,696	23,384	22,169	46,693	35,396
Education (yrs.)	0.054***	0.048***	0.060***	0.054***	0.062***	0.065***
	(63.1)	(48.0)	(97.5)	(92.1)	(121.1)	(129.0)
Age	0.064***	0.042***	0.066***	0.044***	0.074***	0.051***
	(25.7)	(16.8)	(39.4)	(30.9)	(65.9)	(47.0)
Age-squared	–0.0006***	–0.0004***	–0.0006***	–0.0004***	–0.0007***	–0.0005***
	(19.7)	(13.2)	(31.7)	(26.1)	(65.9)	(38.9)
Part-time	–0.047**	–0.006	–0.087***	–0.011**	–0.019***	–0.046***
	(5.5)	(0.9)	(15.1)	(2.6)	(5.7)	(11.5)
Foreign born	–0.065***	–0.059***	–0.076***	–0.053***	–0.112***	–0.060***
	(5.7)	(5.0)	(9.4)	(7.8)	(17.9)	(11.2)
R^2	0.421	0.308	0.396	0.324	0.388	0.388

Note: *t*-statistics (absolute values) are in parentheses. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

Figure 2.6 shows trends in residual wage inequality, e.g. the change in residual wage inequality at each percentile between 2000 and 2008. The changes in residual inequality are relatively low, given the fact that our data cover nine years. Residual wage growth at the top five percentiles of the residual wage distribution was 1.5 percent above average. Wages at the lowest percentiles also increased somewhat above average. This is in clear contrast with workers between the 20th and the 80th percentile, where the distribution remained very flat. When we compare Figure 2.6 with Figure 2.4, we see that the residual wage distribution is relatively flat. However, as Figure 2.6 ranks workers according to their residual wage, while Figure 2.4 sorts workers by their actual wage, it is not possible to assess the extent to which within group (residual) wage inequality explains total wage inequality by comparing these two figures.

Figure 2.6. Trends in male and female residual wage inequality, 2000–2008



2.4 Decomposition of changes in wage inequality

There are several methods to analyze changes in the structure of wages. These methods – like the Theil decompositions used in the previous section – typically decompose differences in average wages between groups of workers with certain characteristics (e.g. education, age, whether a worker is native or foreign born) in two sets of components: (i) changes in average observed worker characteristics, and (ii) changes in the estimated returns or prices of those characteristics. In this section, we use the technique developed by Juhn et al. (1993) to decompose trends in wage inequality into *three* components, (i) a part due to quantitative changes of observable worker characteristics – e.g. the number of workers on the labor market with certain characteristics, (ii) a part that can be attributed to price changes – representing the wages that are associated with each of these worker characteristics given their supply – and (iii) residual changes that are related to unobservable worker characteristics. The method thus takes residual wage inequality explicitly into account, a feature that other models lack. Another important advantage of the method is that it allows us to analyze the entire wage distribution, instead of just the variance of wages.

The method of Juhn et al. is based on estimating wage equations (this is just the Mincer equation, as presented in the previous section):

$$w_{it} = X_{it}\beta_t + u_{it} \quad , \tag{2.8}$$

where w_{it} is a vector with the log hourly wage of individual i in year t, X_{it} is a matrix with individual characteristics, β_t is a vector with separate regression coefficients for each year and u_{it} an error term that captures all unobserved dimensions of the wage. In each year, we sort all workers according to their residual wage. The residual u_{it} can be separated into two components: the position of the individual in the residual wage distribution (a percentile rank θ_{it}) and the cumulative distribution function of the residual wage $F_i(\cdot)$, which gives the relation between the percentile rank and the amount of residual wage inequality, which varies over time. We thus have:

$$u_{it} = F_t^{-1}\left(\theta_{it} \mid X_{it}\right) \quad , \tag{2.9}$$

where the right-hand side term is the inverse cumulative distribution of the residual wage of workers with the characteristics X_{it}. So we are left with three sources of changing wage inequality: (i) changing distributions of the characteristics of workers that are captured in X_{it}, (ii) changes in the prices of various observed characteristics as reflected in the estimated β's and (iii) changes in the distribution of the residuals of the wage regressions that were estimated in each separate year (u_{it}). Changes in the residual wage distribution are changes in the relation between the percentile rank, and the residual wage. We define $\overline{\beta}$ as the average price of observable characteristics, and $\overline{F}_t^{-1}\left(\cdot \mid X_{it}\right)$ as the average cumulative residual wage distribution (taking the average residual at each percentile over the years 2000–2008). Wage inequality can subsequently be decomposed into its three sources as follows:

$$w_{it} = X_{it}\overline{\beta} + X_{it}\left(\beta_t - \overline{\beta}\right) + \overline{F}_t^{-1}\left(\theta_{it} \mid X_{it}\right) + \left(F_t^{-1}\left(\theta_{it} \mid X_{it}\right) - \overline{F}_t^{-1}\left(\theta_{it} \mid X_{it}\right)\right) \quad . \tag{2.10}$$

The first term represents the effect of a changing labor market composition at fixed prices. The second term captures the effects of changing prices of the observables, keeping the quantities of each worker characteristic fixed, and the third and fourth term capture the effects of changes in the residual wage distribution. We can use equation (2.10) to reconstruct the wage under *ceteris paribus* conditions. At a given price level of worker characteristics and a given distribution of residual wages, the wage distribution is given by:

$$w_{it}^{q} = X_{it}\overline{\beta} + \overline{F}_t^{-1}\left(\theta_{it} \mid X_{it}\right) \quad . \tag{2.11}$$

If we keep only the residual wage distribution constant, such that both prices and observed characteristics of workers vary over time, the distribution of wages is given by:

$$w_{it}^{p,q} = X_{it}\beta_t + \overline{F}_t^{-1}\left(\theta_{it} \mid X_{it}\right) \quad . \tag{2.12}$$

If all three sources of wage change vary together, changes in wage inequality are captured by:

$$w_{it}^{p,q,d} = X_{it}\beta_t + F_t^{-1}\left(\theta_{it} \mid X_{it}\right) = X_{it}\beta_t + u_{it} \quad . \tag{2.13}$$

A convenient way to identify these different effects is to start by estimating equation (2.13), which is equivalent to equation (2.8). The regression coefficients of different years are used to obtain average prices $\overline{\beta}$. After sorting the residuals (in each year separately) we can determine the average residual over the years in each percentile. The next step is to calculate quantity effects, using equation (2.11), and price effects, by taking the difference between equations (2.12) and (2.11). The effects of changes in the residual wage distribution are given by the difference of equation (2.13) and (2.12).

Juhn et al. (1993) use their methodology to decompose changes in wage inequality in price and quantity effects for all worker characteristics together. We now propose a simple extension to their framework, which enables us to isolate effects of different worker characteristics. Let $\mathbf{x}_{it}^{m}$ be a vector with the quantities of individual worker characteristic *m* with corresponding price β_{t}^{m}, and X'_{it} a matrix with all other observed quantities (with prices β'_{t}), such that $\mathbf{x}_{it}^{m}\beta_{t}^{m} + X'_{it}\beta'_{t} = X_{it}\beta_{t}$. X'_{it} is thus very similar to X_{it}, but it does not include the variable *m* that we would like to isolate, which is in the vector $\mathbf{x}_{it}^{m}$. We define ϕ_{it} to be the position of an individual in the conditional wage distribution $F_{t}^{-1}\left(\phi_{it} \mid X'_{it}\beta'_{t}\right)$, representing the distribution of wages conditional on quantities and prices of all worker characteristics except characteristic *m*. As before, β_{t}^{m} and β'_{t} are estimated using equation (2.13). By keeping $F_{t}^{-1}\left(\phi_{it} \mid X'_{it}\beta'_{t}\right)$ constant, we can isolate the effects of changes related to characteristic *m* from changes in both the residual distribution and changes in the wage distribution related to all other worker characteristics. The *ceteris paribus* effect of changes in the quantity of *m* is given by:

$$w_{it}^{q} = \mathbf{x}_{it}^{m}\overline{\beta}_{t}^{m} + \overline{F}_{t}^{-1}\left(\phi_{it} \mid X'_{it}\beta'_{t}\right) \quad , \tag{2.14}$$

and the effect of changes in prices and quantities of characteristic *m* jointly give rise to:

$$w_{it}^{p,q} = \mathbf{x}_{it}^{m}\beta_{t}^{m} + \overline{F}_{t}^{-1}\left(\phi_{it} \mid X'_{it}\beta'_{t}\right) \quad . \tag{2.15}$$

A difference between the above equations and equations (2.11) and (2.12) is that $\mathbf{x}_{it}^{m}$ and $\overline{F}_{t}^{-1}\left(\phi_{it} \mid X'_{it}\beta'_{t}\right)$ are correlated, whereas X_{it} and $\overline{F}_{t}^{-1}\left(\theta_{it} \mid X_{it}\right)$ are independent. Within groups with similar characteristics, however, the distribution of $\overline{F}_{t}^{-1}\left(\phi_{it} \mid X'_{it}\beta'_{t}\right)$ remains to be uncorrelated from $\mathbf{x}_{it}^{m}$. This implies that interdependencies between characteristic *m* and the distribution of wages related to all other worker characteristics (for example the fact that older workers are relatively skill abundant) is captured in $\overline{F}_{t}^{-1}\left(\phi_{it} \mid X'_{it}\beta'_{t}\right)$, whereas changes in $F_{t}^{-1}\left(\phi_{it} \mid X'_{it}\beta'_{t}\right)$ that are the result of changes in $\mathbf{x}_{it}^{m}$ are not captured. This implies that, for example, an increasing share of higher educated workers resulting from a higher participation rate of older workers – that have a higher average level of education – will not be captured. We can thus estimate a wage distribution corresponding to changed prices and quantities of characteristic *m* as if all other worker characteristics had remained unchanged.

Panel A in the upper half of Table 2.4 gives the results of the decompositions for all worker characteristics combined, for male workers. Changes in the 99–90th differential are mostly attributed to changes in the residual wage distribution, while there is a small opposite composition effect (observed quantities). Price effects have slightly reduced inequality at the highest percentiles as well. This is consistent with the findings of the previous section, which showed a strong increase of residual wage inequality at the highest percentiles. The increase of the 90–50th differential is the net effect of different opposite forces. Observed quantities have reduced inequality somewhat, whereas observed prices and trends in the residual distribution tended to increase inequality. The lower half of the wage distribution changed little. Here, a changing labor market composition decreased inequality, but increased inequality due to trends in prices of human capital resulted in a close to zero overall change in inequality. Within group inequality remained unchanged in the lower half of the distribution.

The panels B and C show the isolated effects of education and experience on the wage distribution (recall that all variables on human capital are still included in the regression analysis). If the prices and quantities of all other components of human capital would have remained unchanged, a changing composition of the work force in terms of education would have increased wage inequality by 4.2 percent – which is by coincidence equal to the total change in the 99th to 90th percentile wage differential. Similarly, keeping other prices and quantities constant, increasing returns to education would have increased inequality somewhat as well.

The fact that (as panel A showed) all trends in the composition of labor market supply combined reduced inequality at the highest percentiles rather than increase it, implies that the isolated effect of education was (more than) neutralized by other changes in the composition. As panel C shows, a changing age structure reduced inequality (e.g. a reduction in the share of older workers at the 99th percentile relative to the 90th percentile has resulted in a *ceteris paribus* reduction of inequality). A changing educational composition of the labor market resulted in a reduction of inequality at the 90th to 50th wage differential, and to a lesser extent at the lower half of the wage distribution. At the same time, increasing returns to education moderately increased wage inequality, particularly the 90th to 50th differential. The diverged pattern shows that education or experience alone do not provide a clear cut explanation for observed changes in the aggregate wage distribution. Different types of human capital have opposite or interacting effects on the wage distribution.

Table 2.4. Decomposition of wage inequality, 2000–2008

Differential	**Total change in inequality (1)**	**Change due to observed quantities (2)**	**Change due to observed prices (3)**	**Change due to residual distribution (4)**
		MALES		
		A. All characteristics		
99–90th	0.042	–0.011	–0.005	0.058
90–50th	0.024	–0.008	0.013	0.019
50–10th	0.006	–0.014	0.015	0.005
		B. Only education		
99–90th	0.042	0.042	0.009	–0.008
90–50th	0.024	–0.015	0.022	0.017
50–10th	0.006	–0.003	0.006	0.002
		C. Only experience		
99–90th	0.042	–0.007	–0.005	0.055
90–50th	0.024	–0.005	–0.011	0.041
50–10th	0.006	–0.009	–0.004	0.018
		FEMALES		
		A. All characteristics		
99–90th	0.011	0.007	–0.001	0.004
90–50th	0.016	0.010	0.018	–0.012
50–10th	–0.022	–0.022	0.014	–0.014
		B. Only education		
99–90th	0.011	–0.002	0.022	–0.009
90–50th	0.016	0.012	0.029	–0.025
50–10th	–0.022	–0.014	0.010	–0.018
		C. Only experience		
99–90th	0.011	–0.008	–0.004	0.023
90–50th	0.016	0.002	–0.004	0.018
50–10th	–0.022	–0.029	0.002	0.005

The lower half of Table 2.4 shows the results of decompositions for female employees. At the upper half of the female wage distribution, wage inequality increased somewhat due to a changing composition of the labor force. At the lower half, in contrast, a changing composition reduced inequality. Both wage inequality between the 90th and the 50th percentile and inequality between the 50th and 10th percentile has increased due to trends in prices of human capital, while these changes were moderated by decreasing residual inequality (e.g. inequality between workers with similar characteristics). In strong contrast to male top earners, wage inequality at the highest percentiles of the female wage distribution shows hardly any change. Similar to the male wage distribution, increased returns to education have resulted in increased inequality across the entire distribution, though most notably at the upper half of the distribution. Changes in the educational composition of the female work force had mixed effects, having almost no effect on top wage inequality, while slightly increasing the 90th to 50th percentile wage differential and slightly decreasing the 50th to 10th differential.

The broad picture of Table 2.4 is consistent with the findings presented in Figure 2.4. It shows that wage inequality within groups of workers with homogeneous skill characteristics decreased for the lower percentiles (this is consistent with the negative slope in Panel A of Figure 2.5), whereas within group inequality remained stable for most of the above median workers (which implies a zero slope in Figure 2.5). Wage inequality within groups with similar experience has stayed constant at the lower half of the distribution, and is increasing as we approach the highest percentiles.

2.5 The regional dimension of wage inequality

Wages do not only vary across workers with different human capital endowments and across occupations, but there are also substantial regional wage differences (see Glaeser et al., 2008, for the US, and Gibbons et al., 2008, for the United Kingdom). This is to some extent explained by spatial heterogeneity in the distribution of workers and economic activities (and thus different job types), but after correcting for these, there remain regional wage disparities due to differences in the level of productivity that are quite large in some regions. Table 2.5 shows levels and trends in the distribution of pre-tax wages and residual wages between and within the 22 largest agglomerations (as defined by Statistics Netherlands) and the periphery (which we define as all municipalities outside the agglomerations). Jobs in the largest agglomerations pay a clear premium over the periphery (column 4), even after correction for human capital (see also Chapter 3).

Absolute wages in Amsterdam are about 20 percent higher than in the periphery, while the residual wage differential (the average of the residual wage of all workers in a region) is about 10.2 percent. In several other agglomerations there is a negative average spatial residual. A worker with a standardized level of human capital is expected to earn a 7.7 percent lower wage in Enschede than in a peripheral municipality, and a 6.1 percent lower wage in Heerlen. There is a positive and significant correlation of 0.47 between the level of (residual) wages and (residual) wage growth, pointing at enhanced regional disparities over time. Agglomeration externalities provide a partial explanation for the observed differences in residual wages across regions, which is the topic of the next chapter.

When looking at the percentile ratios for different regions presented in the columns 6 to 8 in Table 2.5, it appears that regional differences in the log wage distribution below the median are relatively small. A potential explanation for this is that institutional restraints – that do not differ between regions – are more important at the bottom of the wage distribution than at the top. Above the median, and especially at the top of the distribution, there are some substantial differences. As expected – given the presence of many high quality jobs – the 90–50th percentile differential is slightly higher in the Randstad[11] agglomerations, in particular in Amsterdam, where the differential is (0.686). The lowest 90–50th percentile differentials are found in agglomerations outside the Randstad. The highest 99–90th percentile differential is found in The Hague (0.733), while it is the lowest in ’s-Hertogenbosch (0.474). In general, inequality at the highest percentiles is somewhat higher in agglomerations with high average wages. Furthermore, there is a relation between initial (above median) inequality and trends in inequality. In case of the agglomerations in Table 2.5, there is a correlation coefficient of 0.48 for the 99–90th differential, 0.48 for the 90–50th percentile differential and 0.11 for the 50–10th differential. So inequality in already unequal agglomerations increased relatively fast, especially at the highest percentiles.

[11] The Randstad refers to the area in the Netherlands where the four largest agglomerations – Amsterdam, Rotterdam, The Hague and Utrecht – are located.

Table 2.5. Wage distribution for 22 Dutch agglomerations, levels 2008 and change 2000–2008

Agglomeration	Average real hourly wages		Average residual wage		Log wage differentials			Change of log wage differentials		
	euro	indexed	level	change	99–90th	90–50th	50–10th	99–90th	90–50th	50–10th
Amsterdam	22.40	120	0.102	0.006	0.694	0.686	0.512	0.006	–0.016	–0.022
Utrecht	21.37	115	0.056	–0.023	0.718	0.614	0.500	–0.187	–0.055	–0.017
The Hague	21.30	114	0.065	–0.035	0.733	0.581	0.524	0.035	0.045	–0.059
Haarlem	20.74	111	0.056	–0.019	0.687	0.576	0.481	0.343	–0.018	0.091
Rotterdam	20.70	111	0.090	0.031	0.632	0.634	0.487	–0.025	0.016	–0.090
Eindhoven	20.53	110	0.023	0.032	0.545	0.652	0.462	–0.065	0.108	–0.030
Apeldoorn	20.06	108	0.006	0.060	0.633	0.617	0.481	–0.028	0.068	0.037
Amersfoort	20.03	108	0.039	0.017	0.671	0.678	0.494	0.063	0.362	–0.120
Breda	19.97	107	0.022	0.022	0.664	0.578	0.479	–0.098	–0.022	0.076
Dordrecht	19.95	107	0.067	0.014	0.530	0.601	0.485	–0.252	0.048	0.018
's–Hertogenbosch	19.86	107	–0.001	–0.032	0.474	0.494	0.519	–0.063	–0.005	0.086
Nijmegen	19.84	107	–0.017	0.014	0.668	0.607	0.465	–0.121	–0.177	–0.153
Arnhem	19.66	106	–0.005	–0.046	0.509	0.608	0.483	–0.700	0.047	–0.181
Leiden	19.49	105	0.019	0.017	0.641	0.566	0.439	0.103	0.034	–0.060
Groningen	19.40	104	–0.038	–0.026	0.711	0.522	0.501	0.099	–0.107	–0.062
Tilburg	19.34	104	–0.004	–0.035	0.655	0.583	0.476	–0.201	–0.164	0.028
Geleen/Sittard	19.18	103	–0.019	–0.061	0.588	0.601	0.519	–0.131	–0.051	–0.022
Leeuwarden	19.03	102	–0.029	–0.116	0.699	0.508	0.465	0.279	–0.085	0.175
Zwolle	18.94	102	–0.019	–0.081	0.507	0.504	0.464	0.067	–0.050	0.008
Periphery	18.62	100	0.000	0.006	0.694	0.572	0.452	0.042	0.018	0.004
Maastricht	18.45	99	–0.023	0.005	0.672	0.590	0.499	–0.004	0.020	0.057
Heerlen	17.82	96	–0.060	–0.066	0.503	0.596	0.443	–0.148	–0.011	–0.089
Enschede	17.47	94	–0.077	–0.034	0.669	0.605	0.451	0.317	0.172	–0.094

Notes: Wage regressions have been estimated on log wages. Indexed wages are relative to the periphery.

2.6 Conclusion

This chapter has examined levels and trends in the Dutch wage structure between 2000 and 2008, using micro data from Statistics Netherlands. It has been shown that (real pre-tax) wage inequality has increased slightly across different dimensions, especially at the top of the wage distribution. These changes are, however, mostly the result of composition effects.

Without accounting for changes in the composition of the work force, the 99–90th percentile differential increased by 4.2 percent for male workers and by 1.1 percent for females, the 90–50th differential increased by 2.4 percent for male and 1.6 percent for female workers, while the 50–10th ratio increased by 0.6 percent for male workers while decreasing by 2.2 percent for female workers. When we correct for trends in observed worker characteristics by estimating Mincerian wage equations, changes in residual inequality are respectively 5.8 (0.4) percent, 1.9 (–1.2) percent and 0.5 (–1.4) for male (female) workers. In addition, we find that wages increased faster in regions with a higher initial wage, especially in the large agglomerations in the Randstad area.

This study finds, consistent with previous work, that changes of wage inequality are moderate in the Netherlands, compared to the US and other advanced economies. It is shown, however, that this is in fact the net effect of counteracting underlying changes. Changes in the composition of the labor market – or observed quantities of worker characteristics in the terminology of Juhn et al. (1993) – have generally resulted in lower inequality. This is, however, the net effect of a changing composition with respect to age, resulting in decreasing inequality, and a changing skill composition resulting in higher inequality. Increasing skill prices have resulted in a higher 90–50th percentile ratio, whereas changes in the residual wage distribution have been linked to changes in the 99 – 90th percentile ratio.

The findings of this chapter are consistent with the empirical implications of both skill biased technological progress as well as globalization (due to similar empirical implications of the two). We do not find evidence for polarization in the Netherlands, in contrast with the findings of Goos and Manning (2007) on the United Kingdom and Autor et al. (2008) on the US labor market. Further research will be needed to isolate the empirical effects of different potential explanations for observed changes in the structure of the Dutch labor market.

3 REGIONAL WAGE DIFFERENCES IN THE NETHERLANDS: MICRO EVIDENCE ON AGGLOMERATION EXTERNALITIES

"In almost all countries, there is a constant migration towards the towns. The large towns [...] absorb the very best blood from all the rest [...]; the most enterprising, the most highly gifted, those with the highest physique and the strongest characters go there to find scope for their abilities."

Alfred Marshall (1890)

3.1 Introduction[12]

Regional wage disparities are known to be large in many countries, and they are often a source of public concern. Disparities reflect several forces, including sorting processes of both individuals and firms with different characteristics, as well as agglomeration externalities that affect the productivity of individuals. Most governments have specific policies targeted at regions that structurally lag behind. Properly targeted policies require a thorough understanding of the sources of the productivity differences between regions.

This chapter aims to identify the nature and causes of wage differences in the Netherlands. The Netherlands is an interesting case because of its perceived flatness in both geographical as well as economic dimensions. It has a very characteristic polycentric structure with only middle sized cities according to international standards, as evidenced by, for example, the relatively flat rank-size distribution of cities. Moreover, its institutional setting is known to result in a fairly equal distribution of income (see, for example, De Groot et al., 2006 and Chapter 2 of this thesis).

One of the reasons why regional wage disparities in the Netherlands are relatively small, could be the role of collective wage agreements. Particularly in lower paid jobs and in the public sector, such collective wage agreements – that

[12] This chapter is based on Groot et al. (2011b).

do not differentiate between regions – are likely to result in a more equal compensation of individuals with similar jobs across regions than it would have been otherwise. This could result in higher unemployment in more peripheral regions, as the productivity of the least productive workers will be below the collectively set wage. However, this cannot be observed when comparing unemployment across Dutch regions. In fact, the province of Zuid-Holland (which has the highest density) has the second highest unemployment, while the province of Zeeland (one of the least densely populated provinces) has the lowest unemployment. Even when institutions do not seem to be decisive for regional wage differences, it must be kept in mind that wage differentials are not only the result of agglomeration economies and spatial sorting.

The remainder of this chapter will show that, even though regional wage differences in the Netherlands are relatively small, there are still substantial regional differences, mainly between the main agglomerations in the Randstad region and the more peripheral regions (see also Chapter 2 of this thesis). Considering the spatial characteristics indicated above, our analyses on Dutch data provide us with a lower boundary for effect sizes. In our distinctly non-flat world, where all kinds of regional differences mediate economic relationships (cf. Melo et al., 2009, De Groot et al., 2009), such a benchmark will be helpful to structure future discussion.

To achieve these goals, we first describe the nature and magnitude of regional (pre-tax individual worker) wage differences in the Netherlands. We subsequently relate the spatial component of observed wage differences (after correcting for observed worker heterogeneity) to agglomeration effects. Our analysis is based on micro data provided by Statistics Netherlands (CBS). One of the advantages of micro data is the opportunity to reduce heterogeneity that remains unobserved at a more aggregate level. Previous studies have shown that these effects may be substantial (Duranton, 2010). Our approach is similar to the analysis on spatial wage disparities in France by Combes et al. (2008a). However, the availability of data on human capital allows us to estimate the effects of education on local wages directly. An advantage of this is that it enables us to analyze the importance of different dimensions of worker heterogeneity for regional wage differences.

The inclusion of worker fixed effects (as is done by, for example, by Glaeser and Mare, 2001, and Combes et al., 2008a and 2010) is another often used approach to control for worker heterogeneity. However, including fixed effects has several econometric drawbacks (see, for example, Wooldridge, 2002 and Plümper and Troeger, 2007). First of all, workers who do not move between regions or sectors identify only changes over time in that area. However, the problem is that we are mostly interested in agglomeration economies, which do not vary very much over time. Some authors claim that the inclusion of fixed effects in such a case "throws out the baby with the bath water" (Beck and Katz, 2001). The identification through workers that move to a different region, on the other hand, raises the issue of selection bias, as accepting a job in a different region is related to how favorable the offer is.[13]

Furthermore, even though such fixed effects eliminate biases by time-invariant omitted variables, time-variant omitted variables (such as experience) may still result in biased estimates. This is particularly relevant in the context of agglomeration economies – if we assume that sorting is a relevant process – as workers that accumulate relatively more human capital throughout their careers may be more likely to move to a more productive location than those accumulating less human capital.

Even though we are not the first to estimate the size of agglomeration economies using micro data, it will be insightful to see how our estimates of agglomeration economies in the Netherlands compare to estimates from other countries. Furthermore, adjusting on the choice of relevant variables, methodology, as well as the use of different datasets paves the way for comparative overviews. Meta-analyses enable us to analyze the relative importance of different object-related variables (such as the region and timeframe under observation), and different research-related variables, such as the agglomeration measures that were used.

In the remainder of this chapter, we start by discussing different causes of regional wage differences. Section 3.3 provides a description of the data and methodology that are used. Section 3.4 presents stylized facts about regional differences in wages. Section 3.5 uses the Mincer equation to relate wage differences to observed worker characteristics and to subsequently derive a spatial

[13] Combes et al. (2008a) argue that selection biases are not likely to be relevant, because workers base their migration considerations on future expectations of wages rather than on actual wage offers. However, if we assume that a higher wage is more attractive to an employee than a lower wage, selection effects cannot be fully excluded.

residual that captures wage variation across space that cannot be attributed to individual characteristics. Section 3.6 aims to further explain this spatial residual, and relates it to different agglomeration externalities. Section 3.7 discusses the robustness of the results along several dimensions and Section 3.8 concludes.

3.2 Sources of regional wage differences

Among the different ways to classify sources of regional wage differences, Combes et al. (2008a) provide perhaps the most intuitive. They distinguish between three sources of regional wage differences. The first is the composition of the labor market. Higher wages in a region may reflect a more favorable skill composition. Local non-human endowments (e.g., deep water access) are the second explanation, and agglomeration economies the third. The latter results from spatial proximity of firms to other firms, from thick labor markets, and from knowledge spillovers. We will briefly discuss these three in turn. Rather than developing a mathematical theoretical model, we follow the model developed by Combes et al. (2008a).

Workers with different skills and experience levels, or with different ethnic backgrounds, are not homogeneously distributed across space.[14] As sectors are not spread evenly across regions either, and different industries require a different mix of worker characteristics, workers tend to spatially sort themselves based on the supply and demand for their specific competences. One notable reason for the absence of an isotropic wage landscape is that institutions in higher education, as well as industries that require highly skilled labor, are usually concentrated in densely populated cities. Students that move from the periphery to a city to be educated there, subsequently have little incentive to move back to the periphery (see Venhorst et al., 2010). Therefore, composition can be held accountable for part of spatial differences in wages. In other words, assuming that wages are equal to the marginal product of labor, average wages will differ across regions, even when there are no regional differences in the productivity of workers with equal characteristics. However, when there are regional wage differences that exceed

[14] Gender, which is also a common cause for wage differentials (see, for example, Chapter 2 or Altonji and Blank, 1999), has a more or less uniform spatial distribution in the Netherlands.

such composition or sorting effects, productivity differences come to the surface.[15]

Productivity differences come in (at least) two kinds, and although they can be given different labels, we will use non-human endowments on the one hand, and agglomeration externalities on the other. Regions that have good access to waterways, a favorable climate, or valuable natural resources can have a higher level of productivity than less endowed areas. An especially interesting type of non-human endowments are those with a non-natural nature, like technology, local institutions and private capital, as they are often endogenous. Railway stations in the nineteenth and twentieth century are a nice example. Stations were built on the most populated locations at that time, but as they strongly reduced distance (measured in time), they further reinforced agglomeration forces. This causes substantial endogeneity, since these effects thus coincide with effects of population density. We will therefore use instrumental variables (IV), using density in 1840 as an instrument for current density. The year 1840 was chosen because the population census that took place in that year is the last available before the start of the industrial revolution in the Netherlands – which was rather late, in comparison to other countries – and one year after the first railway was opened.

Starting from the observation that people are not homogeneously distributed across space, and that therefore there must be advantages of clustering, various authors have pointed at the importance of agglomeration externalities for economic growth. Following Marshall (1890), agglomeration economies have been classified into three broad categories: those arising from labor market interactions, linkages between firms, and technological externalities resulting from knowledge spillovers (see Duranton and Puga, 2004, for an overview of the micro foundations of agglomeration externalities). As the empirical implications of externalities from thick labor markets are very similar to those of interactions between firms or knowledge spillovers, the relative importance of these explanations is difficult to test.

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[15] This chapter does not take consumers and their preferences into account. A consumer preference for densely populated regions could also result in spatial sorting of different education groups, as workers with a higher income can pay a higher price for housing in their most preferred areas. Combes et al. (2008a) are convinced that such a preference, which can very well be based on urban amenities, cannot play a role, and we follow them in this regard.

One of the mechanisms through which agglomeration works is a combination of physical proximity with scale effects of both demand and supply. Large local demand and supply reduce transaction costs on markets for final goods and on markets for production inputs, leading to cost reductions as groups of firms enjoy "collective economies of scale" (Harvey, 1981, p. 105). Duranton and Puga (2004) extend this view to all inputs, whether workers or intermediate goods, and note that cities reduce the costs of incomplete information. If such effects are on the side of firms, we choose to label it specialization or concentration; if they are on the side of population, we call it urbanization. However, the literature is quite confounded on this issue. Specialization covers all advantages of local concentrations of firms, or local 'monoculture' of industries. It also includes knowledge spillovers, which promote local innovation (Jaffe et al., 1993), in so far as these spillovers occur within a sector. If they occur across sectors, either in completely different industries (*Neue Kombinationen*, Schumpeter, 1934) or in related industries (Frenken et al., 2007), they are a benefit of diversity or variety.

Glaeser et al. (1992) analyzed this contrast in detail, putting intra-sectoral knowledge spillovers, which they labeled the Marshall-Arrow-Romer (MAR) effect, side by side with cross-sectoral spillovers, labeled Jacobs effects, after Jacobs (1969). In the MAR model, knowledge is industry-specific and regional concentration of certain industries therefore allows more knowledge spillovers between firms in the same industry. In Jacobs' vision, innovations are born where differences meet. Duranton and Puga (2004) support this view, and conclude that heterogeneity is at the root of the mechanisms that explain the advantages from agglomeration. Although the debate on agglomeration economies has centered on these two hypotheses (most notably in Beaudry and Schiffauerova, 2009), Glaeser et al. (1992) distinguished a third category of agglomeration economies: Porter externalities, named after Porter (1990), who pointed at the importance of (local) intra-sectoral competition as a source of productivity gains. Glaeser et al. (1992) found that Jacobs externalities were empirically the most important agglomeration effect. However, in the following decades, many studies have repeated their analysis for different countries, regional definitions, time periods, proxies for the agglomeration externalities, etc., and they found rather mixed results.

Reviews of this strand of literature are provided, among others, by Rosenthal and Strange (2004), Beaudry and Schiffauerova (2009), De Groot et al. (2009)

and Melo et al. (2009). The latter two contributions present meta-analyses of the existing literature, and they show that agglomeration externalities exhibit large variation across space, time and particularly research method. The inclusion of control variables (like industry effects), and the use of micro data instead of macro-level data are of large importance for the outcomes. In general, they show that agglomeration externalities seem to have positive effects, and that over time, they tend to become more important.

3.3 Data and methodology

Similar to the previous chapter, this chapter combines three data sources from Statistics Netherlands (CBS): Dutch census data (SSB, *Sociaal Statistisch Bestand*) – which includes employer reported tax data, the labor force survey (EBB, *Enquête Beroeps Bevolking*), and firm data (ABR, *Algemeen Bedrijven Register*). As census data and the available firm data originate from registers rather than questionnaires, we can calculate our agglomeration variables using data on all Dutch firms and workers. However, as data on the work location of *all* Dutch employees is available only until 2005, this chapter only uses data for the period 2000 to 2005. We cannot construct the agglomeration variables used in this chapter for the years 2006–2008.

In our wage regressions, we rely on the labor force survey to be able to correct for differences in human capital. All records have unique identifiers for individuals and firms, respectively, which enables us to create a linked employer-employee database. In the tax records, the level of observation is that of the job, so a worker can have multiple entries in each year. We use only the job that paid the highest wage. Wages are defined as pre-tax hourly wages of individual jobs, to approximate the productivity level of workers. This approach is often used in the literature (for example by Glaeser and Mare, 2001 and Combes et al., 2008a and 2010), assuming that employees are paid according to their marginal product. From the perspective of the worker, higher wages might be offset by higher costs of living, or higher costs of commuting. However, employers will only choose a location with high labor costs and land prices if these locations offer a productivity advantage (see Puga, 2010, for an overview). Wages do not include untaxed compensation for work related expenses, such as the costs of commuting.

Furthermore, wages have been deflated using the consumer price deflator (CPI, *Consumenten Prijs Index*) of Statistics Netherlands.

The work location is available at the municipality level. For most of the analyses in this chapter we aggregate the location-specific data to the NUTS-3 level (the so-called COROP regions; see Appendix A, for a map of the Netherlands). Briant et al. (2010) discuss the importance of regional classifications for the outcomes of economic geographical research, and conclude that it is important that the chosen scale of a regional classification corresponds with the level of aggregation at which the researched phenomenon is expected to operate. Even though COROP regions are not strictly local labor market areas, they provide us with the most reasonable approximation in the Dutch case. We use the regional classifications of 2005, and have data on 40 NUTS-3 regions and 467 municipalities. The work location is the self-reported job site that is available through EBB. The work location of each employee thus reflects the actual work location, rather than the location of the head quarter. For each employee, we have information on his or her age, gender, ethnicity, hourly wage, and workplace location. For each business unit, we use the sectoral classification on the 2-digit NACE level and the number of employees.

To estimate wage regressions, we combine this large dataset with the Dutch labor force survey. From this dataset, we use the self-reported number of hours worked (which enables us to calculate hourly wages)[16], and the level of education. We exclude all employees earning less than one tenth of the average hourly wage or more than ten times the average, all workers younger than 18 on January 1st and older than 65 on December 31st in each year, and all workers with a working week of less than 12 hours.[17] After merging these three data sets, and performing selections as described above, we have a total of 190 thousand observations. This number is somewhat lower compared to the dataset used in Chapter 2, because the work location is not known for all employees in the labor force survey and

[16] Hourly wages are calculated by dividing the employer reported pre-tax annual wage from SSB (e.g., the fiscal wage) by the self-reported number of hours an employee works in a typical week (from EBB) and the number of weeks the employee worked during a year, which is calculated from the (employer reported) start and end date of the job.

[17] We distinguish between part-time employees, working 12 hours or more per week, but less than 32 hours, and full-time employees working 32 hours per week or more. Having a working week of at least 12 hours is the official definition of Statistics Netherlands of being employed. It should be noted that part-time working is very common in the Netherlands (Bakker et al., 1999).

because only the best paid job of each employee was included in each year. Between 2000 and 2005 the number of observations gradually increased from just over 17 thousand to 45 thousand observations. However, as we use pooled cross-sections rather than panel data, this is unlikely to affect the results.

We construct our agglomeration variables directly from the micro data. For this purpose we use cross sections of tax and firm data, such that we have about 10 million observations annually available. In this case, location is based on employment by business unit.[18] A business unit is defined as an establishment of a firm at a specific location. Proxies for agglomeration effects can be constructed in many different ways, and the choice for a specification has been shown to matter for the results found (De Groot et al., 2009).

We use the share of industries in the economy of the NUTS-3 region or municipality (depending on the specification) to capture MAR externalities (with E for total employment, and subscripts *ind* for industry and r for region):

$$Specialization_{ind,r} = \frac{E_{ind,r}}{E_r} \quad . \tag{3.1}$$

When industry dummies are included, the log of specialization captures the same effect as a location quotient, viz. the effect of a smaller or larger share of an industry relative to the share of that same industry in all other regions.

We use Shannon's entropy (after Shannon, 1948) to capture externalities from diversity:

$$Diversity_r = -\sum_{ind}\left(\frac{E_{ind,r}}{E_r}\cdot \ln\frac{E_{ind,r}}{E_r}\right), \tag{3.2}$$

where we sum over the industries. A high value means that the region is highly diversified in terms of its employment structure, whereas a low value means that the regional economy is rather specialized in only a few large sectors. As a measure for diversity, entropies have several advantages over other measures,

[18] CBS derives local employment by combining tax data (that gives total employment per firm) with a survey where multi-establishment firms with 10 or more employees provide employment in each municipality. Employees of multi-establishments firms with less than 10 employees (with a relatively low share in employment), are allocated to the head quarter. While not usable for linking specific individuals to firms, this reasonably approximates employment per firm per municipality.

because it accounts for the size distribution of sectors (cf. Shannon, 1948, Straathof, 2007).

Finally, competition is measured using a Hirschman-Herfindahl based index on the distribution of employees across firms (subscript f denotes individual firms):

$$Competition_{ind,r} = 1 - \sum_{f} \left(\frac{E_{f,ind,r}}{E_{ind,r}} \right)^2 \quad , \tag{3.3}$$

where we sum over the individual firms in each sector-region combination. Since we calculate the index as one minus the Hirschman-Herfindahl index (HHI), a value close to one indicates fierce competition in a region. When the index is low, regional employment within an industry is highly concentrated in a relatively small number of firms.

Besides these three sector-related agglomeration effects, we capture general urbanization effects with overall employment density in a region (where A stands for the surface of the area):[19]

$$Density_r = \ln\left(\frac{E_r}{A_r} \right) = \ln E_r - \ln A_r \quad . \tag{3.4}$$

We instrument density in 2000 with density in 1840, to account for endogeneity (Ciccone and Hall, 1996, Combes et al., 2008a , Graham et al., 2010). We will present both the results of OLS and IV estimations. If the use of instrumental variables leads to substantially different results, it is likely that the OLS estimates were biased due to the presence of endogeneity.

Similar to Combes et al. (2008a), we apply a two-stage estimation strategy. In the first stage, we regress log hourly wages of individual workers on a set of variables that are related to human capital, as well as a set of industry-region-year fixed effects, or separate industry and region-year fixed effects. This way, we are able to separate the effects of sorting of workers across regions from the effects of

[19] As pointed out by Combes et al. (2008a), when the area of regions has already been included as a separate variable, employment can – with proper reinterpretation of the coefficients – be included directly in the equation without subtracting the log of the area.

agglomeration. The region-year fixed effects can be interpreted as an indicator for the regional wage or productivity level, after correcting for differences in (observed) individual characteristics. In the remainder of this chapter, we refer to this as the spatial residual. As Moulton (1990) points out, estimating the effect of aggregate variables (such as agglomeration variables) on micro units, results in a downward bias in standard errors of the estimates. This is explained by the fact that errors within groups are not independently distributed. In the second stage, we regress the industry-region-year fixed effects on the agglomeration variables that were discussed above, year dummies, and industry fixed effects to control for regional differences in sectoral structure. For the second stage, we estimate several different specifications on both the NUTS-3 and municipality level.

3.4 Stylized facts

Before turning to the econometric analysis, we present some stylized facts about the key variables in our dataset. Table 3.1 presents separate descriptive statistics for the observations in the two stages of our estimation strategy. For the second stage, we present descriptive statistics for observations at both the NUTS-3 level and the municipality level. The average age of the workers in our sample, as well as the shares of female workers and part-time workers, have been gradually increasing over time. The agglomeration variables show little change over time, even when we consider the relatively limited timeframe of the data used in this chapter. Furthermore, it can be observed that there is much more variation between municipalities than between NUTS-3 regions.

Panel A of Figure 3.1 shows average hourly wages per worker in each NUTS-3 region. The corresponding names of the Dutch NUTS-3 classification are included in Appendix A. On average, employees working in the Amsterdam agglomeration receive the highest hourly wages, while those in the North-Eastern part of the Netherlands (Zuidwest-Friesland) earn the lowest. In general, wage levels are relatively high in the western provinces of the Netherlands – mainly in the Randstad (the area where the four largest Dutch cities are located; Amsterdam, Rotterdam, the Hague and Utrecht).

Table 3.1. Descriptive statistics

	2000	2005	Pooled 2000–2005
Descriptives for 1st stage			
# Observations	17,317	44,556	190,497
Log real wage	2.896	2.938	2.928
	(0.37)	(0.37)	(0.37)
Age	41.95	43.53	42.84
	(9.8)	(10.0)	(10.0)
Female	0.432	0.492	0.474
	(0.50)	(0.50)	(0.50)
Foreign born-worker	0.069	0.070	0.069
	(0.25)	(0.26)	(0.25)
Part-time worker	0.383	0.442	0.418
	(0.49)	(0.50)	(0.49)
Descriptives for 2nd stage (NUTS-3 regions × industries × years)			
# Observations	1,145	1,338	7,412
Log employment density	5.482	5.450	5.475
	(0.87)	(0.85)	(0.85)
Specialization (Log industry share)	–4.191	–4.405	–4.318
	(1.31)	(1.41)	(1.37)
Log area	6.585	6.573	6.577
	(0.73)	(0.74)	(0.74)
Diversity (Shannon's entropy)	3.025	2.973	3.002
	(0.09)	(0.08)	(0.09)
Competition (1–HHI)	0.819	0.816	0.819
	(0.23)	(0.24)	(0.23)
Descriptives for 2nd stage (municipalities × industries × years)			
# Observations	3,620	4,998	25,881
Log employment density	5.776	5.681	5.718
	(1.31)	(1.30)	(1.30)
Specialization (Log industry share)	–3.392	–3.505	–3.453
	(1.16)	(1.23)	(1.20)
Log area	4.060	4.016	4.035
	(0.87)	(0.87)	(0.87)
Diversity (Shannon's entropy)	2.841	2.804	2.824
	(0.17)	(0.17)	(0.17)
Competition (1–HHI)	0.665	0.660	0.660
	(0.29)	(0.29)	(0.29)

Note: Standard deviations are reported in parentheses.

As panel B shows, this can be partly explained by a relatively strong concentration of highly educated people in the Northern wing of the Randstad and the agglomeration of The Hague (the residence of Dutch parliament and the political centre of the country). At the same time, panel C indicates that these are also the regions with by far the largest employment density. The difference would have been even more pronounced if we had included the highest incomes (over 10 times the overall average wage), since many high paid jobs are located in the largest cities in the Randstad. Sectoral diversity, presented in panel D of Figure 3.1, does not show a very clear relation with average wages. The relatively high specialization in The Hague might be explained by a high share of not-for profit services, while other agglomerations are relatively specialized in services.

To give an indication of the relation between key variables, Table 3.2 presents some simple correlations. Even after correcting for (observed) worker heterogeneity, the remaining spatial residual has a correlation with the average wage in the region of 0.70. Sorting does thus not fully explain regional wage differences. Both the average wage and the spatial residual are highly correlated with employment density. Other strong correlations exist between average wages in regions and the share of highly educated workers.

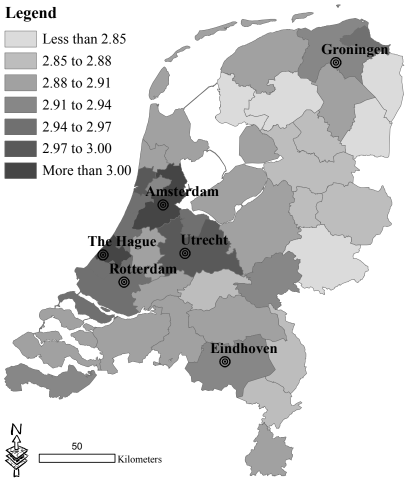
Table 3.2. Simple correlations between NUTS-3 regions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Log average wage	1.00								
(2) Spatial residual	0.70	1.00							
(3) Share higher educated workers*	0.68	0.27	1.00						
(4) Average age	0.14	0.05	–0.25	1.00					
(5) Share of females	–0.50	–0.36	–0.08	–0.28	1.00				
(6) Share of foreign-born workers	0.68	0.77	0.53	–0.08	–0.29	1.00			
(7) Share of part-time workers	–0.41	–0.41	–0.19	–0.07	0.61	–0.56	1.00		
(8) Log employment density	0.74	0.70	0.69	–0.10	–0.28	0.77	–0.33	1.00	
(9) Diversity (Shannon's entropy)	–0.50	–0.40	–0.46	–0.11	–0.16	–0.39	–0.13	–0.45	1.00

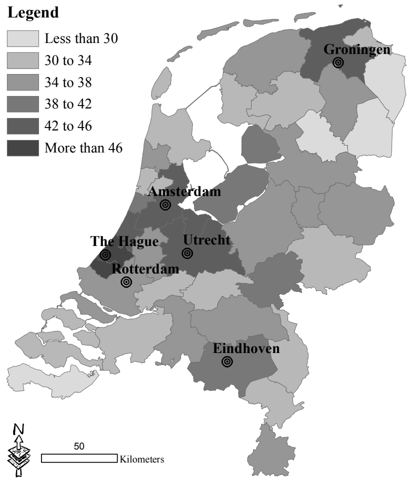
Note: The spatial residual and its estimation is the topic of Section 3.5. It represents the part of the wages that is not explained by (observed) individual worker characteristics.
*Higher educated workers are defined as those with at least higher tertiary education (HBO or university degree).

Figure 3.1. Stylized facts by NUTS-3 region, 2000–2005

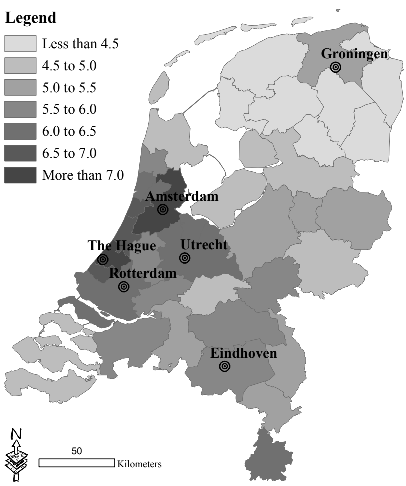
A. Average Log wage



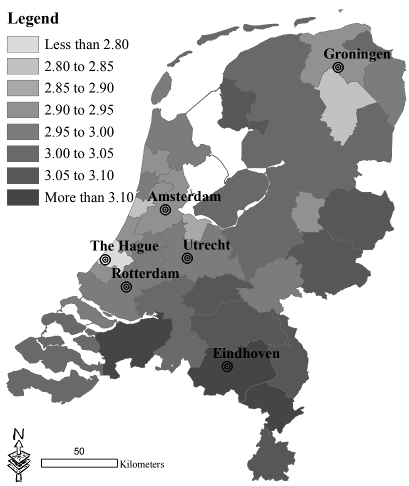
B. Percentage share of higher educated workers*



C. Log employment density



D. Sectoral diversity (Shannon's entropy)**



Notes: *Higher educated workers are defined as those with at least higher tertiary education (HBO or university degree). **A high value implies that the economy is relatively diversified, a low value implies a specialized regional economy.

3.5 Estimation of the Mincer equation

In Section 3.2, we discussed three broad explanations for regional wage disparities. The composition of regional labor markets relates to the characteristics of individual workers that live in a region, whereas regional endowments and agglomeration economies result in higher productivity for a given labor market composition. A method that is often used in economics to analyze wage differences is the Mincerian wage regression (cf. Mincer, 1974).[20] The estimation of the Mincer equation relates the wage earned to a series of factors, starting with personal characteristics, but also including job characteristics, sectoral characteristics and regional characteristics. To estimate the regional component of wages, we include dummy variables (40 in case of NUTS-3 regions, 367 in case of municipalities) for the region ($D_{i,t}^{r}$). Furthermore, we include 58 industry fixed effects ($D_{i,t}^{ind}$) and year fixed effects ($D_{i,t}^{year}$). To estimate the effect of agglomeration variables in the second stage of our econometric approach, we replace these separate region, industry and year fixed effects by combined region-industry-year fixed effects. The latter can then be further analyzed in a second stage, where we can assume that (observed) worker characteristics no longer play a role.

To control for education, we use dummy variables for the highest qualification that was obtained by workers, ($D_{i,t}^{edu}$). This allows for differences in both the quality and quantity of education.[21] We also include age (as a proxy for experience), age-squared to allow for nonlinear effects, as well as dummies for gender (D_{i}^{gender}), for migrant status ($D_{i}^{migrant}$), and for part-time workers (which are defined as workers working less than 32 hours per week),[22] ($D_{i,t}^{part\text{-}time}$). Dependent

[20] Although often applied, it should be noted that the causal relationship between the variables in the Mincer regression and the wages earned is actually not very strong. There exists an extensive literature on this subject, often using instrumental variable (IV) estimation methods in natural experiments where an exogenous shock affects the wages at a specific moment. Some of the contributions to this literature are Griliches (1977); Ashenfelter et al. (1999); Heckman et al. (2003) and Webbink (2004).

[21] We distinguish seven levels of education. The first is primary education (which is the omitted category in our Mincer regressions). We have two levels of secondary education, a lower level (in Dutch: VMBO and MBO1) which has a more practical orientation, and a higher level (HAVO and VWO), which are theoretical and focussed on later enrolment in higher tertiary education. We distinguish two different types of lower tertiary education, whereby MBO2 and MBO3 remain to be mostly practically oriented, while MBO4 has also a theoretical orientation. Finally, we distinguish two levels of higher tertiary education. One with HBO (which is positioned just below the level of universities) and university Bachelors, and one including university Masters and PhDs.

[22] Statistics Netherlands defines a part-time worker as an employee working 12–32 hours per week.

variable is the log real hourly wage, $\log(w_{i,t})$, of individual *i* in year *t*. The regression equation is formally denoted by:

$$\log(w_{i,t}) = \alpha + \sum_{edu} \beta_{1,edu} D_{i,t}^{edu} + \beta_2 age_{i,t} + \beta_3 age_{i,t}^{\;2} + \beta_4 D_i^{gender} + \beta_5 D_i^{migrant}$$

$$+ \beta_6 D_{i,t}^{part\text{-}time} + \sum_{ind} \beta_{7,ind} D_{i,t}^{ind} + \sum_{r} \beta_{8,r} D_{i,t}^{r} + \sum_{year} \beta_{9,year} D_i^{year} + \varepsilon_{i,t} \; . \tag{3.5}$$

The estimated education dummies do not perfectly reflect the effects of education, as education is correlated to unobserved variables like ability. Therefore, our use of education is to be considered as a more general proxy for the ‘knowledge’ of a worker, such that we estimate how much the knowledge of workers is rewarded. It is, however, possible that individuals might also be clustered according to non-observed characteristics. Even though we do correct for the possibility that higher educated workers are attracted to some regions, it is also possible that the most able *among* the higher educated are more attracted to cities. Our estimated spatial residual in part captures this clustering. We leave it for further research to address this issue. It is, however, important to bear in mind that simply including worker fixed effects will not correct for this type of unobserved worker heterogeneity, as becoming one of the most able in a field is typically a process that evolves over time rather than something fixed at birth.

Table 3.3 presents the regression results for the years 2000 and 2005 separately, and for a regression on the pooled cross-sections from 2000 to 2005. We find that the impact on wages of the different worker characteristics that were evaluated has remained fairly constant during the reference period. Estimated coefficients for the effects of education and age/experience are comparable to the values that are generally found in the literature (see, for example, Chapter 2). The region dummies estimated for each NUTS-3 area represent the spatial residual, and are presented in Figure 3.2. This represents the regional wage, after correcting for differences in worker heterogeneity and sectoral composition. As estimation required us to omit an arbitrary region, we have subtracted the spatial residual of the average region from that of other regions to allow for a more straightforward interpretation. The values are thus interpreted as expected log wage differentials relative to the average region, of workers with given characteristics.

Table 3.3. Mincer regression (dependent variable: log of individual wage)

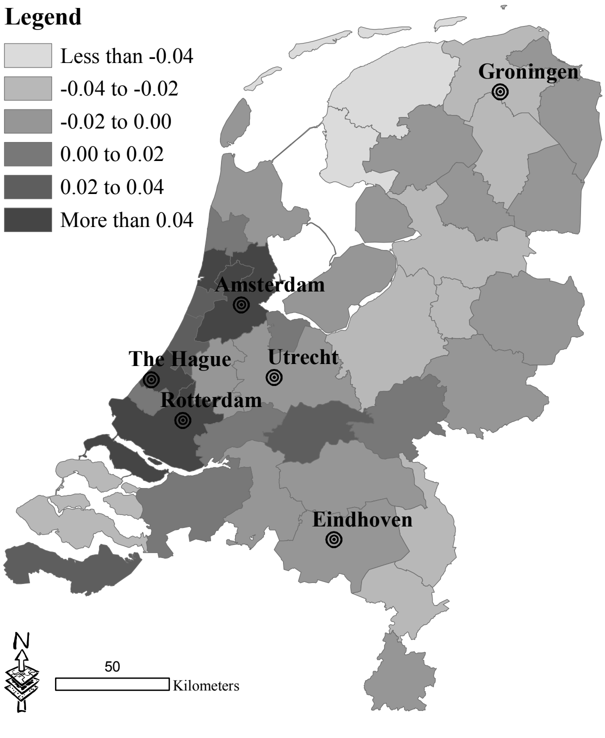
Dependent: Log hourly wage	2000	2005	Pooled 2000–2005
# Observations	17,317	44,556	190,497
Age	0.045^{***}	0.048^{***}	0.047^{***}
	(27.0)	(45.3)	(94.1)
Age-squared	-0.0004^{***}	-0.0004^{***}	-0.0004^{***}
	(19.4)	(35.5)	(72.2)
Female	-0.167^{***}	-0.140^{***}	-0.148^{***}
	(31.1)	(40.8)	(90.5)
Immigrant	-0.081^{***}	-0.091^{***}	-0.084^{***}
	(9.9)	(17.9)	(34.3)
Part-time worker	–0.004	-0.032^{***}	-0.026^{***}
	(0.7)	(9.4)	(15.9)
Education dummies			
Lower secondary education (VMBO, MBO 1)	0.028^{*}	0.060^{***}	0.051^{***}
	(2.5)	(7.3)	(14.0)
Higher secondary education (HAVO, VWO)	0.248^{***}	0.245^{***}	0.256^{***}
	(20.7)	(28.6)	(66.6)
Lower tertiary education (MBO 2 + 3)	0.144^{***}	0.166^{***}	0.161^{***}
	(13.4)	(20.9)	(45.9)
Lower tertiary education (MBO 4)	0.214^{***}	0.238^{***}	0.237^{***}
	(20.0)	(30.7)	(68.3)
Higher tertiary education (HBO, BA)	0.385^{***}	0.420^{***}	0.415^{***}
	(36.1)	(54.5)	(120.0)
Higher tertiary education (MA, PhD)	0.580^{***}	0.605^{***}	0.607^{***}
	(50.3)	(74.6)	(164.7)
Industry dummies	yes	yes	yes
Year dummies	no	no	yes
Region dummies	yes	yes	yes
R^2	0.50	0.48	0.49

Notes: *t*-statistics (in absolute values) are reported in parentheses. Education dummies denote the highest qualification obtained, with as omitted category those individuals who have only primary education. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

Zuidwest-Friesland is the region with the lowest wages after correcting for the spatial sorting of workers. This also happens to be the region where the lowest average wages are paid. The highest premium is paid in the Amsterdam region, where a typical worker can expect to earn 7.4 percent more than if he would have been located in the average region.

When we compare the results presented in Figure 3.2 with those on the distribution of average wages presented in panel A of Figure 3.1, it can be observed that the spatial residual is generally higher in the Randstad. The distribution of the spatial residual across regions looks very similar to the distribution of average wages that have not been corrected for worker heterogeneity, as might be expected given the rather high correlation between the two (see Table 3.2). However, the distribution of the wages is far more compressed after correcting for worker heterogeneity than before. Before (after) correction for worker heterogeneity, the log wage differential between the region with the highest and the region with the lowest wage is 0.232 (0.121), while the standard deviation calculated on regional averages is 0.053 (0.028).

Figure 3.2. Average spatial residual by NUTS-3 region, 2000–2005



Notes: Spatial residuals represent average regional wages after correcting for (observed) worker heterogeneity, as well as regional heterogeneity in sectoral composition. Presented values are relative to the average Dutch region, and are measured as dlogs.

3.6 Explanation of the spatial residual

This section performs the second stage of our empirical approach, by further exploring the part of variation in wages that is not explained by employee characteristics (see Section 3.3 for a discussion of our empirical strategy). We start by re-estimating the Mincer equation (3.5), but instead of separate region, year, and industry dummies, we include a dummy for each combination of industry, region and year:

$$\log(w_{i,t}) = \alpha + \sum_{edu} \beta_{1,edu} D_{i,t}^{edu} + \beta_2 age_i + \beta_3 age_i^2 + \beta_4 D_i^{gender}$$
$$+\beta_5 D_i^{immigrant} + \beta_6 D_i^{part-time} + \sum_{ind}\sum_{r}\sum_{year} \gamma_{ind,r,t} D_{i,t}^{ind} D_{i,t}^{r} D_i^{year} + \varepsilon_{i,t} \quad . \qquad (3.6)$$

We repeat the same procedure using municipalities instead of NUTS-3 regions. Estimated coefficients are very comparable to those estimated in the previous section.

In the second stage of our analysis, we explain the resulting residual by a set of geographical variables, to test for the presence of different types of agglomeration externalities. Here we include the log of employment density in each region (urbanization effect), the log employment share of each industry and region (specialization effect), surface area, Shannon's entropy (Jacobs diversity effect), and a Hirschman-Herfindahl based index on the distribution of employment over firms (Porter competition effect).

The measures we use for the different agglomeration forces have been introduced more extensively in Section 3.2. We thus estimate the following equation:

$$\gamma_{ind,r,t} = \alpha + \beta_1 Density_{r,t} + \beta_2 Specialization_{ind,r,t} + \beta_3 Diversity_{r,t} \qquad (3.7)$$
$$+\beta_4 Competition_{ind,r,t} + \beta_5 \log Area_{r,t} + \sum_{ind} \beta_{6,ind} D_{r,t}^{ind} + \sum_{year} \beta_{7,year} D_{ind,r}^{year} + \varepsilon_{ind,r,t} \quad .$$

We estimate equation (3.7) both on the regional level of NUTS-3 regions and on municipalities. A classical estimation problem when attempting to estimate agglomeration economies is that region size is likely to be endogenous to local wages. If we estimate equation (3.7) using normal OLS, it is therefore not clear whether causality runs from higher population density to higher productivity, or whether higher productivity merely attracts more workers thus increasing density. Following Ciccone and Hall (1996), historical population densities have been used to instrument for current density. As historical population is unlikely to have been altered by current productivity, while historical and current density are at the same time highly correlated, this provides a suitable instrument. We therefore estimate the impact of agglomeration both using OLS and Instrumental Variables (IV), whereby we use the density in 1840 as an instrument for present density. Furthermore, to obtain robust standard errors we have clustered estimated standard errors by region.[23]

The results of our four specifications are presented in Table 3.4. Our preferred specification is the one estimated on the NUTS-3 level using instrumental variables (IV). The interpretation of the most important findings from this specification is that doubling the density of employees working in a region is associated with a 4.8 percent higher wage on average. Doubling the share of an industry in a region results in a 2.9 percent higher wage for the workers in that region. The effects of employment density and specialization are slightly higher when using IV compared to our OLS regressions, which implies that endogeneity has not resulted in an upward bias of our OLS estimates. Additionally, we find a statistically significant negative relation between the residual wage component and both competition and diversity (albeit the latter becomes statistically insignificant in our IV-specification), contradicting the presence of Porter and Jacobs externalities (and consistent with insights from the efficiency wage literature; see, for example, Krueger and Summers, 1988, amongst many others).

If we compare the results estimated for NUTS-3 regions with those for municipalities, which are presented in the two right hand columns in Table 3.4, it emerges that agglomeration effects are found to be considerably smaller. For

[23] Another estimation issue results from using a two-stage estimation strategy. As the standard errors of the estimated fixed effects ($\gamma_{ind,r,t}$) depend on the number of observations within each industry-region-year group in the first stage, using $\gamma_{ind,r,t}$ as dependent variable introduces some heteroscedasticity (Combes et al., 2008a). To correct for this issue, Combes et al. (2008a) use a feasible generalized least-squares estimator (FGLS). However, their results show that the effects of sampling errors in the first stage have little effect on the estimates at the second stage, and they therefore ignore them when dealing with endogeneity for computational simplicity. Consequently, we will refrain from using FGLS.

municipalities, the employment density-wage elasticity is 0.021, while it was 0.048 for the NUTS-3 regions. A possible explanation for these lower estimates is that agglomeration economies operate on a larger spatial scale than that of municipalities. As Briant et al. (2010) show, it is important that the chosen scale of a regional classification corresponds with the level of aggregation at which the researched phenomenon is expected to operate. As different municipalities within the same local labor market function as integrated economies, where large differences in productivity cannot persist, variety in agglomeration measures within those local labor markets may have less relevance and is also likely to introduce noise. Therefore, our preferred estimations are those on the NUTS-3 level.

In addition to the results presented in Table 3.4, we have performed an array of robustness checks on our estimates. Because the number of hours worked (which was included in the first stage of our estimation strategy) might be endogenous, we have re-estimated our model considering only full-time employees. This yields very similar results: all estimates are qualitatively the same and the estimated agglomeration density – using IV estimation on NUTS-3 regions – becomes 4.9 percent. Even though theory suggests that directly estimating the effects of agglomeration would result in biased estimates (see Section 3.3 or Moulton, 1990), we have compared the results from the two-stage approach to single-stage OLS and IV estimates. This resulted in comparable regression coefficients, but far lower (though most likely biased) standard errors.

In underlining the importance of using micro data for the identification of agglomeration externalities, it has often been pointed out that aggregate regional data (especially average sectoral composition and worker characteristics) do not sufficiently correct for worker and firm characteristics (Combes et al., 2008a and 2008b, Puga, 2010). Insufficiently controlling for worker heterogeneity will result in an upward bias when estimating agglomeration economies. Melo et al. (2009) support this observation in their meta-analysis of 34 studies, finding that the use of aggregate data generally results in higher elasticities than the use of micro data, as does Smit (2010) in a meta-analysis of 73 studies.

Table 3.4. Explaining the spatial residual

Dependent:	NUTS-3 regions		Municipalities	
1st-stage spatial residual ($\gamma_{ind,r,t}$)	(OLS)	(IV)	(OLS)	(IV)
# Observations	7,412	7,412	25,881	25,643
Log employment density	0.040***	0.048***	0.020***	0.021***
	(6.8)	(6.8)	(8.7)	(4.3)
Specialization (industry share)	0.028***	0.029***	0.021***	0.021***
	(6.6)	(6.7)	(8.2)	(8.2)
Diversity (Shannon's entropy)	–0.094*	–0.075	–0.030**	–0.027*
	(2.0)	(1.4)	(2.6)	(2.3)
Competition (1–HHI)	–0.060*	–0.075**	–0.013	–0.016
	(2.3)	(2.7)	(1.4)	(1.3)
Log(area)	0.017*	0.021***	0.012***	0.011*
	(2.5)	(3.4)	(3.3)	(2.1)
Industry dummies	yes	yes	yes	yes
Year dummies	yes	yes	yes	yes
R^2	0.31	0.31	0.19	0.19

Note: *t*-statistics and *z*-values (in absolute values) are reported in parentheses.
Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

In view of this discussion, our data allow us to compare our work with previous research that did not use micro data, by aggregating all variables used in the micro regressions to regional averages. Table 3.5 (left) shows an employment density elasticity of 0.043 for NUTS-3 regions. This implies that doubling the number of workers on a given area results in a 4.3 percent increase of productivity. This figure is within the range of the 3–8 percent found in the meta-analysis of Melo et al. (2009), but much lower than the 18 percent found by Gorter and Kok (2009), who also use Dutch aggregate data. However, Gorter and Kok use production density instead of employment density, while not controlling for worker heterogeneity.[24] Estimating our equation using aggregated data on municipalities results in an employment density elasticity of 2.5 percent, when correcting for average age and education.

[24] If we do not include the average level of education and the average age in our macro specification, we find an elasticity of 5.7 percent on the NUTS-3 level.

Table 3.5. Explaining regional productivity differences using aggregate data

Dependent: Average Log regional wage	NUTS-3 regions (OLS)	Municipalities (OLS)
# Observations	7,412	25,881
Average age	0.019	0.009***
	(1.3)	(3.7)
Average education	0.047***	0.062***
	(4.2)	(13.0)
Log employment density	0.043***	0.025***
	(4.0)	(7.8)
Specialization (industry share)	0.000	0.003***
	(0.4)	(4.7)
Diversity (Shannon's entropy)	–0.117*	–0.027
	(2.5)	(1.6)
Competition (1–HHI)	–0.019**	–0.014**
	(2.7)	(2.7)
Log(area)	0.015	0.019**
	(1.6)	(2.7)
Sector dummies	yes	yes
Year dummies	yes	yes
R^2	0.72	0.53

Notes: *t*-statistics (in absolute values) are reported in parentheses. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

Even if a certain worker characteristic has been identified as a strong determinant of individual wages, its contribution to explaining regional wage differences can be limited if its distribution over space is more or less uniform. Table 3.6 therefore presents some information about the economic implications of the findings presented in Table 3.3 and Table 3.4. The economic implications are illustrated by multiplying the Mincer estimates (for both NUTS-3 regions and municipalities) with the standard deviation of the regional averages of each of the independent variables in the analysis. One standard deviation gives us a reasonable proxy for the variation of explanatory variables across space.

Even though the male-female wage gap is substantial (14.8 percent, according to Table 3.3), it has a relatively small regional economic impact due to the fact that the distribution of the share of females on the labor market is fairly uniform across regions. A one standard deviation increase in the share of females in a NUTS-3 region is associated with a 0.48 percent decrease in the average regional wage. As there is large regional diversity in the share of high skilled workers, while education is at the same time one of the most important wage determinants, variation in the share of high skilled workers has a much stronger explanatory power. Employment density – even between NUTS-3 regions – can be considered as an important determinant of observed wage differences between regions. Due to the fact that variety in worker characteristics is larger between municipalities than between NUTS-3 regions, the economic impact of the estimated coefficients is in most of the cases larger for municipalities. Even though agglomeration variables also vary more between municipalities than between NUTS-3 regions, they have less explanatory power for wage differences between municipalities because the estimated size effects are smaller.

Table 3.6. Economic impact of estimates on regional wage differentials

Effect of a one standard deviation change on expected average wage	NUTS-3 regions	Municipalities
Age	0.54	1.79
Share of highly educated workers	1.70	3.27
Share of part-time workers	–0.12	–0.30
Share of female workers	–0.48	–1.72
Share of immigrant workers	–0.22	–0.31
Log employment density	4.47	2.67
Diversity (Shannon's entropy)	–0.67	–0.57
Area	1.65	0.98

Notes: Economic impact is calculated as the expected percentage change in average wage resulting from a one standard deviation increase of the respective variables. Specialization and competition are not included in this table, as they are sector-specific measures. Detailed results for individual sectors are available upon request.

To conclude, Table 3.7 presents the expected and actual wage differences between urbanized and non-urbanized areas (as percentage deviations, which are – for convenience – calculated by multiplying expected log wage differentials by 100). Urbanized areas are taken as the 22 agglomerations that are defined by Statistics Netherlands. The rest of the country is classified as non-urban. In total, the 22 urbanized areas cover about half of the Dutch population. All values are relative to the (weighted) average of municipalities outside the agglomerations. The expected log wage differential is decomposed into different components. Expected log wage differentials were calculated by multiplying the coefficients that were estimated for municipalities (using the IV estimations) by averages of

Table 3.7. Economic implications for 22 agglomerations: decomposition of expected average wage differences with non-urbanized areas

Agglomeration	Expected Wage	Actual wage	Decomposition of expected average wage in different components										
			Gender	Non-natives	Part-time	Age	Education	Density	Diversity	Competition	Specialization	Area	Industry
Amsterdam	11.64	19.52	0.93	–0.66	0.21	0.36	4.12	4.37	0.02	0.00	0.75	1.51	0.93
The Hague	10.62	19.22	0.58	–0.70	0.26	0.12	4.29	4.66	0.36	0.03	–0.03	1.05	0.58
Utrecht	10.67	14.10	0.65	–0.25	0.11	–0.11	4.60	4.19	–0.06	–0.01	0.16	1.38	0.65
Nijmegen	8.52	12.99	–0.14	–0.14	–0.08	0.73	4.56	3.80	0.24	0.03	–0.18	–0.29	–0.14
Amersfoort	7.27	9.88	0.20	–0.10	0.08	0.51	3.39	2.66	0.07	0.01	–0.02	0.48	0.20
Rotterdam	5.83	9.77	0.36	–0.64	0.17	0.00	1.05	3.59	–0.08	0.00	0.58	0.79	0.36
Leiden	4.23	9.04	–0.82	–0.26	–0.14	–0.49	3.42	3.83	0.30	0.03	–1.47	–0.17	–0.82
Eindhoven	7.25	8.57	0.67	–0.21	0.18	0.10	3.12	3.14	–0.14	0.00	0.11	0.28	0.67
Haarlem	5.48	7.71	–0.46	–0.20	–0.02	0.77	1.86	4.01	0.11	0.01	–0.96	0.34	–0.46
Groningen	7.44	7.02	0.16	0.07	–0.06	–0.42	3.37	3.13	0.15	0.02	0.23	0.79	0.16
Arnhem	7.38	6.61	0.17	–0.03	–0.01	1.37	1.91	2.63	0.17	0.02	0.49	0.65	0.17
's-Hertogenbosch	6.00	6.61	0.39	–0.02	0.10	0.40	1.78	2.51	–0.07	–0.01	0.21	0.69	0.39
Apeldoorn	3.55	5.61	0.62	0.10	0.10	–0.05	0.04	–0.05	–0.26	–0.01	1.87	1.19	0.62
Maastricht	4.39	4.60	–0.14	–0.01	0.01	–0.46	2.13	3.18	–0.10	0.01	–0.12	–0.12	–0.14
Geleen/Sittard	4.47	4.52	1.16	–0.05	0.14	2.07	–0.47	1.70	–0.38	–0.03	0.07	0.25	1.16
Breda	4.22	2.90	–0.21	–0.12	0.08	–0.12	1.43	2.00	–0.25	–0.02	0.77	0.66	–0.21
Tilburg	2.29	0.81	0.10	–0.09	–0.03	–1.07	0.88	2.26	–0.02	0.01	0.63	–0.37	0.10
Zwolle	3.68	0.63	–0.03	0.09	–0.08	0.13	0.82	1.93	0.03	0.01	0.65	0.14	–0.03
Dordrecht	1.21	0.63	0.17	–0.12	0.05	0.13	–0.67	2.20	–0.11	0.00	–0.57	0.13	0.17
Heerlen	3.41	0.17	0.58	0.00	0.15	1.16	–0.32	2.39	0.01	0.00	–0.63	0.08	0.58
Enschede	2.89	0.15	–0.02	–0.22	0.01	–0.11	1.48	1.27	–0.24	–0.01	0.89	–0.16	–0.02
Leeuwarden	5.64	0.11	–0.05	0.18	–0.09	–0.18	1.55	2.36	–0.13	–0.01	0.26	1.75	–0.05
Peripheral regions	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Expected wage differences are based on the estimates of the Mincerian wage regressions for municipalities, and measured as percentage deviations from the average municipality outside the 22 Dutch agglomerations as defined by Statistics Netherlands. 'Industry' refers to the contribution of sectoral composition.

the independent variables within each agglomeration (in deviation from their non-urbanized counterparts).

The columns in the right part of Table 3.7 present the contribution of each component to the expected wage differential. On average, wages are 7 percent higher in agglomerations than in peripheral municipalities. In all agglomerations, both the actual average wage and expected wages are above zero (e.g. above the average wage and expected wage in municipalities outside the 22 largest agglomerations). The variables that explain the largest part of the expected wage differential between agglomerations and the periphery are the level of education and density. Other variables do not provide a structural explanation, with the exception of the share of non-native workers, which are relatively overrepresented in the large cities and earn a lower wage *ceteris paribus*.

The explanatory power of the models that were estimated in this chapter is substantial. The correlation between actual wages and expected wages is 0.90 for the 22 agglomerations in Table 3.7, and 0.79 for all 467 Dutch municipalities. Amsterdam and The Hague have a relatively large difference between the expected wage and the actual wage. This suggests that these cities – the capital and the government seat – have something 'extra' that is not captured in any of the variables in our regression model.

The findings presented in Table 3.7 once more illustrate the relatively flat and polycentric geographic and economic landscape in the Netherlands. Combes et al. (2008a) report a 60 percent wage differential between Paris and rural France, and a 35 percent differential between Paris and mid-sized French cities. In the Netherlands, wages in Amsterdam and The Hague are only about 20 percent higher compared to non urbanized regions. Furthermore, there are multiple agglomerations where wages are relatively high, rather than just one.

3.7 Robustness

As we discussed in Section 3.2, there is discussion in the literature regarding the empirical proxies that are to be used to identify the importance of agglomeration externalities. In a meta-analysis, De Groot et al. (2009) found that different proxies can lead to substantially different results, *ceteris paribus*; the use of a location quotient to measure specialization, for example, makes it more likely that a significantly positive agglomeration effect is found.

The proxies we used in the previous sections are our own preference, and also commonly used in the literature. We will now investigate the robustness of our results (and those found in the agglomeration literature more in general) by varying the specification of the agglomeration variables used in the second stage. Our original estimates (Table 3.4) included employment density and area as urbanization variables, the industry share for specialization, a Hirschman-Herfindahl index for competition, and Shannon's entropy as a diversity variable. We will now test three different proxies for specialization, competition and diversity, which we will use in our estimations once together with urbanization effects, and once without controlling for urbanization. This results in 32 estimates for each proxy of one of the agglomeration variables. The variables chosen are presented in Table 3.8. To ease comparison, the variables are defined such that a higher value corresponds to more specialization, competition or diversity.

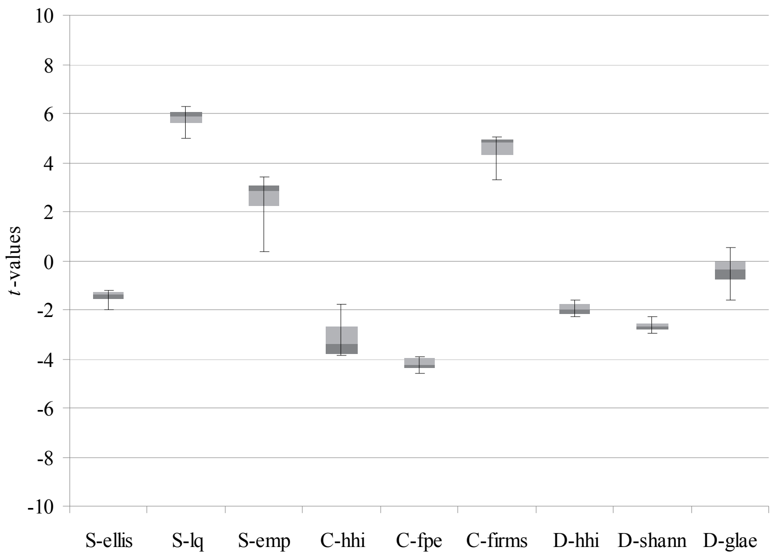
Table 3.8. Agglomeration variables and their correlations

Type		variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specialization	(1)	Ellison-Glaeser index	1.00								
	(2)	Location quotient	0.06	1.00							
	(3)	Local industry employment	–0.06	–0.01	1.00						
Competition	(4)	1–HHI on firm employment shares	–0.06	–0.24	0.24	1.00					
	(5)	Firms per employee in sector-region	0.02	–0.20	–0.11	–0.05	1.00				
	(6)	Number of firms in local industry	–0.07	–0.06	0.82	0.33	–0.09	1.00			
Diversity	(7)	1–HHI on industry employment shares	0.08	–0.03	–0.08	0.05	0.04	–0.04	1.00		
	(8)	Shannon's entropy	0.07	–0.03	–0.04	0.05	0.02	–0.02	0.93	1.00	
	(9)	Glaeser's largest sectors index	0.11	0.05	–0.50	0.26	–0.07	0.42	0.58	0.58	1.00

Note: Specialization refers to the proxies for MAR-externalities, competition to Porter externalities and diversity to Jacobs externalities.

Results of the robustness analysis are presented in the form of box-and-whisker plots in Figure 3.3 and Figure 3.4. A similar plot for the urbanization variables can be found in Figure 3.5. We note that some variables are highly robust to the inclusion of other agglomeration variables: for example, the Ellison-Glaeser index hardly varies across the 2×9 estimations, which is in line with its low correlation with the other variables (see Table 3.8).

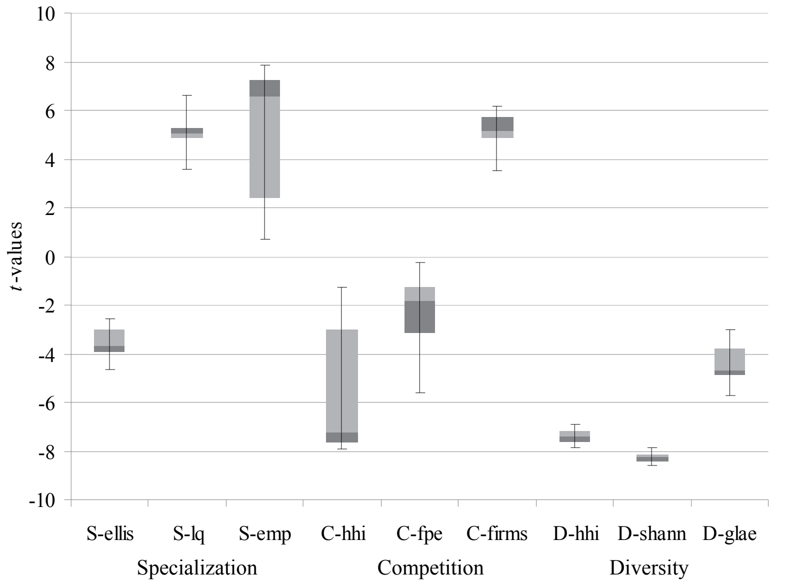
Figure 3.3. Box-and-whisker plot of repeated regressions with different specifications of the variables, controlling for urbanization.



Specialization		Competition		Diversity	
S-ellis:	Ellison-Glaeser index	C-hhi:	1–HHI on firm employment shares	D-hhi:	1–HHI on industry employment shares
S-lq:	Location quotient	C-fpe:	Firms per employee in sector-region	D-shann:	Shannon's entropy
S-emp:	Local industry employment share	C-firms:	Number of firms in local industry	D-glae:	Glaeser's largest sectors' index

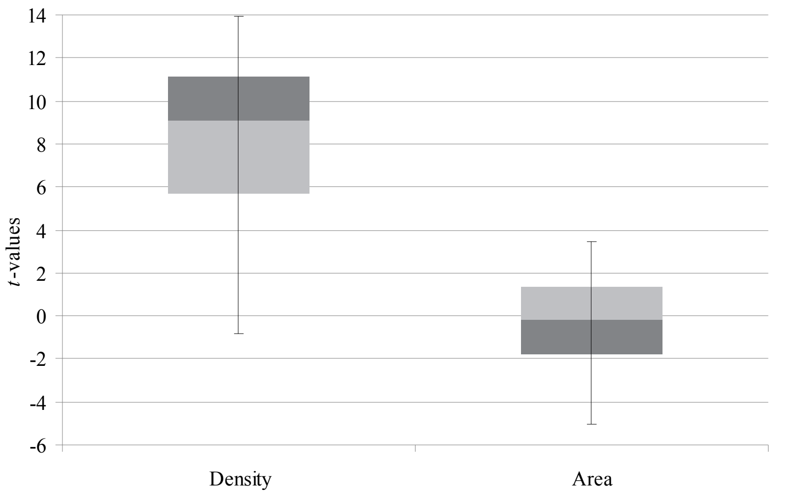
The variation of the results that are found is larger when urbanization variables are not included, and significance levels are higher. However, no variable changes sign (see Figure 3.4), although the Ellison-Glaeser index and Glaeser's largest sectors index become insignificant when controlling for urbanization. Glaeser's largest sectors index is the measure for diversity that Glaeser et al. (1992) use: it takes for every region the share of the largest six sectors (minus the sector under

Figure 3.4. Box-and-whisker plot of repeated regressions with different specifications of the variables, not controlling for urbanization.



S-ellis:	Ellison-Glaeser index	C-hhi:	1–HHI on firm employment shares	D-hhi:	1–HHI on industry employment shares
S-lq:	Location quotient	C-fpe:	Firms per employee in sector-region	D-shann:	Shannon's entropy
S-emp:	Local industry employment share	C-firms:	Number of firms in local industry	D-glae:	Glaeser's largest sectors' index

Figure 3.5. Box-and-whisker plot for urbanization variables



observation) in total regional employment, and interprets a large number as evidence of little diversity. Note that the other two measures for diversity, in contrast, seem quite insensitive to the inclusion of urbanization variables.

Results differ widely within each group of measures. For both competition and diversity, some proxies render quite consistently positive results (the number of firms in the local industry), while others show negative results (the number of firms per employee in the sector-region and the HHI index on industry employment shares). These results confirm the findings of De Groot et al. (2009), who concluded in their meta-analysis that the specification of variables matters for the effect that will be found. This implies that even where some studies claim to look at the same variable, their results will actually not be comparable but depend on the proxies they included. There are a few proxies that give similar results between them, at least for our data and method: those are for example local industry employment and the location coefficient as measures for specialization, or, in most cases, all three diversity variables. Our results suggest that estimations from studies using these variables can sensibly be compared, *ceteris paribus*.

3.8 Conclusion

The first part of this chapter described differences in wages between NUTS-3 regions in the Netherlands. We confirm that wages are substantially higher in the urbanized Randstad area than in the rest of the Netherlands. Also, average wages show a clear pattern of positive spatial association among neighboring NUTS-3 regions. A geographical representation of the spatial residual showed that, after correcting for regional differences in human capital, workers in densely populated areas get paid a premium. The spatial residual, which is the regional average wage corrected for observed worker heterogeneity, is strongly correlated to average regional wage.

At the heart of the analysis is the explanation of the spatial residual. We find that the total size of the regional labor market has a statistically significant and positive effect on wages, even though this explains a relatively small part of the spatial residual. Using the Mincer residuals on the NUTS-3 level, we find an employment density elasticity of 4.8 percent, and also clear evidence for the presence of MAR externalities. Doubling the share of an industry results in a 2.9

percent higher productivity level. In our main specification, we find evidence for small negative effects of Porter and Jacobs externalities. However, we show in an extensive robustness test that the specification of these variables matters to a large degree for the effects found.

The estimated agglomeration economies are lower than those estimated in previous work for the Netherlands by Gorter and Kok (2009), but correspond to what is found in the existing international literature by Combes et al. (2008a) and Melo et al. (2009). The current study for the Netherlands supports the finding that the size of estimates of agglomeration externalities are to a large extent determined by the ability of the data and methods that are used to correct for regional and individual heterogeneity.

An issue that remains unaddressed in most of the current literature, and in this chapter as well, is the endogeneity problem caused by local endowments. The presence of universities, infrastructure and local institutions all increase local productivity while being highly correlated with density. Due to a lack of good instruments, it has proven difficult to isolate the effect of density. Even though agglomeration externalities that have been estimated in the current literature are insightful, the causal relation between agglomeration and productivity will remain unclear until this endogeneity issue has been solved.

4 THE EDUCATIONAL BIAS IN COMMUTING PATTERNS

4.1 Introduction[25]

The past few decades have been characterized by several socioeconomic changes with important consequences for patterns of travel behavior and residential location. Many economic and residential activities have decentralized from old centers to the suburbs of metropolitan and urban areas, and people have begun to travel – on average – longer distances than in the past. Commuting time, in contrast, has remained rather constant, because workers use increasingly faster modes of transport. This phenomenon is known as the 'commuting time paradox' (Van Ommeren and Rietveld, 2005). Of a relatively recent date is a revival of cities with attractive amenities, which seem to be particularly attractive for high skilled people (e.g., Glaeser and Saiz, 2004; Glaeser, 2011). These trends are related to a complex set of developments that occurred in the last few decades, among which are the increase in per capita income, an increase in the number of part-time workers and two-earner households, and the wide diffusion of private cars and technological progress which is most visible in the advent of ICT.

The increase in per capita income and in the number of workers – where the latter is also related to the increase in female participation rates – are important aspects to be taken into account to understand the changing commuting patterns. These facts have made time scarcer, inducing individuals to trade-off money for time (Levinson and Kumar, 1995). This need for substitution, in turn, has increased the number of transactions and the consequent need to travel, affecting both localization patterns and individual travel behavior. At the same time, the income elasticity of demand for housing may increase commuting time because individuals with higher incomes want to live in more spacious housing. As argued by Rouwendal and Nijkamp (2004), commuting is the result of a network economy in which individuals look for earning opportunities outside their

[25] This chapter is based on Groot et al. (2012).

place of residence. As a matter of fact, the spatial organization of earning capabilities – the physical separation between home and fulfilling workplaces – and individual characteristics are the main determinants of commuting patterns.

Travel behavior is affected by both individual attributes and characteristics of the context in which individuals live. Among the individual attributes that are thought to influence travel patterns, education has been often included in empirical analyses as a mere control in order to disentangle the role of other attributes. The goal of this chapter is to understand the role of education as a determinant of differences in travel behavior across individuals in the Netherlands. The empirical literature shows with substantial clarity that more educated workers commute longer and further than low-skilled workers. However, explanations are scarce. Moreover, given the fact that average education is increasing, the implications in terms of the spatial dimension of the labor market and the connected commuting patterns are worth investigating.

The reasons why education can play a role in explaining differences in travel behavior are diverse. In fact, investments in human capital can strongly influence both job and home location. Search frictions in both the labor market and the housing market may be related to the level of education. As higher educated workers are more likely to own, rather than rent housing, residential mobility is likely to be lower. This results – *ceteris paribus* – in longer commutes. On the labor market, search frictions could be relatively high for higher educated workers because of the more specialized nature of their work, which would again increase commuting time. Another reason why commuting distance and time might be higher for workers that are more educated is that educated people are more willing to travel longer distances to realize their human capital investments as well as their professional expectations. Moreover, higher educated people are on average paid more than low-skilled workers, such that the choice of residence also could be influenced by the desire to live in higher quality houses in the low-density hinterland of urban areas. The fact that the largest Dutch cities have a relatively high share of social housing is likely to contribute to this. The full set of factors at the base of the role of education for travel behavior are analyzed in the following sections, trying to disentangle the role of individual attributes from that of the spatial characteristics of the places of residence and work.

The empirical part of this chapter is aimed at finding empirical evidence on the specific role of education on commuting patterns, trying also to disentangle such a role from the effect of higher wages. In fact, despite the always-present correlation between the level of education and the wage of workers, education could have a specific role in terms of commuting behavior that goes beyond its effect on wages. Differences in commuting patterns between well-paid and well-educated workers may occur for several reasons. First, as it was argued before, the spatial extent of the job-search area is wider for highly educated workers, since they are relatively more likely to find a fulfilling job when travelling further relative to lower educated workers. This is because the job market for highly educated workers is more concentrated in large urban centers. Second, highly educated workers may prefer to use public means of transport, since they have the possibility to carry out part of their work during the trip. The successful introduction of Office Buses in some countries, like Finland, is useful to understand that there is a value in the possibility to work during the commute.

It is also possible that the higher use of public transport by higher educated workers is to some extent institutionalized. Many public institutions (such as universities), promote the use of public transport among their employees. While there is often no compensation for the use of personal cars, these public institutions fully or partially compensate their employees when they use public transport for their commutes. As the share of higher educated workers is somewhat higher in the public sector compared to the market sector, this would result in a positive correlation between level of education and the use of public transport.

The remainder of this chapter is structured as follows. Section 4.2 reviews the literature on the determinants of commuting behavior, as well as previous findings about the role of education. Theories that help to interpret the reason behind the role of education for commuting are also discussed in this section. Section 4.3 describes our dataset, as well as commuting patterns in the Netherlands and presents some stylized facts about the differences between commutes of higher and lower educated workers. Section 4.4 specifies the empirical settings that are employed in order to understand the implications of education for commuting patterns and the factors explaining these differences. Section 4.5 gives some concluding remarks, and discusses possible policy implications.

4.2 Related literature and theoretical background

The link between individual education level and commuting behavior is complex, especially if mode choice, distance travelled and time spent travelling are all taken into account simultaneously. There is quite a large amount of scientific work that investigates the role of individual attributes on commuting behavior. Compared with other non-individual characteristics, such as spatial structure, housing markets, and the balance between jobs and residents, individual attributes seem to account for a large part of commuting behavior (Giuliano and Small, 1993). Among these individual attributes, the level of education has often been included as a control, but its nature and the implications of its role have rarely been discussed in detail.

The empirical literature devoted to understanding the determinants of commuting behavior finds that a higher level of education is associated with longer trips in terms of distance (Lee and McDonald, 2003; Papanikolaou, 2006; Vance and Hedel, 2008; Prashker et al., 2008). Similar results are found with regard to commuting time (Lee and McDonald, 2003; Shen, 2000). More specifically, Shen (2000) finds that highly educated people travel longer while low educated people tend to work closer to home. In addition, it has been argued that highly educated people have a higher probability to be long-distance commuters (Öhman and Lindgren, 2003). This may be explained from the fact that the disutility associated with distance travelled is smaller for the highly educated (Rouwendal, 2004).

On the other hand, by taking into account alternative modes of transport, Burbidge et al. (2006) and Coogan (2003) show that highly educated individuals walk significantly more than poorly-educated ones. Dieleman et al. (2002) in their analysis of Dutch commuting patterns find that more educated people are more likely to use private cars for their commutes. They also find that education is relatively important for shopping trips than for work related commutes, since shopping activities are more affected by the type of residential environment. Hence, higher educated workers – which tend to live in the residential suburbs – travel on average longer distances than people living in more central and more shop-served locations. Furthermore, they find that the most educated people travel longer distances by public transport for leisure activities. On the whole, the positive association between the level of education and the length of the commute – both in terms of time and distance travelled – is almost a stylized fact in the empirical literature.

Understanding the role of education

In order to understand the role of individual education on commuting patterns, many factors should be taken into account. The distance and time travelled depend on residential and work location, both of which are chosen by individuals. Some studies have investigated these individual choices using a joint utility approach that considers choices among combinations of residence and job localizations that maximize individual utility (Yapa et al., 1971). Put differently, this approach explains commuting behavior as the minimization of commuting and migration costs, given a certain income level.

As the Dutch housing market is relatively regulated, the costs of migration may be relatively high, thus positively affecting commuting distance and time. However, a possible shortcoming of this hypothesis is that the bulk of workplaces are located within cities, so that the choice of work location is particularly bounded by the localization of firms. In addition, commuters are not identical and individual characteristics are central in explaining observed travel behavior. Of particular importance in the Netherlands are relatively high transaction costs on residential mobility.

Van Ommeren and Van Leuvensteijn (2005) have estimated that a 1 percent-point increase in transaction costs decreases residential mobility rates by at least 8 percent. The 6 percent ad valorem tax on buying housing (reduced to 2 percent in 2011) is likely to have resulted in a substantial reduction of the mobility of house owners. As this increases the costs of reducing commuting time by changing residential location, this is likely to result in higher commuting time. Furthermore, higher educated workers are more likely to own a house relative to lower educated workers (see, for example, Hood, 1999), this is likely to increase the average commuting time of higher educated workers relative to the lower educated.

The joint utility approach does not provide an explanation for excess commuting, e.g. the phenomenon that actual commuting is substantially larger than the amount of commuting that would be optimal given the spatial distribution of the quality of housing and jobs. Van Ommeren and Van der Straaten (2008) estimate that excess commuting due to search imperfections accounts for about half of total commuting. Because of imperfect information regarding all available jobs, workers will regularly accept a job at a certain location that does not optimize their wage and commuting costs, because they do not know if and when better job offers will arrive. As the activities of higher educated workers tend to be more specialized relative to the those of lower educated workers, it is likely that the job arrival rate will be lower for more educated people, which will result in a suboptimal match and thus higher commuting distance and time.

The spatial distribution of activities within regions and urban areas can contribute significantly to explaining the role of education in commuting patterns. In fact, it has been argued that the central cities within metropolitan areas remain to have a good accessibility to less educated jobs, even in those regions that experienced a drastic decentralization of jobs (Shen, 1998). In addition, graduates are becoming less spatially mobile, in the sense that they migrate less toward other regions in order to find a job. However, this trend is mainly explained by macroeconomic factors such as regional economic development rather than by a changing role of education for individuals (Venhorst et al., 2011). Regarding individual characteristics, a higher level of education is associated with a higher income, which in turn has been found to be correlated with longer trips (Giuliano and Small, 1993).

Besides being related to income, education is related to the spatial scale of individuals' social networks and with the area of job search (Holzer, 1987; Wilson, 1987). Educated individuals carry out their daily activities, including the choice of jobs and the related commuting, in a wider space. In addition, it has been argued that well educated individuals travel longer distances because they look for more desirable residential locations, paying relatively less attention to the length of the travel (Prashker et al., 2008). In other words: as the level of education increases, the sensitivity to the distance travelled decreases due to residential preferences. An additional cause for the longer commutes of well-educated individuals is that people with a higher level of education are more likely to find interesting and gratifying jobs, hence they can accept a longer travel (Ory et al., 2004). As a matter of fact, they could value the travel to work less than people with low education levels. Consistently with this idea, Giuliano (1989) argues that education may influence home locations and the ability to absorb transportation costs.

4.3 Data and stylized facts

The empirical part of this chapter builds upon linked micro data from Statistics Netherlands (CBS). The source for data on worker and job characteristics (except for wages) and commuter behavior are the 2000 to 2008 cross-sections of the Dutch labor force survey (EBB, *Enquête Beroeps Bevolking*). As wages are not available through the labor force survey, we have used data from the Dutch tax authority (compulsory employer reported), which is available through the CBS Social Statistics database (SSB, *Sociaal Statistisch Bestand*). For workers with multiple jobs, we include only the (self-reported) most important job. The CBS consumer price deflator (CPI, *Consumenten Prijs Index*) has been used to deflate wages. For most of the analysis in this chapter, we use the natural logarithm of real pre-tax hourly wages. Hourly wages are calculated by dividing the employer reported pre-tax annual wage from SSB (e.g., the fiscal wage) by the self-reported number of hours an employee works in a typical week (from EBB) and the number of weeks the employee worked during a year, which is calculated from the (employer reported) start and end date of the job. Due to methodological revisions of both SSB and EBB, there is a discontinuity between 2005 and 2006, though its effect on outcomes seems to be minor. It is important to note that wages do not include compensation for travel expenses.[26]

To make sure that only workers with a sufficiently strong attachment to the labor market are included, we have dropped some observations. Workers must be aged 18–65 (e.g., older than 18 on January 1st and younger than 65 on December 31st of each year), and work at least 12 hours per week.[27] We have dropped all observations with an hourly wage less than 10 percent of the median hourly wage. Such observations are unlikely to be regular wages, as they are below the minimum wage. Worker characteristics are the level of education (we can

[26] If we would have included employers compensation for travel expenses, this would have resulted in several econometric issues. As many employers in the Netherlands compensate employees for their commuting expenses, this would result in a spurious regression when, for example, estimating the relation between wages and commuting distance.

[27] Statistics Netherlands defines workers with a working week of at least 12 hours as employed, workers with a working week of at least 36 hours are considered full-time employees. Jobs occupied by teenagers are often side-line jobs that would be outliers in our dataset.

distinguish eight different levels), age, municipality of residence, country of birth (a binary variable that indicates whether a worker is born in the Netherlands or not), gender, and whether a worker is employed part-time or full-time. For each job, the self-reported municipality where the employee works is available, as well as the industry (we use the 2-digit NACE industry from the ABR registry). On the commute of each worker, we have data on the (self-reported) mode of transport, average travel distance and travel time. The resulting dataset of nine cross-sections contains 154,238 observations (an average of 17,138 per year). The number of observations is somewhat lower compared to other chapters, because information on commuting is available for only a subsection of the labor force survey.

Commuting distance and time

Table 4.1 presents descriptive statistics concerning the variables that are related to commuting behavior. The average distance of a (one-way) commute is 17 kilometers, the average commuting time 22 minutes. The choice for a mode of commuting is strongly biased towards private means of transport (accounting for a 90.3 percent share). Table 4.1 reveals a strong dependence of commuting distance and time on the employed mode of transport. Most commutes by pedestrians or cyclists are short distances. Cars are used for somewhat longer distances (on average 21 km and 23 minutes). Public transport is – on average – used for longer distance commutes.

Compared to other motorized means of transport, buses, trams, and the underground are relatively slow, taking an average time of 37 minutes for a 16 km average trip. Trains are used for particularly long commutes, with an average distance of 41.1 km and a commuting time of 55 min. The figures from Table 4.1 are consistent with what is generally found in the literature (see, for example OECD, 2010). Compared to other countries, commuting times are relatively long in the Netherlands. According to international comparative research Dutch workers spend an average of 51 minutes[28] on commuting per day in 2005 (the longest commuting time in their sample of 31 European countries), compared to 42 minutes in the EU-27 (Parent-Thirion et al., 2007; OECD, 2010).

[28] If we take into account that our figures refer to single trips per job, while part of the working population have multiple jobs, this figure is very similar to what we find.

Table 4.1. Descriptive statistics, 2000–2008

Mode	Commuters		Distance	Time
	observations	%-share	km	min
Pedestrian	3,561	2.3	1.0	8.1
Bicycle	41,023	26.6	4.4	12.5
Motorbikes or scooter	3,741	2.4	13.0	17.4
Personal car	90,925	59.0	21.2	23.4
Private transport	*139,250*	*90.3*	*15.5*	*19.6*
Bus, tram, underground	6,300	4.1	16.0	36.8
Train	8,688	5.6	41.1	54.6
Public transport	*14,988*	*9.7*	*30.5*	*47.1*
Total	154,238	100.0	17.0	22.3

Note: Travel distance and time correspond to one-way trips.

The interdependence between the commuting distance, commuting time, and private versus public mode of transport is presented in Table 4.2. Whereas only 2.6 percent of all commutes by private means of transport take more than one hour, this figure is almost one fifth for public transport. A major share of 81.9 percent of commutes by private transport take 30 minutes or less, whereas this figure is only 33.5 percent for public means of transport. The most likely explanations for this observation are that public transport is less efficient over shorter distances, possibly because of the distance between location of residence and the nearest bus stop or railway station, and that public means of transport are used more often in densely populated areas that are more congested and are characterized by generally lower speed. At the same time, commuting by foot or bicycle is suitable only for short distances.

Table 4.2. Commuters and distance by commuting time, 2000–2008

Time	Private transport		Public transport	
minutes	%-share	distance (km)	%-share	distance (km)
0-15	66.0	7.1	14.1	9.9
16-30	15.9	19.8	19.4	15.6
31-60	15.4	37.0	47.0	29.2
> 60	2.6	72.2	19.5	64.3

Note: Travel distance and time correspond to one-way trips.

The average distance of a single trip is relatively stable over time, and ranges from 16 km in 2000 to 17.7 km in 2007. Commuting time ranges from 21.5 minutes to

23.3 minutes (in 2000 and 2007, respectively). Even though commuters live about as far from their work in 2000 as in 2008, there are some shifts in the use of different modes of transport. In particular, commutes by bike have become less popular over time (from a 29.0 percent share in 2000 to a 24.9 percent share in 2008), while the share of car users increased somewhat. In 2000, the car was used for 56.7 percent of commutes; in 2008 this figure was 61.2 percent. However, it is important to note that most changes occurred between 2005 and 2006 such that it cannot be ruled out that the observed trends are the result of a data revision.

Commuting behavior and education in Dutch agglomerations

Figure 4.1 shows commuter flows of higher educated commuters (left) and lower educated commuters (right) between municipalities that represent 1,000 or more commuters. The largest commuter flows are within agglomerations, between the central municipalities and their surrounding suburban municipalities, as well as between peripheral municipalities. Although small in relative size, there are also substantial commuter flows between the largest agglomerations. Even though the Randstad [29] is sometimes considered as a unique polycentric urban region, commuting patterns indicate that the agglomerations in this region are best seen as separate local labor markets, albeit with strong connections between some agglomerations in the area and with some overlapping boundaries.

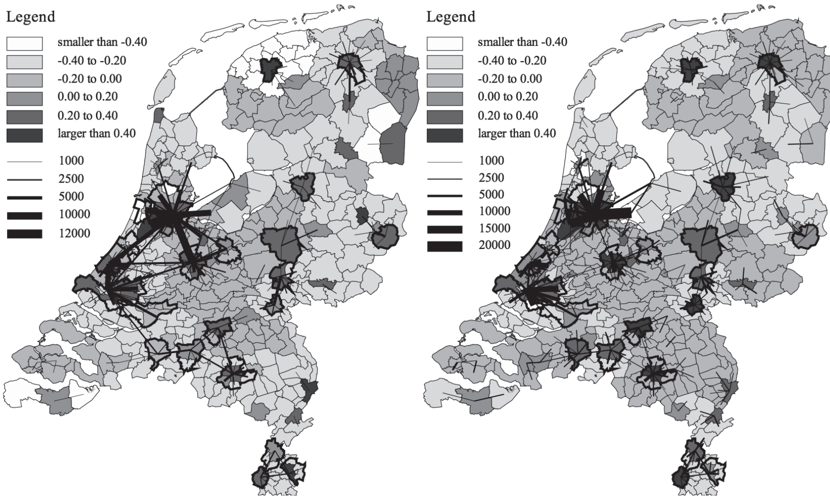
Commuting patterns are not only asymmetric in direction (e.g., with a much higher inflow than outflow of commuters or vice versa); there is a strong interdependence between agglomeration and the level of education as well. The shades in Figure 4.1 represent the balance index of highly educated commuters (defined as the net inflow of highly educated commuters divided by the sum of the inflow and outflow) towards each agglomeration (which we refer to as in-commuters). Because of sample size, we have pooled all municipalities by agglomeration, and by NUTS-3 region in the periphery (see Appendix A for a map with the 40 Dutch NUTS-3 regions). In most agglomerations, the inflow of highly educated workers is larger than the outflow.

Table 4.3 shows the share of private versus public transport by level of education, as well as the average commuting distance and time. While workers

[29] The Randstad refers to the area in the Netherlands where the four largest agglomerations – Amsterdam, Rotterdam, The Hague and Utrecht – are located.

with only primary education commute just over 10 km on average, this figure is about twice as high for workers with a University (Master) degree. Higher educated workers are also more likely to use public transport. Workers with the lowest education levels, however, are somewhat more likely to use public transport than those with average education. This may be related to budget constraints, as lower educated employees are disproportionately likely to use public transport for short-distance commutes.

Figure 4.1. Commuters and balance index of higher educated (left) and lower educated (right) commuters, 2008



Notes: Balance index is defined as (inflow of commuters – outflow) / (inflow + outflow). Higher educated workers are those with at least higher tertiary education, lower educated workers are defined as all other workers. Stroked areas represent the 22 agglomerations (GSA) defined by Statistics Netherlands.

Table 4.3. Commuting distance and time by type of education, 2000–2008

Type of education	Private transport			Public transport		
	%-share	distance km	time min	%-share	distance km	time min
Primary education	92.0	10.5	15.5	8.0	15.7	38.0
Lower secondary education (VMBO, MBO 1)	92.7	12.3	16.6	7.3	21.6	41.1
Higher secondary education (HAVO, VWO)	97.2	15.3	20.4	12.8	27.0	45.2
Lower tertiary education (MBO 2, 3)	93.0	13.5	17.2	7.0	24.3	41.8
Lower tertiary education (MBO 4)	93.7	15.5	19.2	6.3	28.6	45.4
Higher tertiary education (HBO, BA)	91.3	17.5	21.8	8.7	33.4	49.5
Higher tertiary education (MA, PhD)	82.6	20.0	24.9	17.4	41.1	54.3

Note: Travel distance and time correspond to one-way trips.

4.4 Econometric analyses

The attractiveness of locations as a place of residence (due to amenities) and the attractiveness of locations as a place to work (due to higher productivity and wages) are two major driving forces behind commuting patterns. As a location becomes, *ceteris paribus*, more attractive as a place of residence, land rents will go up and the net-inflow of workers will decrease. If a location becomes more attractive to work, land rents will go up as well, but (because of the trade-off between migrating and commuting) the net-inflow of workers will go up. Interestingly, theory predicts that the actual outcomes in terms of commuter flows may differ substantially between low and highly educated workers.

If we assume that higher educated workers can pay more for better residential locations compared to lower educated workers, it is to be expected that better locations to live have a relatively low net-inflow of highly educated compared to the inflow of lower educated workers because of spatial sorting. The effect of productivity is likely to be asymmetric to the level of education as well, but in opposite direction. Agglomeration economies are generally thought to be larger for higher educated workers (explaining the high concentration of jobs for higher educated workers in cities). Therefore, productivity effects are likely to increase the net-inflow of higher educated workers stronger than the net-inflow of lower educated workers.

Direction of flows

Table 4.4 presents the share of highly educated workers in the flow of in-commuters towards each of the 22 Dutch agglomerations, the flow of out-commuters, and the flows within the same municipality. Furthermore, it shows balance indexes for both higher and lower educated commuters, and land rents. The average share of highly educated commuters (e.g., with at least higher tertiary education) is 38 percent for workers who live and work in the agglomeration, 44 percent in the flow of commuters towards the agglomerations, and 47 percent in the outflow. Higher educated workers are thus far more likely to commute than lower educated, regardless of the direction.

We find that commuters that live in an agglomeration but work somewhere else are relatively highly educated. This is clearly consistent with the prediction that higher educated workers are more likely to find a better paid job further away than lower educated. Even though the finding that the flow of out-commuters from the largest agglomerations consists of such a high share of highly educated workers is puzzling at first sight, it is in fact rather intuitive. As lower educated workers living in the larger agglomerations are very likely to work close by – they have little incentive to commute due to relatively high costs of commuting relative to their wage and because of a less complex job match – the remaining out-commuters from the large cities are highly educated workers. This is particularly the case for agglomerations that are far away from other agglomerations, like Groningen.

Table 4.4. Share of highly educated workers by type of commuter, 2000–2008

Agglomeration	Share of higher tertiary educated (percent)			Balance index		Land rent
	in-commuters	out-commuters	Within municipality	higher educated	lower educated	Euro/m^2
Amsterdam	47.0	49.7	44.8	0.386	0.431	582
The Hague	53.8	47.4	40.3	0.337	0.218	568
Haarlem	41.2	51.7	34.7	–0.263	–0.055	542
Leiden	45.9	52.3	40.4	–0.155	–0.027	478
Utrecht	48.9	56.1	45.7	0.187	0.321	389
Rotterdam	39.6	35.8	30.6	0.237	0.160	292
's-Hertogenbosch	45.2	56.3	34.0	0.282	0.473	277
Amersfoort	46.2	51.7	32.4	–0.093	0.016	259
Maastricht	46.0	52.8	41.1	0.400	0.508	242
Zwolle	38.3	51.5	38.5	0.359	0.567	234
Eindhoven	46.2	48.8	41.9	0.260	0.307	233
Groningen	43.7	64.4	49.2	0.312	0.633	225
Breda	40.9	59.0	36.3	0.021	0.370	225
Dordrecht	32.2	33.6	28.3	–0.126	–0.095	217
Tilburg	43.2	49.2	32.7	0.048	0.168	213
Leeuwarden	40.5	47.0	35.6	0.586	0.667	197
Nijmegen	45.0	68.5	50.8	0.142	0.560	192
Arnhem	43.6	50.8	38.6	0.420	0.531	187
Periphery	35.3	36.5	26.2	–0.181	–0.157	143
Enschede	44.1	39.1	31.6	0.388	0.297	118
Geleen/Sittard	31.8	38.6	32.2	–0.031	0.119	110
Apeldoorn	40.6	43.0	29.7	0.269	0.313	103
Heerlen	37.4	28.5	25.5	0.214	0.015	89

Notes: Persons who live and work in the same municipality. The periphery is defined as all municipalities outside the 22 agglomerations defined by Statistics Netherlands. For the periphery, this can be either from another peripheral municipality or from a municipality in one of the agglomerations, but not from the same municipality. Balance index is defined as (inflow of commuters – outflow) / (inflow + outflow).

Even though most agglomerations have a substantial net-inflow of higher educated workers, there are a few notable exceptions to this. Haarlem and Leiden, which have the lowest balance indexes for highly skilled commuters in the Randstad, are amongst the top four agglomerations with the highest land rents. Both Haarlem and Leiden are known as particularly attractive residential locations. Also interesting are the stylized facts for the four largest Dutch agglomerations. Amsterdam and Utrecht are generally considered to be cities where people want to live because they are attractive in terms of amenities, while people go to Rotterdam and The Hague for work. Not coincidental (as further analyses later in this chapter will show), Amsterdam and Utrecht have a relatively high share of highly educated workers that both live and work locally, while out-commuters are higher educated than in-commuters. For Rotterdam and The Hague these figures are the exact opposite. The same holds for the balance indexes: Amsterdam and Utrecht attract relatively more lower educated commuters, while Rotterdam and The Hague attract higher educated commuters that prefer to live elsewhere.

Figure 4.2 presents two scatter diagrams that show the relation between land rents and the balance index for higher educated workers (left panel) and lower educated workers (right panel). Generally, municipalities with higher land rents have a higher balance index, which implies that there are relatively more incoming than outgoing commuters. As the size of the data points indicate, however, this is mostly explained by the fact that larger municipalities have both relatively high land rents and more commuters arriving from the surrounding area.

To disentangle the effects of productivity and amenities, we have estimated two (OLS) regressions that explain the direction of commuter flows (as measured by the balance index) for 445 Dutch municipalities; one for lower educated workers, and one for higher educated workers. To control for agglomeration, we have included (the natural logarithm of) population and density. As an indicator for productivity, we have included the wage premiums that were estimated by Groot et al. (2011b).[30] As an indicator for land rents, we have included the estimates of De Groot (2011).

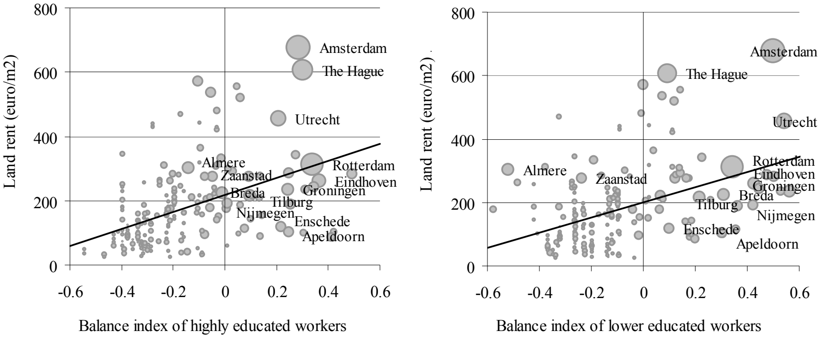
[30] These are obtained by estimating a Mincerian wage regression, and represent the regional component of the part of individual wages that is not explained by observed individual characteristics (see Chapter 3).

We thus estimate the following equation:

$$Balance_i = \alpha + \beta_1 \log(population)_i + \beta_2 \log(density)_i$$
$$+\beta_3 wage_i + \beta_4 \log(land\ rent)_i + \varepsilon_i \quad . \tag{4.1}$$

It is important to note that our methodology considers labor supply as exogenous. In reality, however, it is well possible that a worker considers commuting distance and supply of labor simultaneously. Even though we do not account for this, empirical evidence shows that the effect of distance on the supply of labor (both in terms of total labor supply and number of working days per week) is rather weak (Gutiérrez-i-Puigarnau and Van Ommeren, 2010). Therefore, endogeneity of labor supply is unlikely to result in biased estimation results.

Figure 4.2. Land rents and balance index of higher educated (left) and lower educated (right) commuters by municipality, 2008



Notes: Balance index is defined as (inflow of commuters – outflow) / (inflow + outflow). Higher educated workers are those with at least higher tertiary education, lower educated workers are defined as all other workers. The size of the data points represents population size.

The estimation results are presented in Table 4.5. As predicted, agglomeration has a stronger effect on commuting of higher educated workers relative to lower educated workers. Doubling population in a given area (such that both population and density double), is expected to result in a 26 percent increase in the net-inflow of higher educated workers while this figure is only 13 percent for lower educated workers. Furthermore, the symmetry of the flow of lower educated workers is insensitive to the wage premium, while it is positive and statistically significant for the flow of higher educated workers. The effect of land rents on the net-inflow of commuters is negative and statistically significant for higher educated workers, and positive and significant for lower educated workers. Even though the regressions may be somewhat vulnerable to multicollinearity (because the independents are correlated), regressions with additional control variables that were estimated as a robustness check yield similar results as those presented here.

Table 4.5. Regression results, direction of commuter flows

Dependent variable: balance index	Lower educated workers	Higher educated workers	All workers
# Observations	437	437	437
Log population	0.147***	0.199***	0.165***
	(7.0)	(11.1)	(10.1)
Log population density	–0.015	0.060**	0.015
	(0.8)	(3.1)	(0.8)
Wage residual	0.096	0.596*	0.451
	(0.3)	(2.2)	(1.9)
Land rent	0.090***	–0.094***	0.012
	(3.4)	(3.7)	(0.5)
R^2	0.272	0.362	0.333

Notes: *t*-values (in absolute values) are in parentheses. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

Explanation of commuting distance and time

In the previous sections, several stylized facts on commuter distance and time were presented. We have seen that higher educated commuters travel longer distances on average, while commutes towards the larger agglomerations tend to have a longer commuting time on average as well. Furthermore, the previous section has presented the results of regression analyses on the meso (municipality) level to gain insight in asymmetries in the direction of commuter flows that are related to education. We now revert to micro level analyses, to explain commuting behavior of individual employees.

This section uses OLS regressions to estimate the impact on distance and time travelled of personal characteristics of commuters and of characteristics of the municipality of destination. To account for the latter, we include employment density of the destination municipality and the population density and ratio between job and population of the residence municipality. Because the latter variable is endogenous – as a lower ratio between job and population automatically implies that more residents have to commute – we estimate our regression equation both including and excluding this variable. Dependent variables are the natural logarithm of distance and time (of a one-way commute). We thus estimate four similar regression equations:

$$\begin{aligned} Log(dist_i) &= \alpha + \sum_{edu=1}^{8} \beta_{1,edu} D_{edu} + \beta_{2,age} D_{age} + \beta_3 D_{female} + \beta_4 D_{part-time} + \beta_5 D_{married} \\ &+ \beta_6 \log(w_i) + \sum_{ind=1}^{4} \beta_{7,ind} D_{ind} + \beta_8 \log(emp.\ density_i) + \beta_9 \log(pop.\ density_i) \\ &+ \beta_{10} ratio_i + \beta_{11} \log(wage\ premium_i) + \beta_{12} \log(land\ rent_i) + \sum_{year=1}^{9} \beta_{13,year} D_{year} + \varepsilon_i \ . \end{aligned} \tag{4.2}$$

To account for both the quantity and the quality of education, we include a set of dummies for each level of education. Additional dummies are included for 5-year age groups (to account for nonlinearities in the effect of age), female gender, part-time work, whether a commuter is married or not, and the industry of employment. As an additional control variable we include the log of the hourly wage. It is, for example, well possible that differences in commuter behavior of workers with different levels of education that were observed in the previous section are in fact due to wage differences (where high paid workers have a stronger incentive to commute). Hence, by controlling for the wage, education variables can take into account the system of preferences that can be shaped by education.

While there is no strong relationship between commuting distance and wages (Manning, 2003; Gutiérrez-i-Puigarnau and Van Ommeren, 2010), wages are often thought to be endogenous with respect to commuting time. Workers with a higher wage are likely to travel faster because they have a higher opportunity cost of time. We must therefore be careful not draw any conclusions from the estimated wage effect but rather include the individual wage as a control. The log of the density of the municipality where each employee works is calculated by dividing total employment in this municipality by area. The ratio between jobs and population is calculated by dividing total employment in the municipality where a worker lives by the total working population. Because of the trade-off between commuting time and wage, we include the regional wage residual (at the work location) that was introduced earlier in this section. Also, we include land rents at the residence location. As we use pooled data, we include year dummies to account for year specific effects.

The results of the estimated models are presented in Table 4.6. Males commute further distances than females. Older workers make shorter commutes and part-time workers somewhat shorter commutes as well. Somewhat unexpectedly, given the literature that was discussed earlier, the (log) hourly wage has a rather strong effect on commuting distance. Workers with higher wages commute further. The effect of individual wages on commuting time is much weaker, about half of the effect on distance. Taking into account that most explanatory variables have a similar effect on commuting time and distance, a straightforward interpretation of this difference would be that workers with higher wages indeed travel faster. Even when hourly wages are included, however, the level of education has a strong effect of its own.

The higher the level of education, the longer the distance from home to work and the time needed to travel. Whether a worker is married or not has almost no effect on commuting. This is consistent with the finding of Rouwendal and Van der Straaten (2004) that dual earners do not have a higher commuting time compared to single earners, because they have a relatively high willingness to pay for housing close to large labor markets. For almost all variables, the effects of the independents on commuting distance are similar to that on commuting time. The employment density of the job location is, however, an exception to this. Workers who travel to more densely populated municipalities commute considerably further in terms of commuting time, but only slightly further in terms of distance. A one percent higher economic density results in a 0.16 percent longer commuting time. The effect of population density in the residence municipality on commuting distance is opposite: workers who live in densely populated areas commute over shorter distance. Congestion provides a possible explanation for the differences in the effect on commuting distance versus travel time. It is, however, also possible that workers who commute to or from more densely populated municipalities are more likely to use less efficient modes of transport (like bicycles or public transport instead of cars).

Table 4.6. Regression results: commuting distance and time, 2000–2008

Dependent variable:	**Log distance**		**Log time**	
	(I)	(II)	(III)	(IV)
# Observations	118,757	67,606	146,759	83,343
Female	–0.147***	–0.146***	–0.143***	–0.143***
	(24.4)	(17.6)	(25.1)	(18.2)
Part-time worker	–0.074***	–0.083***	–0.066***	–0.081***
	(12.7)	(10.2)	(12.1)	(10.5)
Log hourly wage	0.287***	0.269***	0.161***	0.154***
	(34.7)	(23.3)	(20.6)	(14.1)
Married	–0.039***	–0.050***	–0.023***	–0.033***
	(7.0)	(6.8)	(4.3)	(4.7)
Manufacturing*	0.145***	–0.073	0.180***	–0.003
	(4.3)	(1.1)	(5.7)	(0.1)
Private services	0.275***	0.097	0.235***	0.085
	(8.2)	(1.4)	(7.5)	(1.3)
Public services	0.147***	–0.059	0.144***	–0.037
	(4.4)	(0.9)	(4.6)	(0.6)
Log employment density	0.040***	0.042***	0.163***	0.167***
(job location)	(14.5)	(11.3)	(60.0)	(45.9)
Log population density	–0.087***	–0.078***	–0.060***	–0.061***
(residence location)	(21.6)	(14.4)	(15.6)	(11.6)
Ratio jobs to population		–0.201***		–0.157***
(residence location)		(17.9)		(14.8)
Wage residual	4.227***	4.562***	4.856***	5.166***
(job location)	(63.1)	(51.2)	(76.7)	(61.5)
Land rent	–0.193***	–0.181***	–0.140***	–0.129***
(residence location)	(29.8)	(21.0)	(22.8)	(15.9)
Lower secondary education	0.035*	0.056**	–0.007	0.014
(VMBO, MBO 1)	(2.4)	(2.9)	(0.5)	(0.8)
Lower tertiary education	0.113***	0.139***	0.063***	0.094***
(MBO 2, 3)	(8.1)	(7.6)	(5.0)	(5.7)
Lower tertiary education	0.185***	0.206***	0.165***	0.193***
(MBO 4)	(13.5)	(11.3)	(13.3)	(11.8)
Higher secondary education	0.200***	0.215***	0.204***	0.220***
(HAVO, VWO)	(13.0)	(10.7)	(14.7)	(12.1)
Higher tertiary education	0.287***	0.303***	0.274***	0.282***
(HBO, BA)	(20.4)	(16.5)	(21.6)	(17.1)
Higher tertiary education	0.379***	0.411***	0.387***	0.416***
(MA, PhD)	(24.7)	(20.3)	(27.6)	(22.6)
Year dummies	Yes	Yes	Yes	Yes
Age dummies (5-year groups)	Yes	Yes	Yes	Yes
R^2	0.135	0.154	0.145	0.161

Notes: *t*-values (in absolute values) are in parentheses. Omitted industry is agriculture; omitted education category is primary education. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively. In model (1), the regression coefficients by age group are as follows: –0.02 (20–25), 0.01 (25–30), 0.00 (30–35), –0.06 (35–40), –0.11 (40–45), –0.16 (45–50), –0.18 (50–55), –0.21 (55–60) and –0.24 (60–65). As the estimated effect of age is comparable across models, we do not report our estimations for all models.

Workers who commute towards municipalities that offer relatively high wages (after correcting for worker characteristics, as measured by the wage residual) have on average a far larger commuting distance and time. This effect is economically very significant: a one percent increase in the non-competitive wage component is associated with a 4.2 (4.8) percent longer commuting distance (time). At the same time, workers who live in municipalities where land rents are low tend to live further from their work. This is consistent with the view that there is a trade-off between commuting time (and thus costs including opportunity costs of time) and residential location choice.

There is no strong relationship between commuter distance and time and the industry in which a worker is employed, although workers in private services commute somewhat further and those in agriculture somewhat less. Including industry dummies at the 2-digit NACE rev. 1.1 level, as a robustness check, did not have a substantial effect on the key variables in our regression model. Trends in the year dummies that were included in all regressions indicate changes over time in commuting behavior after correcting for composition effects. Across all estimated models, however, there is almost no year-specific trend in travel distance and time.

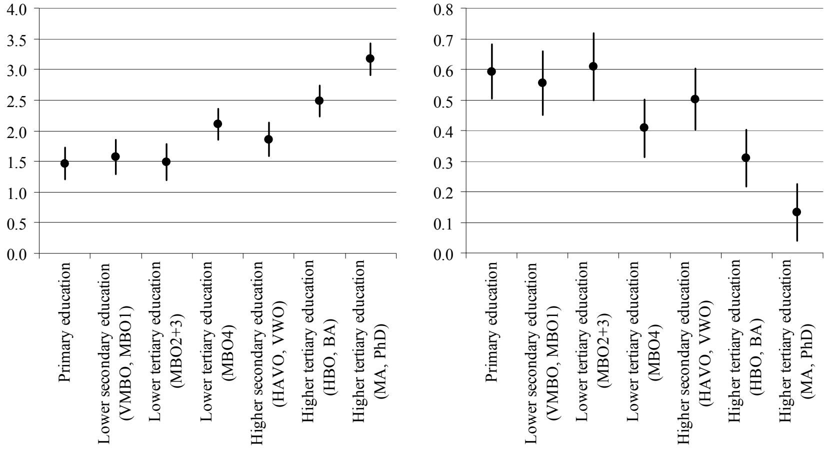
It is well possible that the effect of income on commuting distance and time depends on the level of education of workers. For example, it is well possible that, even at a given level of income, higher educated are more often able to work while commuting. This would explain their higher use of the train as a mode of transport (as a train is more suitable as a working environment compared to other modes of transport). To account for this possibility, we have added interaction effects between wages and education in our regression models.[31]

Figure 4.3 graphically displays the estimation results of a model that is similar to model (I) in Table 4.6 on all accounts other than the inclusion of wage-education interaction effects. Independent of income, higher educated workers travel further. The effect of wage on travel distance, however, is particularly high for lower educated workers while it almost disappears for university graduates.

[31] As a robustness check, we have also estimated models that include interaction effects between education and other variables. These, however, did not show strong interaction effects.

Figure 4.3. Education dummies (left) and interaction of education and wage (right)

Dependent variable: log commuting distance



Note: Bars correspond to 95% confidence intervals for the estimated coefficients. Estimates are obtained by adding interaction effects to regression (I) in Table 4.6 and removing log wage and the constant term.

As discussed in previous sections of this chapter, there is a strong interdependency between regional productivity on the one hand, and the structure of the work force on the other (see also, for example, Combes et al., 2008a and the previous chapter of this thesis). Even though we include several control variables to account for regional characteristics (in particular for the attractiveness of regions), we cannot rule out the possibility that spatial sorting of workers – resulting in a correlation between level of education and other worker characteristics – has resulted in biased estimates due to multicollinearity. To check whether the relation between education and commuting still holds independently of residence and work municipality, we re-estimate equation (4.2) with fixed effects for residence municipality and work municipality, thus controlling for all region-specific effects. Estimation results are shown in Table 4.7. Including fixed effects does not result in any notable change in parameter estimates. The results once more indicate that higher educated workers commute substantially further than lower educated workers, both in terms of distance and time. Also, the effects of level of education on commuting distance and time are again quantitatively similar, which indicates that higher educated workers do not commute faster.

Table 4.7. Regression results with region fixed effects, 2000–2008

Dependent variable:	Log distance	Log time
# Observations	118,757	146,759
Female	–0.129***	–0.128***
	(22.2)	(23.1)
Part-time worker	–0.068***	–0.057***
	(12.0)	(10.7)
Log hourly wage	0.278***	0.148***
	(34.9)	(19.5)
Married	–0.040***	–0.016**
	(7.3)	(3.1)
Manufacturing*	0.165***	0.190***
	(5.0)	(6.1)
Private services	0.256***	0.190***
	(7.8)	(6.2)
Public services	0.143***	0.112***
	(4.3)	(3.6)
Lower secondary education (VMBO, MBO 1)	0.026	–0.010
	(1.9)	(0.8)
Lower tertiary education (MBO 2, 3)	0.096***	0.077***
	(7.2)	(5.4)
Lower tertiary education (MBO 4)	0.168***	0.144***
	(12.6)	(11.9)
Higher secondary education (HAVO, VWO)	0.178***	0.173***
	(12.1)	(12.8)
Higher tertiary education (HBO, BA)	0.270***	0.249***
	(19.9)	(20.2)
Higher tertiary education (MA, PhD)	0.384***	0.364***
	(25.8)	(26.7)
R^2	0.168	0.100

Notes: *t*-values (in absolute values) are in parentheses. Omitted industry is agriculture; omitted education category is primary education. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively. Specifications include fixed effects for year, age (5-year groups), residence municipality and municipality of job location.

Explanation of the choice of mode of transport

In this section, we employ multivariate logit models to explain the use of five different modes of transport by a total of 139,127 commuters.[32] Our basic specification is the same as equation (4.2) that was estimated in the previous section. Additionally, we include the commuting distance. We have calculated marginal effects for the pedestrians (column I), the use of bicycles (column II),

[32] For computational reasons we have chosen to use multinomial logit rather than multinomial probit. As a robustness check, we compared the two estimators on a 5% subsample of our dataset. Both methods yield qualitatively comparable results.

personal cars (column III), bus, tram and underground (column IV) and the train (column V). The estimated marginal effects are reported in Table 4.8.

The distance of commutes is the variable with the strongest explanatory power. Doubling the distance of a commute decreases the probability that the bicycle is used by 25 percent, while it increases the probability that a car is used by 22 percent. For all modes of transport, with the exception of trams, buses and the underground, distance has a very strong effect on the probability that each mode is used. Females are somewhat less likely to commute by bike, and more likely to commute by car or bus, tram or underground. There is no relation between age and mode of commuting, hence we do not report the estimated results for the nine age dummies that were included. Workers commuting to higher paid jobs are more likely to commute by car, and less likely to commute by bicycle.

As noted in the introduction, the higher use of public transport by higher educated individuals could be to some extent institutionalized because public sector employees (who are somewhat higher educated on average) often receive compensation for commuting expenses when they use public transport, but not when using personal cars. Our empirical results are, however, inconsistent with this hypothesis. There is no statistically significant difference between the effects of working in private services and working in public services on the probability that busses, trams, underground railways or trams are used. Public servants do, however, seem to use bicycles somewhat more often than workers in other sectors.

The results in Table 4.8 should be interpreted as the expected marginal effect of a change in the independents by one on the probability that a commuter uses each respective mode of transport. The level of education has almost no effect on the probability that an individual will walk from home to work. Higher educated workers are more likely to commute by bike or by train, but less likely to commute by personal car or bus, tram or underground. Having a university degree is associated with a *ceteris paribus* 26 percent higher probability to commute to work by bicycle compared to having only finished elementary school, while the probability to commute by personal car is 27 percent lower and the probability to use the train is 2.6 percent higher.

Table 4.8. Regression results: multinomial logit by mode of transport, 2000–2008

Marginal effects by mode of transport	Pedestrian	Bicycle	Personal car	Bus, tram, underground	Train
	(I)	(II)	(III)	(IV)	(V)
# Observations	3,292	38,577	83,122	5,918	8,217
Female	–0.001	–0.094***	0.072***	0.021***	0.003***
	(6.1)	(28.5)	(20.6)	(14.4)	(5.3)
Part-time worker	0.000**	0.022***	–0.019***	–0.003*	0.001
	(0.8)	(6.8)	(5.7)	(2.4)	(1.1)
Log hourly wage	–0.002**	–0.125***	0.156***	–0.025***	–0.004***
	(10.0)	(26.4)	(31.4)	(12.3)	(4.6)
Log travel distance	–0.006***	–0.250***	0.219***	0.009***	0.028***
	(27.9)	(161.3)	(122.1)	(16.6)	(58.3)
Married	–0.001***	0.009**	0.017***	–0.018***	–0.007***
	(7.0)	(2.8)	(5.4)	(12.7)	(11.3)
Manufacturing	–0.001**	0.029	–0.181**	0.043	0.111
	(1.8)	(0.9)	(2.8)	(1.4)	(1.2)
Private services	0.000	–0.030	–0.177***	0.086**	0.121
	(0.1)	(1.2)	(3.4)	(2.9)	(1.7)
Public services	0.001	0.074***	–0.228***	0.068***	0.085*
	(1.6)	(3.4)	(6.7)	(3.3)	(2.0)
Lower secondary education	–0.001**	0.028***	–0.005	–0.018***	–0.004*
(VMBO, MBO 1)	(3.1)	(3.5)	(0.6)	(9.6)	(2.2)
Lower tertiary education	–0.001***	0.036***	–0.010	–0.024***	–0.001
(MBO 2, 3)	(4.3)	(4.6)	(0.3)	(13.9)	(0.5)
Lower tertiary education	–0.001**	0.076***	–0.047***	–0.029***	0.001
(MBO 4)	(3.0)	(10.9)	(5.7)	(16.7)	(0.6)
Higher secondary education	0.001	0.110***	–0.116***	–0.010***	0.016***
(HAVO, VWO)	(1.3)	(10.9)	(11.7)	(4.4)	(4.6)
Higher tertiary education	0.000	0.145***	–0.120***	–0.031***	0.005*
(HBO, BA)	(0.9)	(16.4)	(13.6)	(15.8)	(2.4)
Higher tertiary education	0.001	0.255***	–0.266***	–0.017***	0.026***
(MA, PhD)	(1.6)	(22.8)	(25.3)	(7.5)	(6.4)
Pseudo R^2			0.268		

Notes: *z*-values (in absolute values) are in parentheses. Omitted category when estimating the model was pedestrian. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively. Year and age (5-year groups) fixed effects are included.

These results are consistent with the hypotheses formulated in Section 4.3. Even when controlling for wages, well-educated workers do not only travel more than lower educated, they are also less willing to use the car and other private means of transport, except for the bicycle. The finding that higher educated workers are (*ceteris paribus*) more likely to take the train supports the view that higher educated workers are better able to use time spent in a train (for either work or leisure). The finding that workers with higher wages are more likely to use the car is consistent with the view that there is a positive relation between income and speed. As was the case for the regressions on commuting distance and time from the previous section, an analysis of the time specific effect showed that the choice for different modes of transport remained fairly constant between 2000 and 2008.

4.5 Conclusion

The level of education of individuals has almost always been treated as a statistical control in the empirical literature on commuting, but it rarely has been the object of a specific analysis and discussion. This chapter has made an attempt to analyze the effects of education on travel behavior of Dutch employees, trying also to understand the difference between higher levels of education and high wages, which are often strongly correlated. Results show that, even after controlling for their wage, commutes of highly educated workers are substantially longer compared to commutes of lower educated workers. At the same time, we find strong interaction effects between wages and education on commuting time and duration. For lower educated workers, we find a strong relation between wages and commuting distance and time. For higher educated workers this relation is less strong, while it has almost no effect for university graduates. There is no effect of education on the *speed* of commuting. Across different specifications, the effect of education on commuting distance is similar to the effect on commuting time. In addition, higher educated workers are more frequent users of public transport and of bicycles.

Many factors could explain observed heterogeneity in commuting patterns between lower and higher educated workers. Even though future research will need to address this more thoroughly, the empirical evidence in this chapter provides some preliminary insights. First of all, we find that higher educated workers are more likely to commute *towards* agglomerated areas and areas that pay higher wages compared to less educated. As was discussed in Chapter 3, there is substantial sorting of employees across regions, whereby higher educated workers are more likely to work in locations with a high economic density and productivity. Productivity thus attracts high skilled employment to the cities. Supply of housing and heterogeneity in demand for housing, on the other hand, tend to have the opposite effect. Because higher educated workers have on average relatively high incomes. The largest Dutch cities (that are the most attractive for higher educated employees as a location to work because of productivity advantages) are characterized by a relatively high share of social housing. This is likely to – at least to some extent – explain the finding that higher educated individuals are relatively more likely to commute from a low density municipality towards a high density municipality. Furthermore, higher educated workers are more often house owners, which reduces their labor mobility.

Sorting of employees is not only taking place due to differences in productivity or the kind of houses people want to live in, but also due to differences in the willingness to pay for amenities. If, at a given density and average productivity level, housing prices go up, lower educated workers are more likely to commute *towards* this municipality than *from*. For higher educated workers this is opposite. Furthermore, whereas it is rather unlikely for lower educated workers to commute between larger cities, there are many higher educated workers that commute even between the largest Dutch agglomerations.

A possible explanation for both the finding that higher educated workers commute more than lower educated, and the finding that higher educated workers are more likely to commute between the largest cities, are relatively higher search frictions. Because higher educated workers perform generally more specialized work, the probability to find a good match close to the current residence location is relatively low. Such specialized workers are therefore more likely to accept a job offer further away, giving them the choice between commuting or moving. Particularly excess commutes is an indication for the existence of search frictions. The large bidirectional flows of highly educated commuters between pairs of cities are likely to be excess commuting (though in theory they could represent local scarcity of certain types of very specialized high skilled labor) is consistent with the view that higher search frictions for high skilled employees causes their commutes to be longer.

The finding that higher educated workers are more likely to commute by train could be explained by, for example, the possibility to carry out part of their work while commuting. However, it is also possible that the locations where higher educated workers are employed are generally closer to a train station. A healthier lifestyle may explain their preference for the use of bicycles. Besides the other mentioned factors, it could be worth considering possible effects on the set of individual's preferences driven by education, which could also affect the disutility associated with the use of non-motorized or non-private means of transport.

5 ESTIMATING THE IMPACT OF TRADE, OFFSHORING AND MULTINATIONALS ON JOB LOSS AND JOB FINDING

5.1 Introduction[33]

Advancements in information and communication technology as well as the removal of formal and informal barriers to international trade and investments have resulted in supply chains that are more international and less vertically integrated. Lower costs of communication and coordination reduce the need to perform manufacturing stages within close vicinity. This has enabled firms to benefit from increased international specialization, by further breaking up the production process, and by participating in global supply chains in which the many tasks required to manufacture goods and services are performed at locations with a comparative cost advantage.

The ongoing integration of the world economy has given rise to some concerns among politicians and the general public. The recent recession has exacerbated these concerns, resulting in widespread public attention for multinational firms that are downscaling operations, the supposed danger of firms losing market share due to competition from the BRIC countries, and employees losing their jobs due to outsourcing. According to an OECD poll, even before the financial crisis far more people considered globalization to be a threat rather than beneficial (OECD, 2007). Unfounded fear for globalization could result in a demand for protectionist measures, which could result in a reduced growth potential of the economy.

At the same time, the general consensus that international trade in products and tasks is beneficial for the average individual does not necessarily imply that it is good for everyone. The effects on workers with different levels of education, or different industries and occupations, are far from trivial. Furthermore, the general

[33] This chapter is based on Groot et al. (2013).

consensus among economists regarding the long-run positive effects on higher productivity, increased incentives to innovate, and higher economic growth (see Crino, 2008) does by no means exclude the possibility that there are some short-term – both positive and negative – transition effects along the way. Even though the public fear for these transitional effects is related mostly to unemployment, the empirical literature has focused largely on aggregate employment and wages of workers who stayed fixed within certain industries or occupations (e.g., Feenstra and Hanson, 1996; Autor et al., 2003; Crino, 2010; Goos et al., 2009).

This chapter aims to answer two questions. First, we estimate the extent to which the probability to become unemployed is related to different dimensions of globalization and worker characteristics. Second – in case an individual has been fired – we estimate how unemployment duration is related to the interaction of globalization (related to the old job) and worker characteristics. We devote attention to the impact of several dimensions of globalization, which are exporting behavior of firms, offshoring, and the presence of multinational companies.

Empirical evidence shows that the task composition of occupations has changed substantially during recent decades (Borghans and Ter Weel, 2006), and that the observed trend of increased fragmentation and internationalization of production processes could be a major explanation behind increased wage inequality and polarization in some countries (Autor et al., 2006; Goos et al., 2009; Van Reenen, 2011; Fortin et al., 2011). Even though Chapter 2 showed that aggregate wage inequality did not change much in the Netherlands, it also showed substantial heterogeneity between different types of workers. This heterogeneity could be – at least to some extent –related to globalization.

Studies that address the relationship between globalization and unemployment at the individual level are relatively rare (e.g., Egger et al., 2007; Munch, 2010). This chapter aims to fill this gap in the literature by following individual workers over time and by investigating the factors that affect job loss and job finding. By applying Cox proportional hazard models and Cox regression models (Cox, 1972) – which are tools for duration and survival analysis – we estimate the effects of these three dimensions of globalization on job-to-unemployment and unemployment-to-job transitions. By combining several large Dutch micro datasets regarding workers, unemployment benefits, and firms, we are able to relate both worker characteristics and employment characteristics to the probability that an individual will become unemployed and the probability that a new job will be found. Our data set includes the full employment record of workers, containing information on wages in previous and current jobs as well as number of days spent unemployed.

This chapter is organized as follows. Section 5.2 reviews the recent literature on globalization and unemployment specifically focusing on research conducted at the individual level. The next section explains the data in detail and presents summary statistics and stylized facts. Our empirical framework is discussed in Section 5.4. Section 5.5 presents the results of the empirical estimations. Section 5.6 concludes.

5.2 Globalization and unemployment

There is a clear link between the three indicators for globalization – offshoring, multinationals, and export activities – that we take into consideration.[34] Even though the activities of multinationals could be limited to strictly horizontal multinational activities (for example, to evade trade barriers and transportation costs), an important part of the activities of multinationals involves vertical interdependencies where each location is specialized in certain tasks according to local comparative cost advantages. This vertical component involves both the relocation of tasks, and trade linkages when intermediate products are shipped between subsidiaries. Offshoring can also take place outside multinationals, although in that case international trade is still involved.

In total, the Dutch input-output table for 2009 (as published by Statistics Netherlands) shows that 62 percent of Dutch imports (excluding imports that are transferred or re-exported) are used as intermediary inputs, while only 38 percent consists of final goods. Empirical evidence shows that the importance of imported intermediaries as a share of the total use of non-energy intermediaries – which is often used as a raw indicator for offshoring – is increasing across virtually all industrialized economies (Crino, 2008). Apart from international task specialization, export activities can be considered as a proxy that indicates the extent to which firms face foreign competition.

[34] Even though the use of imports by firms is at least as relevant as exports, we have to limit this chapter to exports as the only trade measure, due to a lack of firm level import data.

There has been a recent surge of interest in the labor market effects of globalization. As early as the 1990s, researchers studied the role of international trade and increasing imported inputs on employment and productivity (e.g., Feenstra and Hanson, 1996 and 2001; Brainard and Riker, 1997; Anderton and Brenton, 1999). The recent literature argues that the globalization processes, together with advances in technology, has resulted in job and wage polarization.

Relatively simple extensions of Heckscher-Ohlin and Stolper-Samuelson trade models predict increased demand for the abundant factor (which are tasks that require high skilled labor), and a shift in relative factor prices that increases the wages of high skilled workers. Contrary to the expectations of the basic Heckscher-Ohlin arguments, this trend is also observed in less developed countries (Goldberg and Pavcnik, 2007).

In contrast, the task-based literature argues that technological advancements permit the breaking up of jobs into small pieces of tasks, such that offshoring affects employment through its effects on task demand rather than on demand for low skilled versus high skilled workers (Grossman and Rossi-Hansberg, 2008). The skill biased technological change (SBTC) literature argues that technology complements skills, which implies that skilled labor demand and wages increase at the expense of low skilled jobs (Acemoglu, 1998; Berman et al., 1998). Autor et al. (2003) argue that the decrease in the demand for manual routine tasks may explain job polarization in the US. The main argument of the task-based explanations of polarization is that some tasks are separable from the occupation bundle (which is defined as the set of tasks that composes an occupation), which later can be offshored to low-wage locations (e.g., Blinder, 2009; Akçomak et al., 2011).

The empirical evidence regarding these theories is mixed. Some researchers have found evidence that is consistent with a negative relationship between offshoring and job and wage polarization (e.g., Feenstra and Hanson, 2001; Scheve and Slaughter, 2004; Crino, 2010; Baumgarten et al., 2010; Fortin et al., 2011; Goos et al., 2009), while others found negligible or zero effects (Amiti and Wei, 2005; Mankiw and Swagel, 2006; Liu and Trefler, 2008; Koller and Stehrer, 2009; Criscuolo and Garicano, 2010).

The empirical literature discussed above mostly relies on aggregate data at the industry or occupation level. Only a few studies employed worker level data to assess the impact of the globalization process on employment. These studies have combined industry level offshoring measures with individual level data, which makes it possible to follow workers for a specific time period.[35] Researchers investigated the impact of offshoring on job displacement in general and transitions to unemployment, weeks spent unemployed between two jobs and earnings differentials in particular. This strand of literature is related to previous research on job turnover at the worker level (e.g., Royalty, 1998; Gomes, 2012). One of the first studies that assesses the short-run employment effects of offshoring in a longitudinal setting is the work of Egger et al. (2007). Using Austrian data between 1998 and 2001, they estimated a dynamic fixed effect multinomial logit model. They find that offshoring reduces the probability to remain in the manufacturing sector, as well as the probability of switching to the manufacturing sector.

Liu and Trefler (2008) have used US data from 1996 to 2006 to assess the impact of offshore outsourcing in the service sector to India and China on four labor market outcomes. They consider switching of employees between industries and occupations, number of weeks spent unemployed, and the earnings difference between two jobs. They find small negative or zero effects of offshoring on all labor market outcomes that were taken into consideration. These results validate earlier findings of Eberstein et al. (2009), regarding the small negative impact of offshoring to low wage countries on employment levels in the US.

In a later study for the years 1996 to 2007, Liu and Trefler (2011) differentiated between upward and downward switching (i.e., switching to an occupation that pays less on average). They find that the cumulative 10-year impact of imports of services from India and China caused downward occupation switching to rise by 17 percent and transitions to unemployment to rise by 0.9 percentage points. In the studies above, much of the negative impact of offshoring on earnings is observed when workers in the manufacturing sector had to switch to a job in services that pays less on average.

Within the existing empirical literature, the study that is perhaps closest to our approach is Munch (2010). He used Danish manufacturing sector data from 1990 to 2003 to investigate the effect of offshoring on short-run job displacement.

[35] Most studies use measures that are similar to those introduced by Feenstra and Hanson (1996), where offshoring is proxied by the intermediate imported inputs as a share of total inputs.

The work focuses on unemployment spells that end with a transition into a new job and considers three outcomes: occupation switching, job to unemployment and job to non-participation transitions. They find that there are small effects of offshoring on unemployment. Offshoring increases the unemployment risk by one percent. However, this effect is much larger for men, workers above 50 and low skilled workers.

We assess the short-term relation between offshoring and unemployment duration using longitudinal data at the worker level. Egger et al. (2007) have used a somewhat similar setting, but controlled only for age thus failing to account for worker heterogeneity. Munch (2010) estimated a duration model controlling for various individual characteristics such as age, education and gender. One of the contributions of this chapter is that we not only estimate job-to-unemployment transition but unemployment-to-job transition as well. Offshoring and other individual characteristics may increase unemployment duration and at the same time may decrease the probability of finding a new job. For instance our estimations show that foreign workers are more likely to become unemployed and once they are unemployed they are also likely to remain unemployed for a much longer time.

5.3 Data and stylized facts

Data

This chapter uses micro data that are available through Statistics Netherlands (CBS). For data on worker characteristics – like date of birth, gender, country of birth, and the wage – we rely on census data and tax data from registers, available through the CBS social statistics database (SSB, *Sociaal Statistisch Bestand*). We use two branches of the social statistics database of Statistics Netherlands, one regarding jobs (*SSB Banen)* and one regarding unemployment benefits (*SSB WW*). Of each job, we have the (employer reported) exact date when a worker starts working for a certain establishment of a firm, and (if this applies) the date when the job ends, as well as the pre-tax wage an employee earned in a job in a given year (the fiscal wage). As this dataset covers all Dutch employees and firms with employees, we use this data source to calculate the number of employees per firm and per municipality. Data are available for 2000–2008. Country of birth is used to determine whether a worker is native, non-native born in a developed country (with at least a GDP of US$ 20,000 in 2010),[36] or non-native born in any other country.

For each person with unemployment benefits, we use the codified social security number combined with the date when they were first entitled to unemployment benefits – as well as the date when entitlement ended – to match unemployment benefits to the end date of the previous and (if applicable) the starting date of the next job. The unit of observation is thus a job of an employee, that may or may not end in unemployment. Even though the cause of unemployment is unknown, is has to be involuntary, as only involuntary unemployed are entitled to unemployment benefits according to Dutch law. Because the registration processes of the end date of a job and the start of entitlement to unemployment benefits are independent (and rather imprecise, as turned out), we consider a merge successful if the difference between the two is at most two months.

A rather large part of individuals that receive unemployment benefits, do not have a strong attachment to a previous job. Some workers have many succeeding jobs that do not last long, or multiple jobs at the same time, while others even seem to start receiving unemployment benefits when their job has not ended.[37] Including these workers would generate noise in the dataset for two reasons. First, the environment and occupation of the last job are not well defined. Second, it is well possible that workers who get unemployed frequently are fired not because of the characteristics of their last jobs, but rather due to some (unobserved) worker characteristics. It is unclear in these cases whether unemployment is related to globalization. To exclude this source of noise, we have limited our dataset to only those workers who were employed by one single employer for at least two years prior to losing their job. When an unemployed worker has found a new job, we require that it lasts for at least two months before we consider it a successful exit

[36] According to the World Economic Outlook Database of the International Monetary Fund these include Luxembourg, Norway, Qatar, Switzerland, Denmark, Australia, Sweden, the United Arab Emirates, the United States, the Netherlands, Canada, Ireland, Austria, Finland, Singapore, Belgium, Japan, France, Germany, Iceland, the United Kingdom, Italy, Kuwait, Hong Kong, New Zealand, Spain, Brunei, Cyprus, Greece, Israel, Slovenia, Portugal, the Bahamas and South Korea.
[37] This can happen, for example, when the number of working hours of a worker with a flexible contract is reduced.

from unemployment. Another difficulty is to obtain a good estimate of the last wage earned by an employee. As employees who get fired may receive a bonus when getting fired, this may result in an overestimation of their wage. We therefore use the fiscal wage of the year prior to getting unemployed. This implies that we do not include workers who entered unemployment in 2000 in our analyses, the first year for which we have data available, as their jobs cannot be observed in the year before they were fired.

To make wages comparable over time, we have corrected all wages for the change in average wage (the base year is 2008).[38] The wage differential between the wage of a worker prior to getting unemployed and the wage earned from the next job is thus based on the relative position of the worker in the wage distribution. Because we have no reliable indicator for hours worked (though we have an indicator for the number of *days* worked, the so-called social insurance days which are employer reported and available through SSB), we limit our dataset to jobs of at least 0.8 fte (fulltime employment equivalents), which are calculated by dividing the number of social insurance days reported for an employee by the total number of social insurance days. Finally, we exclude all employees younger than 20 or older than 60 (as they may enter into an early retirement schedule) when getting unemployed, and we have excluded all jobs earning less than the equivalent of the minimum yearly wage in 2008 (corrected for inflation). Table 5.1 shows the results of this matching process.

To compare workers who entered unemployment to workers who remained employed, we applied the same criteria to workers remaining employed. The resulting dataset includes 4.41 million employees (representing 35 percent of the total Dutch labor force) working at some point in time during the 2000–2008 period. 163 thousand out of those 4.41 million employees were fired at least once with the individual entitled to unemployment benefits. This accounts for 7.1 percent of total unemployment benefits. Even though our dataset is thus more or less representative for a typical full-time employee with a stable employment relationship, it is not representative for the typical unemployed. Information about

[38] The advantage of this approach compared to, for example, using real wages is that the wage difference between the last full year an individual worked prior to unemployment, and the first year in a new job, is not affected by growth in real wages. This is especially important as the time between jobs is not fixed.

the last known job is a necessary condition when estimating the effect of characteristics of this job on job loss. Furthermore, it is likely that the determinants of job loss of workers outside our sample are at least to some extent similar to the determinants of job loss of workers with similar observed characteristics that are in our sample. It is possible that workers outside our sample have less favorable unobserved characteristics, or that the lack of stability in the employment records of the workers outside our sample itself is caused by globalization, but this falls beyond the scope of this chapter.

Table 5.1. Results of matching jobs to unemployment benefits

Year	New entrants entitled to unemployment benefits	Successfully merged to a job of at least 0.8 fte, paying at least minimum wage during the previous 2 years	
2001	224,055	10,474	4.7%
2002	279,697	20,051	7.2%
2003	358,049	27,294	7.6%
2004	370,517	31,459	8.5%
2005	332,913	27,702	8.3%
2006	287,179	18,101	6.3%
2007	245,423	15,124	6.2%
2008	203,750	13,949	6.8%
Average	287,698	20,519	7.1%

Table 5.2 presents descriptive statistics concerning key variables of interest for workers that had at least one job between 2001 and 2008, while never being unemployed (left column), as well as for workers who experienced at least one episode of unemployment during the same period. Workers who enter unemployment are somewhat younger than the average employee in our sample. Furthermore male workers and non-natives (both those born in developed and those born in developing countries) are substantially overrepresented in the group of workers who have experienced unemployment. An interesting finding that emerges from Table 5.2 is that almost 20 percent of workers that experienced unemployment had been previously working at a foreign firm, while less than 14 percent of all workers who were never unemployed worked at a foreign firm.

Table 5.2. Descriptive statistics of workers and unemployed, 2001–2008

	Never unemployed	Unemployed at least once
Observations (*N*)	4,245,683	163,091
Age	43.30	42.58
	(10.61)	(9.78)
Female	0.280	0.239
	(0.449)	(0.427)
Non-native (developed)	0.024	0.032
	(0.152)	(0.175)
Non-native (other)	0.070	0.118
	(0.255)	(0.322)
Last wage (2008 euros)	42,957	41,731
	(24,457)	(23,819)
Foreign firm	0.138	0.197
	(0.345)	(0.398)

Notes: Standard deviations are in parentheses. All differences are statistically significant at significance levels far beyond 0.001.

Stylized facts by industry, level of education, and occupation

Table 5.3 presents a number of descriptive statistics by industry. All data on industries and firms relate to the job an individual had *before* getting unemployed. The highest incidence of unemployment can be observed among workers that were previously employed in the manufacturing industry, where 3.6 percent of the workforce has received unemployment benefits at least once. In manufacturing, workers are much more often fired during mass layoffs compared to any other industry.[39] Workers in other private industries have a lower probability to become unemployed, generally between 2 and 3 percent. The lowest incidence of unemployment is observed in public services, particularly amongst government employees.

There is no strong relationship between the incidence of unemployment and average unemployment duration. However, unemployment duration of individuals that were fired from a manufacturing job is notably higher than in all other industries (except for the relatively small mining sector), indicating relative

[39] We define a mass layoff as a situation in which at least 20% of the work force is being fired in a single year for firms with 20 or more employees (prior to the layoff), 40% for firms with 10 to 20 employees, and 60% for firms with 5 to 10 employees. The reason to use a somewhat higher percentage for smaller firms is that in small firms 20% of the work force corresponds to just a few employees. Though this definition is somewhat arbitrary, it could be interesting to see whether lay offs are random within industries, or whether they are concentrated within some specific firms.

difficulty in the job search process. There is a strong (negative) correlation between average unemployment duration within industries and the share of unemployed that will eventually succeed in finding a new job. The largest average wage differential between the job prior to unemployment and the next job is found for construction workers, who earn about 6 thousand euro less. Workers who were employed within the education sector, on the other hand, gain about 8 thousand euro annually if they succeed to find a new job.

Table 5.3. Descriptive statistics by industry, 2001–2008

	# Observations	Average annual fiscal wage (all workers)	% Unemployed at least once	Average unemployment duration (months)	% Of unemployed that finds a new job before 2009	Average wage differential*	% Share of mass layoffs in total layoffs
Agriculture	82,447	34,354 (13,088)	2.04	10.5 (15.5)	75.9	–16 (9,624)	2.9
Mining and quarrying	10,894	73,394 (40,712)	1.94	15.1 (19.5)	70.1	–3,410 (25,404)	4.3
Manufacturing	1,152,705	42,163 (21,662)	3.63	14.9 (18.2)	71.4	–2,286 (13,251)	18.6
Construction	536,943	40,355 (14,842)	2.95	10.7 (15.4)	75.6	–6,238 (9,644)	6.3
Trade	637,211	43,826 (27,075)	3.30	11.3 (14.8)	77.8	–562 (16,306)	5.1
Hotels and Restaurants	101,734	31,972 (15,118)	3.05	9.1 (11.6)	79.8	–842 (9,769)	1.7
Transport	490,893	42,725 (22,439)	2.21	13.3 (16.7)	71.7	–2,293 (16,313)	4.3
Commercial services	1,330,582	53,256 (34,414)	2.73	11.9 (15.0)	76.4	–381 (18,113)	4.3
Government	671,872	43,196 (15,159)	0.64	11.7 (16.0)	72.5	–1,662 (10,787)	0.6
Education	362,978	42,401 (14,279)	1.64	13.0 (16.9)	63.1	8,122 (13,190)	0.8
Healthcare	547,297	37,868 (19,074)	1.62	11.1 (13.0)	70.8	1,466 (14,619)	2.5
Other	197,589	40,861 (22,228)	3.33	11.5 (14.4)	72.0	–366 (14,514)	3.9
Total	6,123,175	44,155 (24,619)	2.56	12.5 (16.1)	73.8	670 (15,121)	8.0

Notes: Standard deviations are in parentheses. *Compares the normalized annual fiscal wage differential between the job prior to unemployment and the job after unemployment. Differentials larger than 100,000 euro are excluded.

Additional data on worker characteristics (viz. education and occupation on the 2-digit Statistics Netherlands occupation classification) are drawn from different cross-sections of the annual labor market survey (EBB, *Enquête Beroeps Bevolking*), 2000–2008. We distinguish eight different levels of education and 90 different occupations. After merging the dataset with data on employees and unemployed – which was constructed as described above – with EBB, about 159 thousand observations remain (2 thousand of these jobs end in unemployment).[40]

Table 5.4 presents descriptive statistics by level of education. Indeed, workers with a university Master degree earn about twice as much as workers with only primary education. However, the relation with unemployment is nontrivial. Even though workers with only primary education have the highest probability to get unemployed and have the highest average unemployment duration, workers with intermediate levels of tertiary education have the lowest probability to get fired and have the shortest unemployment duration. These types of schooling are often focused on a specific (skilled) profession. Workers with a PhD or university Master degree are somewhat in between on both accounts. The share of workers who find a new job before 2009 (e.g., within our period of observation) is average for individuals with the highest level of education, while it is much higher for individuals educated at the intermediate levels.

Table 5.5 presents key statistics on unemployment for workers previously employed in 24 different 2-digit ISCO-88 occupations. Not surprisingly, there are substantial differences between occupations. Teaching professionals (ISCO code 23) and life science and health associate professionals (ISCO code 32) have the lowest unemployment incidence. Within our dataset, unemployment is observed for only 0.3 to 0.4 percent of the employees with these occupations. Occupations with the highest unemployment incidence are precision, handicraft, craft printing and related trade workers (ISCO code 73), followed by machine operators and assemblers (ISCO code 82).

[40] Note that only 1.23 percent of the observed individuals is fired according to the dataset that resulted after merging with the labor force force survey, whereas this figure was 2.56 percent prior to merging. This implies that workers with comparable jobs have a relatively smaller probability to be included in the labor force survey if they are fired at some point in time. The main explanation for this is that workers who are fired are only in the labor survey at a moment they were still employed when they were inverviewed *prior* to their being fired. If we assume that both the probability to be fired and the probability to be interviewed at a certain day in a year are random, this results in an underrepresentation of workers who get fired. However, as this probability is unrelated to what determined their unemployment, it does not bias our results.

Table 5.4. Descriptive statistics by level of education, 2001–2008

	# Observations	Average annual fiscal wage (all workers)	% Unemployed at least once	Average unemployment duration (months)	% Of unemployed that finds a new job before 2009	% Share of mass layoffs in total layoffs
Primary education	7,651	34,634 (11,729)	1.56	16.3 (18.7)	66.4	16.0
Lower secondary education (VMBO, MBO 1)	8,132	38,338 (17,735)	1.71	15.5 (18.8)	67.6	10.1
Lower tertiary education (MBO 2, 3)	26,703	38,329 (13,562)	1.22	11.8 (16.2)	74.8	7.1
Lower tertiary education (MBO 4)	33,837	41,286 (16,213)	1.06	9.6 (12.7)	80.7	7.8
Higher secondary education (HAVO, VWO)	11,137	44,906 (23,009)	1.39	11.2 (13.0)	81.9	7.1
Higher tertiary education (HBO, BA)	33,257	52,070 (23,956)	1.05	11.3 (13.3)	75.1	3.1
Higher tertiary education (MA, PhD)	17,721	68,414 (38,982)	1.21	11.6 (14.3)	76.2	2.8
Total	159,170	45,158 (23,501)	1.23	10.7 (12.4)	75.6	7.3

Note: Standard deviations are in parentheses.

It has often been suggested that rigid labor markets in Europe have resulted in a more compressed wage distribution with higher unemployment as compared to, for example, the United States (see, for example, Nahuis and De Groot, 2003; Acemoglu and Newman, 2002). As the upward pressure from labor market institutions on wages is particularly large for lower paid jobs, this would be likely to result in higher unemployment in lower paid occupations, as wages are not allowed to sufficiently adjust to clear the labor market. However, in the Netherlands this cannot be observed, as the correlation between the average wage within occupations and the risk of unemployment is close to zero. That is: it cannot be observed for the workers in our sample, who all managed to hold jobs for at least several years prior to getting fired. There is also a substantial pool of workers who do not manage to hold steady jobs, or who are structurally unemployed. It is possible that one of the reasons of their unemployment is that the type of jobs they *could* have done have been outsourced. As this chapter addresses only transitional unemployment (because we need to know the previous

Table 5.5. Descriptive statistics by 2-digit ISCO-88 occupation, 2001-2008

	# Observations	Average annual fiscal wage (all workers)	% Unemployed at least once	Average unemployment duration (months)	% Of unemployed that finds a new job before 2009	% Share of mass layoffs in total layoffs
12. Corporate managers	15,967	62,308 (37,838)	1.42	12.4 (15.5)	71.4	8.4
13. Managers of small enterprises	6,055	59,488 (35,633)	1.39	12.0 (13.6)	70.2	1.2
21. Physical, mathematical and engineering science professionals	9,374	55,974 (21,967)	1.23	9.5 (12.3)	82.6	7.0
22. Life science and health professionals	2,172	60,199 (35,385)	0.78	10.1 (11.1)	NA	NA
23. Teaching professionals	7,435	46,410 (13,696)	0.32	19.0 (24.8)	NA	NA
24. Other professionals	7,131	52,602 (25,466)	1.67	12.6 (13.2)	69.7	1.7
31. Physical and engineering science associate professionals	9,622	45,695 (20,417)	1.05	13.5 (19.3)	74.3	10.9
32. Life science and health associate professionals	4,170	34,375 (9,416)	0.38	8.1 (11.1)	NA	NA
34. Other associate professionals	14,165	45,516 (21,333)	1.15	13.4 (15.8)	74.2	2.5
41. Office clerks	11,627	38,033 (13,527)	1.26	13.3 (17.0)	78.9	2.7
42. Customer services clerks	1,613	31,870 (11,949)	1.74	11.0 (14.5)	NA	NA
51. Personal and protective services workers	5,751	34,284 (12,890)	0.90	12.9 (15.8)	63.5	0.0
52. Models, salespersons and demonstrators	4,335	38,027 (20,306)	1.48	9.9 (11.3)	85.9	0.0
61. Skilled agricultural and fishery workers	2,084	30,435 (8,056)	0.86	7.1 (10.5)	NA	NA
71. Extraction and building trades workers	9,431	36,596 (7,880)	1.86	9.0 (14.3)	83.3	8.0
72. Metal, machinery and related trades workers	9,338	36,723 (9,443)	1.18	11.5 (15.4)	80.0	14.5
73. Precision, handicraft, craft printing and related trades workers	905	36,036 (9,867)	2.32	17.8 (18.4)	NA	NA
74. Other craft and related trades workers	1,430	32,496 (18,721)	1.61	6.4 (5.9)	NA	NA
81. Stationary plant and related operators	1,964	45,241 (13,885)	0.87	11.8 (9.6)	NA	NA
82. Machine operators and assemblers	4,224	34,893 (9,143)	1.92	12.9 (15.6)	77.8	33.3
83. Drivers and mobile plant operators	7,760	37,444 (8,180)	0.86	8.4 (11.8)	79.1	10.4
91. Sales and services elementary occupations	1,885	29,694 (7,750)	1.33	10.5 (11.0)	NA	NA
93. Laborers in mining, construction, manufacturing and transport	357	38,813 (8,237)	1.68	3.0 (2.5)	NA	NA
Total	138,820	44,964 (23,483)	1.22	11.7 (15.0)	75.4	7.4

Note: Standard deviations are in parentheses. We report no results (NA) if less than 50 individuals in an industry were fired.

job to observe the covariates of individuals getting fired), we leave the quest for the determinants of this structural unemployment for future research. At the same time, however, we must note that what determines unemployment of individuals who were recently employed is likely to be related to what determines unemployment of those without steady employment records.

Employees fired from manufacturing have a higher probability to find a new job, and relatively low average unemployment duration compared to many of the services industries. It is, however, likely that there are some selection effects in place. For workers with occupations where many individuals are fired, or where there are relatively many mass layoffs, their individual performance may be less related to their being fired. On the other hand, when a police officer – working in an occupation where unemployment is relatively rare – is fired, this may be more likely due to personal characteristics, which may make it more difficult to find a new job.

Indicators for trade, offshoring and activities of multinationals

We use three measures for exposure to globalization. On the firm level, we determine whether a firm is foreign owned or not, using the Statistics Netherlands indicator on the home country of the Ultimate Controlling Institute (UCI) of each firm. This indicator draws on multiple data sources. It is important to note that subsidiaries of foreign firms can be considered part of a multinational firm, but do not cover Dutch owned firms that have activities in multiple countries. Also on the firm level, we have used the Dutch production Statistics to calculate exports as share of total turnover. For our third measure, offshoring, we use four different and detailed indicators, which have been constructed for 374 occupations (on the 4-digit ISCO-88 level).

Three of these indicators are based on the O*NET database, a database developed for the US Department of Labor on the nature of work, as well as required skills, abilities and knowledge for 862 US occupations.[41] Many recent papers that use the task content of jobs and offshorability rely on this database (Goos and Manning, 2007; Goos et al., 2009; Crino, 2010; Blinder, 2009; Fortin et al., 2011). A concordance table has been used to map the SOC classification to

[41] This database is available at http://online.onetcenter.org.

the ISCO-88 classification. Autor et al. (2003) use the Dictionary of Occupational Titles (DOT), which is the predecessor of O*NET, to construct a measure of routine vs. non-routine occupations. We use a routine measure similar to that developed by Fortin et al. (2011) "in the spirit of Autor" (Fortin et al., 2011, p. 11), using the "degree of automation", "importance of repeating same tasks", "structured versus unstructured work", and "pace determined by speed of equipment" (which are variables that are included in the O*NET database).

Our second offshoring indicator captures face-to-face contact. The need for face-to-face personal contact is a key determinant of the offshorability of jobs (Blinder, 2009; Fortin et al., 2011), as jobs that require regular meetings with customers (e.g., doctors, social workers, sales persons) cannot be offshored. Our face-to-face index is similar to the one used by Jensen and Kletzer (2010) and Fortin et al. (2011), using "coaching and developing others", "face-to-face discussions", "assisting and caring for others", "performing for or working directly with the public", and "establishing and maintaining interpersonal relationships".

The information provided by the O*NET database is not suitable to capture another defining characteristic that determines whether a job is bound to a specific location: the importance of proximity. Both the task routine index and the face-to-face index therefore consider jobs such as cleaners, construction workers, mail carriers and garbage collectors to be quite offshorable. Hence, Blinder (2009) creates a subjective classification of offshorability, using the job descriptions and characteristics of O*NET, but applying subjective judgment rather than mathematical rules. We use the resulting Blinder index as third indicator for offshorability. As this data is also reported using the SOC classification, we use a concordance table to map it to the 4-digit ISCO-88 level. As the Blinder index is unavailable for some occupations, this results in a dataset with about 240 occupations, thereby reducing the number of observations somewhat.

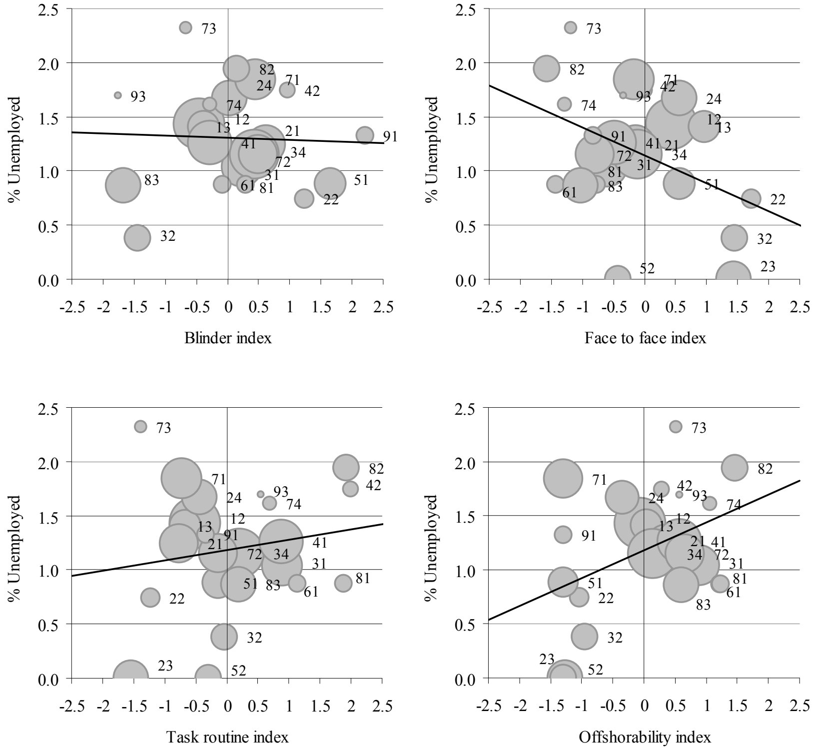
To benefit from the advantages of an objective mathematical classification while at the same time addressing some of the critique on such measures, we have created a new offshorability measure that combines the O*NET based routine task and face-to-face indexes with a subjective list of occupations that are bound to a specific location. While the overall offshorability of occupations is rather difficult to observe – which makes a subjective ranking difficult to reproduce (see, for example, Blinder, 2009) – we argue that making a list of occupations that are non-tradable because of an inherent need to be performed at a specific location is rather straightforward. This list includes 112 occupations, such as waiters, plasterers, haircutters, police officers, government officials, cleaners, medical personnel, library clerks, and athletes.

We consider only occupations that are tied directly to the *end user* as being tied to a location. For example, it is not clear how different a farmer is from a factory worker in terms of being tied to a specific location. While it may be true that (as Blinder, 2009, argues) the work at a specific piece of US land cannot be done from abroad, the same holds for the work inside a specific US factory. However, both agricultural and manufactured products can be traded, and the domestic production and employment structure may change accordingly. Our offshorability indicator is constructed as follows. We start by normalizing the task routine and face-to-face indexes (to a 0 mean and 1 standard deviation). Subsequently, we subtract the face-to-face index (which is a negative offshorability index) from the task routine index, and standardize the result between 0 (least offshorable) and 1 (most offshorable). Changing offshorability of all occupations that are bound to a location to 0 results in our offshorability indicator.

The four panels of Figure 5.1 relate the different offshoring indicators to the probability of becoming unemployed. The size of the circles reflects the share of each occupation in total employment in our dataset. There is no apparent relation between the Blinder index and unemployment. In contrast, the importance of face-to-face contact – which is presented in the second panel of Figure 5.1 – is clearly associated with less unemployment (with a correlation coefficient of –0.42). Task routine is associated with higher unemployment, although this relation is not as strong as was the case for face-to-face contact (correlation 0.17). Our newly constructed overall offshorability index associates higher offshorability to higher unemployment, with a correlation coefficient of 0.42.

It has been argued that many lower paid occupations are not easily offshored or replaced by technology (see, for example, Autor et al., 2003 and 2006). While occupations with many routine tasks are generally occupations that pay low average wages (correlation –0.43), and occupations that require face-to-face contact are generally higher paid occupations (correlation 0.56), combining those two indicators and correcting for occupations that are location bound results in an offshorability index that is in fact negatively correlated to the average wage (correlation –0.10). Indexes that are highly correlated to other (favorable) characteristics of occupations may find a negative spurious relation between pretended offshorability and unemployment due to omitted variable biases.

Figure 5.1. Share of workers becoming unemployed by offshorability of occupations, 2001–2008



Notes: Size of circles denotes total employment within each occupation. The occupation codes correspond to those in Table 5.5. All offshorability measures have been standardized at 0 mean and a standard deviation of 1.

Table 5.6 presents the exposure to different indicators for globalization for workers with different levels of education. Both the lowest and the highest educated workers are somewhat less likely to work in foreign owned firms. For exporting this pattern is opposite: workers with higher tertiary education on average work in firms with a relatively high share of exports in turnover. For comparison, all four offshorability measures have been standardized at 0 mean and a standard deviation of 1. The Blinder index is generally higher for higher educated workers, implying that their jobs are generally more easily offshored. There is a strong relationship between both the importance of face-to-face contact, and task routine, and level of education: the least educated workers are less likely to have face-to-face contact, and much more likely to do routine work, relative to educated workers. Our combined offshorability index is mostly unrelated to level of education. As some offshorability measures are highly correlated with the level of education, it is interesting to see whether our empirical section will reveal any interaction effects between globalization indicators and the level of education.

Table 5.6. Globalization indicators by level of education, 2001–2008

	Share of foreign firms in employment	Average share of exports in turnover	Average of Blinder index	Average of face-to-face index	Average of task routine index	Average of offshorability index
Primary education	14.2	24.7	–0.394	–0.635	0.387	0.200
	(32.9)	(32.6)	(1.12)	(0.81)	(0.99)	(1.09)
Lower secondary education (VMBO, MBO 1)	13.7	24.3	–0.237	–0.523	0.210	0.119
	(34.3)	(32.7)	(1.07)	(0.82)	(0.99)	(1.07)
Lower tertiary education (MBO 2, 3)	12.6	25.9	–0.086	–0.200	0.106	–0.021
	(33.2)	(34.6)	(0.94)	(0.96)	(0.97)	(1.05)
Lower tertiary education (MBO 4)	14.3	23.5	0.055	–0.044	0.130	0.116
	(35.0)	(33.2)	(0.99)	(0.95)	(0.92)	(0.96)
Higher secondary education (HAVO, VWO)	15.5	23.6	0.100	0.051	0.280	0.101
	(36.2)	(33.3)	(0.97)	(0.94)	(0.93)	(0.97)
Higher tertiary education (HBO, BA)	13.3	27.2	0.087	0.473	–0.370	–0.165
	(34.9)	(34.7)	(0.97)	(0.95)	(0.98)	(0.93)
Higher tertiary education (MA, PhD)	12.3	28.2	0.132	0.626	–0.580	–0.292
	(32.9)	(34.7)	(0.96)	(0.93)	(0.90)	(0.89)
Total	13.6	25.1	0.000	0.000	0.000	0.000
	(34.2)	(33.7)	(1.00)	(1.00)	(1.00)	(1.00)

Note: Standard deviations are in parentheses.

5.4 Empirical framework

This section provides a description of the Cox proportional hazard models and Cox regression models (Cox, 1972) that are used to estimate the impact of human capital and a number of variables that are related to internationalization on employment spells and unemployment spells. In particular we would like to see whether offshoring and multinational activity affect the worker's occupation switching from employment to unemployment and vice versa. An overview of the methodology and application of duration and survival analysis can be found in, for example, Therneau and Grambsch (2001) or Klein and Moeschberger (2005). Even though the application of survival and duration models in economics is far from novel, they are – with few exceptions (e.g., Munch, 2010) – not regularly applied in the empirical literature that focuses on the effects of offshoring, international trade, and multinational firms on unemployment.

Part of the literature (for example, Liu and Trefler, 2008) focuses on shifts in aggregate wages and employment within occupations or industries (that differ on dimensions of globalization), thus not optimally exploiting the possibilities offered by micro data. Other studies (such as Liu and Trefler, 2011) do use individual level unemployment data, but apply probit or logit specifications in which the probability that a worker with certain characteristics will become unemployed is estimated. Duration models make much more efficient use of the available data, because they allow for a flexible relation between job spell and the probability that a worker gets fired (or is hired again). As this relationship is rather strong (e.g., workers are much more likely to be fired in the first few years after being hired, compared to when they have been working for the same employer for several decades), this has a potentially large effect on estimation results.

The central variable used to model the transition from a job to unemployment is the exit or hazard rate, which is in essence the conditional probability density function of becoming unemployed given that one has been working in a job for a certain number of years. If we denote the survival time (e.g., in the case of the transition from a job to unemployment this is the duration of the job in years) by T, the distribution function P that measures the probability of survival up to time t is given by:

$$P(t) = P(T \leq t)\,. \tag{5.1}$$

The survival function, which denotes the probability that the spell is of at least length *t*, can be expressed as:

$$S(t) = P(T > t) = 1 - P(t). \tag{5.2}$$

The hazard function gives the probability that, given that the spell has lasted until time *t*, it will end in the next short time interval Δt, and is known as the hazard rate, *h*:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T \leq t + \Delta t \mid t \geq T)}{\Delta t}. \tag{5.3}$$

An increasing hazard rate implies a higher probability that an event occurs.

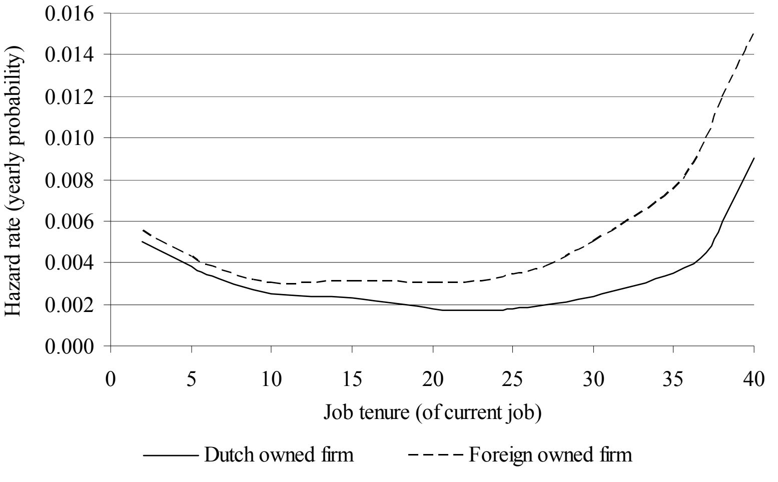
Figure 5.2 shows (as an example) the hazard time path for workers employed in Dutch owned firms, as compared to those working in foreign owned firms. On the horizontal axis is tenure (in years), on the vertical axis the probability to become unemployed in a year. There is a substantial difference between Dutch and foreign firms: across the entire career the probability to enter unemployment is higher in foreign firms.

Throughout most of their careers, the probability of becoming involuntary unemployed is less than 0.5 percent per year. After about 25 years of service, the probability starts to increase, to about 1.5 percent.[42] This is a somewhat unexpected result, as the Dutch system is such that it becomes progressively more expensive to fire workers as they become older. Hassink (1999) and Gielen and Van Ours (2004) independently find that the probability to become unemployed increases for older workers in the Netherlands. Though they do not provide a full explanation for this phenomenon, it is attributed to the fact that older workers are relatively expensive, while their productivity decreases because of their – supposedly – out-dated knowledge and insufficient abilities regarding technological advancements (the so-called efficient layoff rule of Lazear, 1995).

[42] As a robustness check, we have estimated the econometric models in this section while excluding employees with a tenure that is above a certain number of years (20, 25, 30 and 35). This does not result in substantial changes in parameter estimates, which could be explained by the fact that the number of workers with a high tenure (e.g., above 20 years) is rather limited.

As older workers experience relative difficulty to find a new job, it is likely that the probability that they will find a job in the months that pass between being informed about them being fired and actually being fired is lower as well. Furthermore, older workers are less likely to leave the firm in advance when they notice business is going bad. Therefore, the probability to be fired *and receive unemployment benefits* is likely to increase more than the probability to be fired.

Figure 5.2. Hazard rates of the transition to unemployment



In duration analyses, the (natural logarithm of the) hazard rate is generally the dependent variable. The Cox (1972) proportional hazard model is a semi-parametric approach to estimate the effect of different covariates on the hazard rate. The base regression equation that is estimated in Section 5.5, regarding the transition from a job to unemployment is:

$$\log h_i(t) = \alpha(t) + \beta_1 D_i^{female} + \beta_2 age_i + \beta_3 offshorability_i + ... + \beta_k x_i \,. \qquad (5.4)$$

The dependent variable is the natural logarithm of the hazard rate. The right hand side variables are a flexible base-hazard rate (which models the hazard rate as a function over time), and a number of covariates that enter the model linearly. In this model, the base-line hazard function:

$$\alpha(t) = \log h_0(t) \,, \qquad (5.5)$$

is unspecified. Its function is similar to that of the constant in a normal regression model, but instead of having a single value it represents the change in the hazard rate as a function of time. The covariates, in contrast, express the hazard rate as a time invariant function of the independent variables. The estimated model is semi-parametric, because while the baseline hazard function is flexible, the other variables in the model are linear. The regression model is estimated using the partial likelihood estimator developed by Cox (1972). The interpretation of the estimated coefficients is that an increase in the value of the independent variable by one results in a change of the log hazard ratio by β, and thus a change in the hazard ratio by e^{β}. All coefficients reported in Section 5.5 are exponents of β, and can therefore be interpreted as hazard ratios. As we include a number of firm level variables in our regressions, the reported results are based on robust standard errors that are clustered within firms.

5.5 Empirical results

From employment to unemployment

This section applies the hazard models that were introduced in the previous section to estimate the impact of human capital and a number of variables that are related to internationalization on employment spells.

The dependent variable in this section is always the natural logarithm of the hazard rate (e.g., the hazard to become unemployed). We have estimated six different models. Model (I) is estimated without education or occupation variables. This gives us the advantage of a large number of observations. Model (II) repeats the estimation of model (I) for workers that are present in the labor force survey, and adds education dummies, while the models (III) to (VI) add our four occupation based offshoring indicators. Because of multicollinearity we estimate separate models for these indicators. Including our offshoring indicators slightly reduces the number of observations, as the job specification was not known for all workers in the labor force survey. Model (III) includes the Blinder index (Blinder, 2009). Model (IV) includes the face-to-face index, (V) the task routine index, and (VI) our combined offshorability index that takes into account both the need for face-to-face contact, task routine, and whether an occupation is bound to a specific location. For presentational reasons, we present the main results (Table 5.7), the estimated education dummies (Table 5.8) and industry dummies (Table 5.9) in separate tables.

The results indicate that women have a somewhat higher probability to become unemployed relative to males. In a given year, the probability is about 16 percent higher in specification (I) and – for unknown reasons – about 45 percent higher in all other specifications.[43] The finding that females are more likely to be fired is somewhat surprising. A possible explanation that would be consistent with this finding is that the variance in productivity of females (at a given wage offer) is larger compared to males. This would result in a larger fraction of females performing less than expected, who might be fired. Discrimination could theoretically also provide an explanation, but it is not clear why discriminating firms would first hire female employees to subsequently fire them. Productivity differences are unlikely to provide an explanation, as in that case this should also be reflected in wages.

Older workers have a substantially lower probability to become unemployed (please note that this is after correcting for tenure, so the reported effect is an isolated effect of age). The effect of age is very robust across specifications. Foreign-born workers have a much higher probability to become unemployed than Dutch workers. The probability is about two-thirds higher for foreign workers who were born in advanced nations, and more than twice as high for foreign workers from less developed countries. Even in the specifications that correct for level of education (non-western born immigrants are on average lower educated relative to natives), the probability of becoming unemployed remains far higher. Again, we suspect that the predictability of the productivity of workers might be related to this. In the case of foreign workers, it might also be a problem that they are less flexible compared to natives because of their lack of language skills. As was the case with the gender differential, the large difference between natives and foreign workers is an interesting topic for further research. If the probability to get fired is twice as large in a single year, the probability to get fired over a longer

[43] As a robustness check, we have also estimated equation (II) without education dummies, which implies estimating the specification of (I) on the population of (II). Except for gender, all estimates are robust. This implies that the relatively high female unemployment risk found in specifications (II) to (VI) is not explained by the addition of education, but rather due to sampling.

period of time will be a multiple of that. As this has consequences for the net fiscal contribution of foreign workers, it may have implications for policies that aim at attracting high skilled foreign workers. Even though substantial positive externalities are known to be associated with the presence of high skilled workers in general, the findings of this chapter call for more thorough research into the specifics of foreign workers.

Workers who work at larger firms have a lower probability to become unemployed. Workers who are employed at foreign owned firms have a slightly higher probability to become unemployed (although this becomes insignificant once we control for education), as have workers in firms that export relatively more. Workers who live in more densely populated areas have a lower probability to become unemployed.

We do not find any relationship between the Blinder index and unemployment. This implies that having a job that is relatively easy to offshore – according to the ranking of Blinder (2009) – does not seem to result in a higher probability to become unemployed. Even though the stylized facts presented in Section 5.3, and in particular Figure 5.1, showed that both the face-to-face index and task routine index are related to unemployment, the results in Table 5.7 indicate that almost nothing of this relationship is left once we correct for other worker and job characteristics. Our combined offshorability index is negatively related to unemployment (e.g., higher offshorability of a job results in a lower probability of unemployment), although it is only marginally statistically significant given the size of our dataset, particularly when compared to other determinants of unemployment.

The effect of education – which is presented in Table 5.8 – is rather linear, but little (statistically) significant. Workers with lower secondary or tertiary education have the lowest probability to become unemployed. These are usually more practically oriented types of education, which aim at a specific profession (for example, electrician or nurse). University graduates, on the other hand, have the highest probability to become unemployed. Workers with only primary education are somewhat in the middle. As the wages of workers is strongly correlated to their level of education, these findings may indicate that the Dutch labor market is working rather efficient, such that demand and supply on the labor market is cleared by the wages rather than by unemployment.

Table 5.7. Estimation results for the transition to unemployment

Dependent: Log hazard rate	(I)	(II)	(III)	(IV)	(V)	(VI)
# Observations	6,396,518	159,167	97,666	142,488	142,488	142,488
# Transitions to unemployment	164,136	1,950	1,336	1,767	1,767	1,767
Female	1.16***	1.45***	1.57***	1.46***	1.47***	1.46***
	(8.4)	(5.9)	(6.4)	(5.8)	(5.9)	(5.7)
Age	0.95***	0.95***	0.96***	0.96***	0.96***	0.96***
	(–28.5)	(–13.6)	(–10.8)	(–12.9)	(–12.9)	(–13.0)
Foreign-born worker	1.75***	1.52**	1.48*	1.55**	1.55**	1.56**
from advanced country	(25.4)	(2.8)	(2.2)	(2.8)	(2.8)	(2.8)
Other foreign worker	2.23***	2.09***	2.31***	2.13***	2.13***	2.14***
	(52.8)	(8.5)	(8.5)	(8.3)	(8.3)	(8.3)
Blinder index			1.01			
			(0.2)			
Face-to-face index				1.03		
				(0.8)		
Task routine index					0.97	
					(–1.0)	
Offshorability index						0.93**
						(–2.5)
Log firm size	0.89***	0.87***	0.86***	0.87***	0.87***	0.87***
	(–14.8)	(–8.1)	(–8.4)	(–8.1)	(–8.0)	(–8.0)
Foreign firm	1.08***	1.11	1.16	1.17	1.17	1.17
	(4.5)	(1.0)	(1.4)	(1.5)	(1.5)	(1.5)
Share of export	1.56***	1.30	1.14	1.31	1.32	1.32*
	(5.9)	(1.7)	(0.8)	(1.7)	(1.7)	(1.7)
Log residence density	0.96	0.91**	0.95	0.89***	0.89**	0.89**
	(–3.3)	(–2.6)	(–1.2)	(–3.1)	(–3.1)	(–3.1)
Education dummies (Table 5.8)	No	Yes	Yes	Yes	Yes	Yes
Industry dummies (Table 5.9)	Yes	Yes	Yes	Yes	Yes	Yes

Notes: z-values are in parentheses. Positive (negative) z-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively. For computational reasons, clustered robust standard errors reported in column (I) are based on subsamples. We have calculated clustered robust standard errors for subsamples of 10, 20, 30, 40, 50 and 60 percent of the total sample, and extrapolated them to 100 percent. As the estimated parameters are more precise when estimated on the full sample, and do not depend on whether standard errors are clustered or not, we present estimated coefficients for the full sample.

Table 5.8. Estimation results for the transition to unemployment – education

Dependent: Log Hazard rate	(II)	(III)	(IV)	(V)	(VI)
Lower secondary education	0.91	0.97	0.91	0.91	0.91
(VMBO, MBO 1)	(–0.9)	(–0.2)	(–0.8)	(–0.8)	(–0.8)
Lower tertiary education	0.85	1.03	0.84	0.84	0.84
(MBO 2, 3)	(–1.5)	(0.2)	(–1.5)	(–1.5)	(–1.5)
Lower tertiary education	0.75**	0.82	0.75*	0.75*	0.76*
(MBO 4)	(–2.6)	(–1.4)	(–2.4)	(–2.4)	(–2.4)
Higher secondary education	1.05	0.98	1.09	1.10	1.11
(HAVO, VWO)	(0.4)	(–0.1)	(0.7)	(0.7)	(0.8)
Higher tertiary education	1.01	1.10	1.03	1.03	1.04
(HBO, BA)	(0.1)	(0.6)	(0.3)	(0.3)	(0.3)
Higher tertiary education	1.41**	1.42*	1.37*	1.37*	1.38*
(MA, PhD)	(2.7)	(2.2)	(2.3)	(2.3)	(2.4)

Notes: Omitted category is primary education. z-values are in parentheses. Positive (negative) z-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

Table 5.9 presents the coefficients that correspond to the industry dummies that have been estimated simultaneously with the results presented in Table 5.7 and Table 5.8. While the stylized facts presented in Section 5.3 indicated a substantially higher incidence of unemployment within the manufacturing industry, most of this difference disappears when controlling for worker and firm heterogeneity. Unemployment, however, remains rare within the public sector, and particularly among government employees. Employees working in commercial services are relatively likely to become unemployed. Interestingly, when including the Blinder index (specification III), this effect disappears.

Table 5.9. Estimation results for the transition to unemployment – industry

Dependent: Log Hazard rate	(I)	(II)	(III)	(IV)	(V)	(VI)
Mining and quarrying	0.90	0.37	0.44	0.43	0.43	0.44
	(1.0)	(–1.4)	(–1.1)	(–1.2)	(–1.2)	(–1.2)
Manufacturing	1.27***	0.96	0.89	1.00	1.00	1.03
	(4.3)	(–0.3)	(–0.7)	(0.0)	(0.0)	(0.3)
Construction	1.23***	1.21	1.08	1.27	1.26	1.23
	(3.9)	(1.5)	(0.4)	(1.8)	(1.8)	(1.5)
Trade	1.16**	1.10	1.06	1.15	1.14	1.17
	(2.9)	(0.8)	(0.3)	(1.1)	(1.0)	(1.2)
Hotels and Restaurants	1.21**	1.31	1.29	1.35	1.36	1.30
	(3.2)	(1.3)	(0.9)	(1.4)	(1.5)	(1.3)
Transport	0.91	0.70*	0.61*	0.72	0.72	0.73
	(–0.8)	(–2.1)	(–2.2)	(–1.8)	(–1.8)	(–1.7)
Commercial services	1.46***	1.29*	1.09	1.36*	1.36*	1.38**
	(7.6)	(2.1)	(0.6)	(2.4)	(2.5)	(2.6)
Government	0.35***	0.20***	0.17***	0.19***	0.19***	0.19***
	(–4.7)	(–6.9)	(–5.8)	(–7.0)	(–7.0)	(–7.0)
Education	0.97	0.47***	0.83	0.43***	0.43***	0.42***
	(0.9)	(–3.9)	(–0.7)	(–4.2)	(–4.2)	(–4.4)
Healthcare	0.73**	0.52***	0.58**	0.56***	0.57***	0.55***
	(–2.7)	(–4.1)	(–2.6)	(–3.4)	(–3.4)	(–3.6)
Other	1.53***	1.47**	1.40	1.57**	1.57**	1.58**
	(7.5)	(2.5)	(1.8)	(2.9)	(2.9)	(2.9)

Notes: Omitted industry is agriculture. *z*-values are in parentheses. Positive (negative) *z*-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

Because it is widely acknowledged that effects of globalization could be different for higher than for lower educated workers, we have re-estimated some of the regressions whilst adding interaction terms between education and our globalization indicators. The regression coefficients for these interaction effects are presented in Table 5.10. Note that these results are based on different regressions than those in Table 5.7, Table 5.8 and Table 5.9 (the regression equation has been extended by adding interaction effects). In contrast to, for example, Munch (2010) we do not find any evidence for interaction effects. This suggests that, consistent with the task-based literature, the effects of globalization are rather independent from education (if present at all).

Table 5.10. Interaction effects between education and globalization indicators

Dependent: Log Hazard rate	Share of foreign firms in employment	Share of exports in turnover	Average of Blinder index	Average of face-to-face index	Average of task routine index	Average of offshorability index
Lower secondary education	1.12	1.08	1.06	1.16*	0.99	0.93
(VMBO, MBO 1)	(0.6)	(0.3)	(0.8)	(2.0)	(–0.1)	(–1.3)
Lower tertiary education	1.11	1.12	1.14	0.96	1.03	0.95
(MBO 2, 3)	(0.6)	(0.4)	(1.7)	(–0.7)	(0.6)	(–0.8)
Lower tertiary education	0.90	1.24	1.05	0.96	0.90	0.89
(MBO 4)	(–0.6)	(0.7)	(0.7)	(–0.6)	(–1.6)	(–1.9)
Higher secondary education	1.35	0.87	0.97	1.03	0.95	0.83*
(HAVO, VWO)	(1.4)	(0.3)	(–0.3)	(0.3)	(–0.6)	(–2.0)
Higher tertiary education	1.17	1.59	0.89	1.07	0.93	0.94
(HBO, BA)	(1.0)	(1.9)	(–1.9)	(1.0)	(–1.1)	(–0.8)
Higher tertiary education	0.87	1.29	0.93	1.03	1.06	1.06
(MA, PhD)	(–0.6)	(0.8)	(–0.9)	(0.3)	(0.7)	(0.7)

Notes: Omitted category is primary education. The effects of exporting and foreign owned firms are estimated by extending model (II) with interaction terms, the effects of offshorability, the Blinder index, and the task routine index are estimated by extending respectively (III) to (VI). *z*-values are in parentheses. Positive (negative) *z*-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

From unemployment back to a job

After considering the transition from a job to unemployment, we now apply the same methodology to explain unemployment duration. Because we now model the transition from unemployment back to a job, the hazard rate represents the probability that an employee finds a job in a given *month*. The average incidence rate is 5.8 percent per month. It is important to note that all job related characteristics – including those related to globalization – represent the job an individual had before getting fired.

The dependent variable in this section is again the natural logarithm of the hazard rate (e.g., the hazard to find a job). We have estimated six different models. Model (I) is again estimated on our full data set, without merging to the labor force survey for education or occupation variables. Model (II) adds education dummies, while model (III) includes the Blinder index (Blinder, 2009), (III) the face-to-face index, (V) the task routine index and (IV) our combined offshorability index. Again, all offshoring indicators have been standardized. The main results are presented in Table 5.11, the estimated education dummies in Table 5.12 and industry dummies in Table 5.13.

Table 5.11. Estimation results for the transition from unemployment to a new job

Dependent: Log Hazard rate	(I)	(II)	(III)	(IV)	(V)	(VI)
# Observations	162,131	1,930	1,324	1,748	1,748	1,748
# Transitions to a new job	119,480	1,455	992	1,313	1,313	1,313
Female	1.00	1.00	1.01	0.99	0.96	0.97
	(0.0)	(–0.1)	(0.1)	(–0.2)	(–0.5)	(–0.4)
Age	0.95***	0.95***	0.95***	0.95***	0.95***	0.95***
	(–56.1)	(–15.9)	(–13.7)	(–14.9)	(–15.0)	(–15.2)
Expat	0.87***	0.76	0.74	0.73	0.74	0.72*
	(–7.9)	(–1.8)	(–1.7)	(–1.9)	(–1.8)	(–2.0)
Other foreign worker	0.75***	0.75**	0.77*	0.72**	0.72***	0.72***
	(–27.7)	(–3.1)	(–2.4)	(–3.3)	(–3.3)	(–3.3)
Blinder index			0.98			
			(–0.6)			
Face-to-face index				0.91**		
				(–2.6)		
Task routine index					1.08**	
					(2.5)	
Offshorability index						1.11**
						(3.2)
Log firm size	0.97***	0.95***	0.95**	0.96**	0.96**	0.96**
	(–5.2)	(–3.3)	(–3.0)	(–3.0)	(–3.0)	(–3.0)
Foreign firm	1.10***	1.01	1.08	1.02	1.01	1.01
	(3.8)	(0.1)	(0.8)	(0.2)	(0.1)	(0.1)
Share of export	0.87***	0.80	0.76	0.79	0.80	0.79
	(–2.8)	(–1.5)	(–1.6)	(–1.5)	(–1.5)	(–1.5)
Log residence density	0.97***	1.01	1.05	1.00	1.01	1.00
	(–5.1)	(0.2)	(1.0)	(0.1)	(0.1)	(0.1)
Fired during a mass layoff	1.10***	1.20	1.20	1.16	1.17	1.15
	(4.2)	(1.7)	(1.6)	(1.4)	(1.4)	(1.3)
Education dummies (Table 5.12)	No	Yes	Yes	Yes	Yes	Yes
Industry dummies (Table 5.13)	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *z*-values are in parentheses. Positive (negative) *z*-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***.

While we showed earlier that females have a relatively high probability to become unemployed, gender does not matter for unemployment duration. Even though Section 5.2 showed that older workers have a relatively lower probability to become unemployed, once they are unemployed they have a low probability to find a new job. Foreign-born workers, and particularly foreign workers that were not born in advanced nations, have a substantially lower probability to find a new job. They are thus not only far more likely to become unemployed, once unemployed they are also likely to remain unemployed for a relatively long time. Workers who worked for larger firms before getting unemployed have a somewhat lower probability to find a new job. Workers who were fired during a mass layoff have a relatively high probability to find a new job. It is likely that employees with low unobserved skills (which may have been unknown to the employer during wage negotiations) generally have a higher probability to be fired. During mass layoffs, however, unemployment is mostly exogenous to the abilities of the employee, which could result in a higher average ability of workers that were fired.

The effects of globalization do not show a clear pattern. When correcting for the level of education, having worked for a foreign firm does not seem to have any effect. Workers who were previously employed at a firm with relatively high exports seem to have a somewhat lower probability to find a new job, but this effect is statistically insignificant in all specifications except (I). While offshorability of the previous job as measured by the Blinder index is almost completely unrelated to the probability of finding a new job, the face-to-face index, task routine index and combined offshorability index indicate that higher offshorability of the previous occupation (thus indicating that the occupation could be offshored more easily) results in a significantly higher probability to exit unemployment. This implies that offshorability is related to less difficulty, rather than more, to finding a new job once an individual has been fired. Even though this might seem somewhat unexpected at first sight, this could be explained by a less complex matching process for routine jobs and jobs that require little face-to-face contact. For instance, teaching professionals have rather specific skills and thus may have longer unemployment duration because it may be difficult to find a new job that match their skills (see, for example, the work of Gathmann and Schönberg, 2010, on task specificity). The fact that certain jobs allow for a relatively simple match between employer and employee is likely to result in a *ceteris paribus* quicker transition back to a job domestically, while this simple matching also increases offshorability.

Table 5.12 shows the estimation results for the education dummies that were included in regression models (II) to (VI). Higher educated workers have a higher probability to find a job relative to lower educated. University graduates, however, do not have a higher hazard rate towards a new job than other workers with at least the highest level of tertiary education (MBO 4). This means that they experience more unemployment: they have a higher probability to become unemployed and once they are unemployed they do not find a job faster than other workers with an above average level of education.

Table 5.12. Estimation results for the transition to unemployment – education

Dependent: Log Hazard rate	(II)	(III)	(IV)	(V)	(VI)
Lower secondary education	1.23	1.32	1.29	1.30	1.29
(VMBO, MBO 1)	(1.7)	(1.6)	(1.9)	(2.0)	(1.9)
Lower tertiary education	1.25	1.56**	1.26	1.29	1.29
(MBO 2, 3)	(1.8)	(2.6)	(1.7)	(1.9)	(1.9)
Lower tertiary education	1.47**	1.65**	1.47**	1.50**	1.48**
(MBO 4)	(3.1)	(3.1)	(3.0)	(3.1)	(3.0)
Higher secondary education	1.41*	1.72**	1.44*	1.43*	1.44*
(HAVO, VWO)	(2.3)	(2.9)	(2.4)	(2.3)	(2.4)
Higher tertiary education	1.41**	1.63**	1.50**	1.50**	1.45**
(HBO, BA)	(2.7)	(3.0)	(3.0)	(3.0)	(2.8)
Higher tertiary education	1.41**	1.50*	1.41*	1.40*	1.35*
(MA, PhD)	(2.6)	(2.3)	(2.4)	(2.3)	(2.1)

Notes: Omitted category is primary education. *z*-values are in parentheses. Positive (negative) *z*-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

Table 5.13 presents the estimated industry dummies. As the stylized facts presented in Section 5.3 indicated, employees that were fired from a job in the education sector have a relatively low probability to find a new job. However, the effect is no longer statistically significant when reducing the number of observations and correcting for education. Other former public sector employees have somewhat less chances on the labor market as well. Apart from having worked in the government sector, it does not matter from what industry an individual was fired.

Table 5.13. Estimation results for the transition to unemployment – industry

Dependent: Log Hazard rate	(I)	(II)	(III)	(IV)	(V)	(VI)
Mining and quarrying	0.91	2.84	3.28	2.80	3.09	2.75
	(–1.1)	(1.5)	(1.7)	(1.5)	(1.6)	(1.5)
Manufacturing	0.98	0.94	1.02	0.91	0.92	0.86
	(–0.8)	(–0.5)	(0.1)	(–0.7)	(–0.6)	(–1.2)
Construction	0.95	0.90	1.00	0.88	0.91	0.92
	(–1.8)	(–0.7)	(0.0)	(–0.9)	(–0.8)	(–0.6)
Trade	1.04	0.88	0.93	0.87	0.89	0.84
	(1.9)	(–1.0)	(–0.4)	(–1.0)	(–0.8)	(–1.3)
Hotels and Restaurants	1.01	0.99	1.17	1.01	0.99	1.00
	(0.2)	(–0.1)	(0.5)	(0.0)	(–0.1)	(0.0)
Transport	1.01	1.02	0.97	0.96	0.98	0.93
	(0.4)	(0.2)	(–0.2)	(–0.2)	(–0.1)	(–0.5)
Commercial services	0.99	0.96	1.02	0.96	0.97	0.93
	(–0.3)	(–0.3)	(0.1)	(–0.4)	(–0.3)	(–0.6)
Government	0.92	0.75	1.08	1.00	0.99	0.96
	(–1.6)	(–1.3)	(0.3)	(0.0)	(0.0)	(–0.2)
Education	0.75***	0.74	1.09	0.78	0.80	0.77
	(–7.0)	(–1.6)	(0.3)	(–1.2)	(–1.0)	(–1.2)
Healthcare	1.04	0.81	1.01	0.89	0.89	0.88
	(1.4)	(–1.3)	(0.0)	(–0.7)	(–0.7)	(–0.8)
Other	0.84***	0.62**	0.76**	0.65**	0.66**	0.63**
	(–6.2)	(–3.1)	(–1.3)	(–2.8)	(–2.7)	(–3.0)

Notes: Omitted industry is agriculture. *z*-values are in parentheses. Positive (negative) *z*-values indicate a positive (negative) effect on the hazard rate. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

5.6 Conclusion

International trade, offshoring and the activities of multinationals are generally thought to result in increased productivity in the long run, because they allow for increased specialization and economies of scale. However, in the short run such forces of internationalization may have adverse labor market effects for some groups of workers. This chapter employs a large micro dataset of Dutch matched firm-worker data to analyze the effects of different dimensions of globalization on unemployment.

We find that females and foreign-born workers (who also have a lower probability to find a new job once unemployed) have a higher probability of getting fired, while older workers (at a given tenure) are somewhat less likely to become unemployed, but also less likely to find a new job when unemployed.

Both the lowest educated workers (e.g., those with only elementary education) and university graduates have a somewhat higher probability to get unemployed.

Workers employed at exporting firms have a significantly higher probability of getting fired. The effect is, however, not very strong. Our estimates imply that an average worker has a 0.8 percent point higher probability of getting fired during a 10-year employment spell when the share of exports in total turnover goes up by 10 percentage point. We find some limited evidence for a higher unemployment incidence among workers employed at foreign owned firms, but its effect becomes insignificant once we control for human capital.

The estimated effects of offshoring on unemployment risk consistently fail to associate offshorability to higher unemployment incidence. We find no statistically significant effect of the Blinder index (Blinder, 2009), the need for face-to-face contact, and task routine, while we find that a higher score on a proposed offshorability index that combines face-to-face contact, task routine, and whether a job is bound to a specific location is negatively related to unemployment (although this effect is not strong). We do not find any evidence for interactions between international trade, offshoring, or activities of foreign firms and level of education on the risk of unemployment.

Without correcting for level of education of workers that have been fired, our data seem to suggest that individuals fired from foreign owned firms have a somewhat higher probability to find a new job, and those fired from firms with higher exports a somewhat lower probability. However, once we correct for level of education these effects disappear. While offshorability as measured by the Blinder index is unrelated to the probability to find a new job, our (three) other offshoring indicators indicate that employees fired from occupations that are relatively offshorable are somewhat more likely to leave unemployment. The findings thus imply that offshoring is unlikely to have a negative effect on unemployment incidence and duration.

To conclude, our findings suggest that the short-term effects of globalization on unemployment are either absent or ambiguous, and have a relatively small effect on unemployment compared to other worker and firm related predictors of unemployment and the probability of finding a new job. This implies that the short term transitional effects of globalization are most likely small.

6 THE IMPACT OF FOREIGN KNOWLEDGE WORKERS ON PRODUCTIVITY

"Great cities have always been melting pots of races and cultures. Out of the vivid and subtle interactions of which they have been the centers, there have come the newer breeds and the newer social types."

Park, Burgess, and McKenzie (1925)

6.1 Introduction

Since the 1960s, nearly five decades of increased cross-border labor mobility have transformed Europe's cities into a melting pot of cultures. Even though such cultural diversity may result in a mismatch of (social) skills or Babylonian confusion of languages, a variety of knowledge, skills and cultures may also enhance productivity and innovation. For example, the Dutch economic successes during the Golden Age are often (at least partially) attributed to migrants (cf. Esser, 2007). Relatively wealthy migrants, such as the Huguenots, brought knowledge and social (trade) networks, which resulted in a positive contribution to GDP (Foldvari et al., 2012).

The purpose of this chapter is twofold. First, it aims to provide an overview of the literature that is concerned with the effects of diversity on productivity. Second, we estimate the wage differential between highly educated natives and foreign workers with similar observed worker characteristics, as well as the relationship between the presence of highly educated foreign-born workers from advanced countries and the wages of other Dutch workers. For this purpose, we rely on an extensive set of micro data.

This chapter considers foreign knowledge workers as a special type of highly educated workers, who have certain characteristics that are not captured by the observed level of education. These characteristics may either increase or decrease the productivity and wages of foreign workers compared to natives with similar other characteristics. As knowledge is to some extent transferrable, it is also possible that the productivity of workers that *interact* with foreign knowledge workers increases, due to the exchange of knowledge or skills. In contrast, because of the need for communication and coordination, the presence of foreign workers that are not familiar with local language and culture may also decrease the performance of natives.

In addition to making foreign labor more valuable (resulting in a higher wage), knowledge spillovers could result in higher productivity and wages of other workers in firms or regions. This would result in a *ceteris paribus* wage differential between similar workers that differ only in the number of foreign knowledge workers within the firm (intra-firm spillovers) or region (intra-regional spillovers) where they work.[44] As knowledge and skills are relatively more important for educated workers, the focus in this chapter is on the effects of the presence of highly educated foreign workers, which we define as workers with at least higher secondary education or tertiary education.

As is argued by, for example, Bellini et al. (2008), the use of a more disaggregated spatial level seems more appropriate as relevant interactions between individuals are far more likely to occur within cities. We propose to go one step further. Because the exchange of knowledge that is relevant for the productivity of workers is even more likely to occur on the work floor, the most straightforward level of aggregation is that of the firm. Not only do workers spend a large share of their time on the work floor, it is also likely that conversations that take place within firms are more often work related compared to talks with family, friends or neighbors. In addition to this, colleagues – being insiders – are far more likely to be in the possession of skills or knowledge that are relevant.

Even though we focus only on knowledge spillovers that take place within firms, our findings will have implications for the effects of diversity on the regional level, as the average diversity of firms in a region is highly correlated to the average diversity of the region.

[44] A changed productivity level may not be fully transferred through the wages, but could also change the profitability of firms. However, if firms discriminate against foreign workers, this implies that their competitors can hire an all-foreign work force that does the same work for less money. The resulting cost differences will cause some firms to prosper, while firms that discriminate cannot sell at competitive prices. As this results in non-discriminating firms gaining market share, thus increasing demand for foreign labor, wages of foreign workers will increase. Micro evidence on the relationship between wages and productivity supports the assumption often made by economists that wages reflect productivity (see, for example, Hægeland and Klette, 1999).

The structure of the remainder of this chapter is as follows. The next section discusses theoretical and empirical insights from the existing literature on migration and knowledge spillovers. Section 6.3 introduces the data and methodology used to identify the relationship between the presence of foreign knowledge workers and wages. This section will also present several stylized facts and descriptive statistics. The empirical findings will be presented in Section 6.4, where augmented Mincerian wage equations are used to estimate the wage differential between foreign knowledge workers and comparable natives, as well as the effect of the presence of foreign knowledge workers in the same firm on the wages of other workers. Section 6.5 concludes.

6.2 Theories and evidence on diversity and knowledge spillovers

The idea that diversity may have a positive effect on productivity is certainly not new, and translates back to – at least – the seminal work of Jane Jacobs (1969). The concept is traditionally applied to industries, where it is thought that cities with a more diverse sectoral structure provide more opportunities for spillovers between these sectors. Empirical evidence is consistent with this hypothesis (see De Groot et al., 2009, for a meta-analysis). More recently, the concept of Jacobs externalities has been generalized to the context of migration studies, arguing that a diverse mix of languages, cultures and other knowledge is beneficial for productivity.

Cox et al. (1991, p. 827) describe this as the "value-of-diversity hypothesis", and put the focus on the potential positive effects that diversity can have for organizations, arguing that heterogeneous groups are more likely to produce a variety of creative ideas than homogeneous groups. Alesina et al. (2000) introduce a model where more variety of human capital increases productivity in a Dixit-Stiglitz production function.

Lazear (1999), in contrast, argues that organizational diversity imposes a trade off. On the one hand, a firm can benefit from diversity because certain elements of skills and knowledge are specific to ethnicity or culture. On the other hand, combining workers from different cultures, legal systems, and languages introduces costs for firms due to coordination problems or conflict. The gains of diversity are determined by the difference between the information possessed by the representatives of different groups, the relevance of that information, and the ability to communicate. One of the goals of a firm operating in today's global economy is thus to optimize the costs and benefits of diversity.

Micro foundations of positive diversity effects

Let us elaborate a bit more on the channels through which the presence of foreign knowledge workers could cause a change in the productivity level of firms. From the literature on diversity, we know that foreign workers may have access to knowledge that is different (and possibly complementary) to that of local workers. As more skilled and knowledgeable workers are more productive, they will most likely earn a higher wage (these are the private returns to their knowledge). To assess the broader impact of such workers on their environment, we borrow from the human capital literature.

Rauch (1993) proposes that individuals do not fully capture the benefits from their human capital, and that the average local level of human capital can thus be considered as a public good. Formal and informal interaction results in the sharing of knowledge, skills and ideas between workers (see Jovanovic and Rob, 1989). As these knowledge spillovers result in a higher (lower) productivity of identical workers in an environment where human capital is relatively abundant (scarce), a wage differential is likely to occur. Citing the work of Jacobs (1969), Lucas (1988) and Rauch (1993) argue that interactions between educated and skilled individuals generate externalities. Moretti (2004b and 2004a) finds empirical evidence in support of these theories on the firm and regional level. Canton (2009) uses micro data to test whether a higher presence of highly educated individuals in firms or regions results in knowledge spillovers. He finds a positive and significant relation on the regional level, but it disappears when the firm's knowledge stock is included. The extension of this generic work on human capital spillovers to migration studies is a small one, as the knowledge possessed by workers from abroad is likely to be more diverse than that of native workers. In a globalized world, however, there are more reasons why an ethnically diverse workforce could increase productivity.

Dekker et al. (2006) show that cultural diversity in the EU restricts international trade, in a way similar to physical distance. As firms – in particular in a small and open economy like the Netherlands – operate on global rather than national markets, the insider information of foreign employees about their home countries is likely to be of high value. There is little empirical evidence on the micro foundations of local knowledge spillovers through diversity, and studies that find a positive association are often related to diversity of task specific skills or fields of discipline in problem solving, rather than broader diversity in terms of race or gender (see O'Reilly et al., 1997, for an overview).

Micro foundations of negative diversity effects

While the evidence on the positive effects of diversity is mixed, empirical evidence has shown that there can also be negative effects of diversity. As workers with different mother tongues have to communicate in a foreign language, information is lost almost by definition. Empirical evidence of Vinke (1995) shows that as much as 30 percent of all information can get lost when two non-native English speakers communicate in English.[45] In organizations where communication is important, the presence of diverse languages can therefore be costly.

Language barriers are not the only factor that may reduce productivity in diverse organizations. As culture – which may be defined as fundamental assumptions, values, behavioral norms and expectations, and larger patterns of behavior (Rousseau, 1990) – plays a crucial role in group processes, cultural heterogeneity may increase the incidence of misunderstanding, tension, and conflict.

It has been shown that being different is generally considered as a deficiency, while people that are (by self categorization) perceived as similar in terms of characteristics such as ethnicity, gender and age, are seen as more trustworthy, honest, and cooperative (Brewer, 1979, Tajfel, 1982, and Loden and Roserer, 1991). Dekker et al. (2006) show that cultural distance is strongly related to trust, while Beugelsdijk et al. (2004) show that trust is an important determinant of economic outcomes. Empirical evidence has shown negative associations between

[45] The work of Vinke (1995) is based on the communication between Dutch university lecturers and their students, such that both senders and recipients had a far above average English language proficiency. The average amount of information loss in the entire society is thus likely to be even higher than the estimated 30 percent.

heterogeneity and conflict (Jehn, 1997), absenteeism (Tsui et al., 1992) as well as a less open communication and more distortion of messages (Rogers and Bhowmik, 1971).[46] As a result, productivity is likely to be lower in more diverse environments.

The theoretical and empirical evidence presented above strongly supports the tradeoff theorem of Lazear (1999): in order to receive net benefits from diversity it is important for organizations to optimize diversity in areas that provide maximum opportunity for knowledge spillovers – and thus productivity gains – while minimizing the negative effects of diversity it in other areas. O'Reilly et al. (1997) investigate 32 project teams from a large corporation with a highly diverse work force, and find a positive effect of diversity on group performance, but an even larger negative effect due to increased conflict. This indicates that the net effect of diversity can easily become negative.

Macro level empirical evidence

Apart from the diverse literature on the micro foundations of the relationship between diversity and productivity (mostly originating from the social and organizational sciences), economists have produced a large literature that attempts to estimate this association in a more indirect manner. This literature often models the effects of migrants on wages through supply and demand – for example by assuming that foreign and native workers with similar education and experience are either perfect substitutes (Card, 1990, Borjas, 2003), or imperfect substitutes (Ottaviano and Peri, 2005b). This approach, however, ignores the fact that migrants may not only change the price of distinct types of labor, but may also affect productivity itself. Ottaviano and Peri (2005a) find that cultural diversity in American cities is associated with substantially higher wages in diverse cities compared to relatively homogeneous cities. For European regions in twelve countries, Bellini et al. (2008) show that cultural diversity is positively related to productivity.

Many recent studies on the returns to diversity have used country level, or regional data (for example, Easterly and Levine, 1997; Glaeser et al., 1995;

[46] A distinct but related example of the impact of diversity on social interactions is provided by Becker et al. (1977), who show that divorce is more likely for couples from different cultures, languages or religions.

Ottaviano and Peri, 2005a; and Bellini et al., 2008). A disadvantage of this type of data is, however, that it is difficult to control for unobservable heterogeneity or to find suitable instruments when using panel estimations. This type of research is therefore likely to run into reverse causality problems: as foreign workers do not have an existing bond with a certain region in a destination country, they are more likely to locate themselves in regions with a high level of wages and productivity (see Manski, 1993, for a discussion of some of the problems related to the identification of social interactions).

Another pitfall in estimating the returns to diversity is related to migrant heterogeneity. Even though the present literature has extensively addressed the fact that the effects of foreign workers are heterogeneous across different groups of native workers (see, for example, Ottaviano and Peri, 2005b), it is also plausible that different types of migrants have a different effect on native wages. The current literature tends to focus on the effects of migration in general, albeit acknowledging differences in terms of education, gender and age. The reality is, however, that 'the' migrant as such does not exist, but represents a heterogeneous mix ranging from highly skilled expats to refugees from war zones and illiterate migrants from low-income countries. Not addressing this issue thus implies that an engineer from Canada working for an American university is expected to have the same effect on wages as an engineer who fled a war zone and is now working as a cleaner.

As the composition of migrants present in the US is different from that in Europe, it is well possible that the net effects of migration are different as well. We therefore focus on just one type of migrants in our empirical analysis: highly educated foreign-born workers from advanced countries. As we have seen that the most likely cause of a positive productivity effect of diversity would be the contribution of valuable knowledge, either directly or through knowledge spillovers, we expect that the probability to find such effects is the highest among high skilled foreign knowledge workers. Additionally, higher educated workers are likely to have a higher ability to learn foreign languages and the basics of a different culture, which reduces the costs of ethnic diversity.

6.3 Data and stylized facts

Data

This chapter relies on the 2000–2008 cross sections of the Dutch labor force survey (EBB, *Enquête Beroeps Bevolking*), combined with complementary data originating from tax-records to construct a linked employer-employee database (SSB, *Sociaal Statistisch Bestand* and ABR, *Algemeen Bedrijfs Register*). All data were made available by Statistics Netherlands (CBS). It is important to note that our data include only workers who pay taxes in the Netherlands, and who currently have an address in the Netherlands. Our results do thus not apply to expats who are sent abroad while still being paid in their home countries.

We use employer reported pre-tax real hourly wages (e.g., the so-called fiscal wage) of individual workers and jobs as main indicator for productivity. The Dutch labor force survey does not include data on wages. Instead, we calculate hourly wages by taking the quotient of the annual fiscal wage from tax data and the number of hours worked in a typical week from the labor force survey multiplied by the number of weeks the employee worked during a year, which is calculated from the (employer reported) start and end date of the job. The consumer price deflator of Statistics Netherlands has been used to correct wages for inflation (the base year is 2008).

For each employee we have data that are related to individual characteristics such as age, gender, country of birth (which originate from census data), self-reported (all from the labor force survey) level of education, job type (we use the 2-digit ISCO-88 occupation), the number of hours worked, and work location (at the municipality level), and the firm establishment where the individual is occupied. If we talk about diversity within multi-plant firms, we thus refer to diversity at the location where the individual works rather than within all establishments of the firm.

For each firm, we have the corresponding industry (at the 2-digit NACE rev. 1.1 level) available. We determine whether a firm is foreign owned or not, using the Statistics Netherlands indicator on the home country of the Ultimate Controlling Institute (UCI) of each firm. This indicator draws on multiple data sources. We have used the Dutch production Statistics to calculate firm level exports as share of total turnover.

As we focus on a very specific type of migrant, we use four criteria to operationalize what we consider foreign knowledge workers from advanced countries. Foreign knowledge workers must have been born in a country with a nominal GDP per capita in 2010 of at least 20,000 US$[47]. This definition is somewhat arbitrary, and if the minimum threshold for what we consider as an advanced country is changed, the results change somewhat due to the fact that there is a positive correlation between GDP per capita in the country of origin, and the wage that foreign-born workers earn in the Netherlands. OECD membership could also be used as a classification. However, the OECD includes several middle-income economies in Eastern Europe, Mexico and Turkey. The IMF (2011) uses a subjective classification of advanced countries, which is close to our classification, but includes a number of countries (particularly in eastern Europe) with a nominal GDP per capita that is slightly lower than $20,000. Relaxing the GDP per capita threshold would increase heterogeneity within countries that we consider advanced, while increasing the threshold would exclude countries such as Portugal and South Korea, countries that are generally considered to be developed.

In addition to having been born in an advanced country, high skilled foreign workers must have successfully completed higher secondary education or tertiary education, they must be between 28 and 65 (to exclude foreign students), and their observed job must have generated an income of at least the minimum wage.

In our wage regressions, we include only workers that comply with these criteria, except – for natives – country of birth (such that we compare native and foreign-born individuals that are as similar as possible on all other accounts), and we exclude all workers earning in excess of 10 times the average wage.[48] In addition to the above, we have excluded all foreign-born workers that migrated to the Netherlands less than ten years prior to the date of observation from our wage regressions. This is the result of an unfortunate (from a research perspective) tax-

[47] According to the World Economic Outlook Database of the International Monetary Fund these include Luxembourg, Norway, Qatar, Switzerland, Denmark, Australia, Sweden, the United Arab Emirates, the United States, the Netherlands, Canada, Ireland, Austria, Finland, Singapore, Belgium, Japan, France, Germany, Iceland, the United Kingdom, Italy, Kuwait, Hong Kong, New Zealand, Spain, Brunei, Cyprus, Greece, Israel, Slovenia, Portugal, the Bahamas and South Korea.

[48] Because of the limited sample size, the number of individuals earning very high incomes is very small. For example, in one year the highest wage in the sample was around 5 million, in another year it was just 2 million. As such outliers have a relatively large impact on the estimates, we exclude these workers. Note that wages above three times the median are rare in the Netherlands.

exempt, specifically targeted at attracting foreign knowledge workers. This exempt allows employers to pay a fixed 30 percent of the taxable gross wage as expense reimbursement. For workers that are entitled to use this arrangement, we observe only 70/30th of their wage (their gross wage according to the legal and fiscal definition).

Diversity indicators

All variables related to firms and municipalities – these are total employment, average job duration, and two indicators for the presence of foreign workers that were born in advanced economies – are constructed directly from the micro data. As the labor force survey has only about 50,000 observations annually – which implies that for a middle-sized firm with 100 employees only one employee is expected to be included, we use tax data for this purpose (which covers, after applying the criteria from the previous section, just over 6 million observation annually). As we do not have the actual work location of all workers, we use work locations that are derived by Statistics Netherlands from a number of sources.[49] Because the level of education is not available in this dataset, we have to exclude it from our definition of expats. The first indicator is the share of migrant knowledge workers:

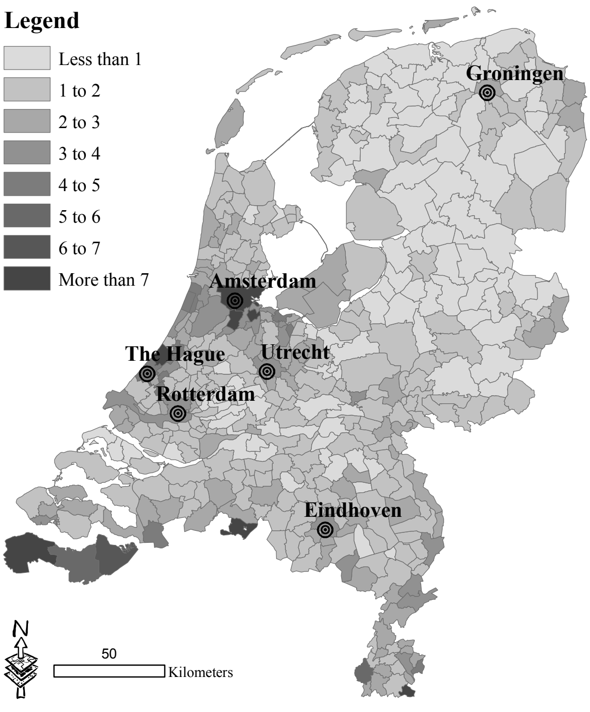
$$share_{j,t} = \frac{\sum_c \left(migr_{j,t}^c \right)}{employment_{j,t}} \quad , \tag{6.1}$$

calculated as the sum of migrant knowledge workers from all countries c in firm j and year t, divided by total employment in the firm in that year. We have calculated the share of foreign-born workers from advanced countries for municipalities as well, using the same formula. Their share ranges from 0.4

[49] CBS first derives employees per firm and municipality by combining tax data (that gives total employment per firm) with a survey where multi-establishment firms with 10 or more employees provide employment in each municipality. Employees of multi-establishment firms with less than 10 employees (with a relatively low share in employment), are allocated to the headquarter. Subsequently, CBS allocates individual employees to establishments by an algorithm that minimizes the distance between residence locations of employees and firm establishments of the same firm. Even for multi-firm establishments this works rather well, except for firms with multiple nearby establishments. Even though derived work locations are inaccurate for a limited share of the work force, the derived work location is generally not far from the actual work location and misallocations tend to average out.

percent to just over 10.1 percent. Figure 6.1 shows the share of foreign workers from advanced countries by Dutch municipality. In most municipalities, the share of foreign knowledge workers is less than two percent. In the largest agglomerations, however, it is much higher. If the presence of these workers is related to productivity, the effect on the regional economy will thus be most significant in these regions.

Figure 6.1. Share of foreign-born workers from advanced countries in the labor force by municipality, 2008



The share of foreign-born workers in a firm does not differentiate between workers from different advanced countries. As we know from the discussion in Section 6.2 on the micro foundations of the spillovers from diversity, however, a heterogeneous mix of foreign knowledge workers can be expected to have a higher potential for spillovers than a homogeneous mixture. Not only because the knowledge of migrant workers can be specific to different foreign markets or cultures, but also because the productivity of – say – a US worker in a Dutch firm could benefit from knowledge possessed by a German coworker. Therefore, we use the fractionalization index as an additional measure, which is a standardized measure for diversity. Following the work of Mauro (1995), this index is widely used to capture the probability that two individuals randomly selected from a set of different groups belong to the same ethnic group. It is defined as 1 minus the Herfindahl index on the shares of workers born in each country in the region, or formally:

$$frac_{j,t} = 1 - \sum_{c} \left(\frac{migr_{j,t}^{c}}{employment_{j,t}} \right)^2 \quad . \tag{6.2}$$

The fractionalization index is calculated using workers born in advanced economies only, rather than foreign employees from all countries. Furthermore, it excludes natives, such that it only measures diversity *within* the group of foreign workers born in advanced economies.[50]

Stylized facts and descriptive statistics

Before we continue with the econometric analyses, we present some stylized facts about our data, paying special attention to the differences between highly educated foreign workers and native workers. Throughout the remainder of this chapter, all figures that we present are about highly educated workers only. For comparison, we present many figures not only for natives and foreign workers that were born in advanced countries, but also for foreign workers that were born in other (lower and middle-income) countries.

Table 6.2 presents descriptive statistics for selected variables that are of interest. On average, the share of foreign-born workers (that have been a resident of the Netherlands for at least ten years) from advanced countries is on average about 1.6 percent, the share of workers born in other (foreign) countries is about 3.8 percent. Between 2000 and 2008, the number of observations gradually increased from 22 thousand to 53 thousand. In total, there are 414 thousand observations. As we use pooled cross-sections rather than panel data, the change

[50] Overall diversity and the share of foreign workers are highly correlated, which results in multicollinearity when simultaneously including these two variables in the model. Therefore, we estimate the impact of diversity at a given share of foreign workers.

in the number of observations over time is unlikely to be a problem. Hourly wages increased by about 8.4 percent in real terms. Furthermore, the average age, the share of females and part-time workers, and the share of foreign-born workers (both from advanced countries and from other countries) of the individuals in our sample all increased substantially over time.

Table 6.1. Descriptive statistics, 2000–2008

	2000	2002	2004	2006	2008
# Observations	21,778	42,774	51,786	53,887	53,457
Log real hourly wage	2.969	2.981	2.989	3.028	3.053
	(0.363)	(0.367)	(0.368)	(0.404)	(0.411)
Age	41.85	42.32	42.87	43.59	44.20
	(8.63)	(8.62)	(8.85)	(8.95)	(9.21)
Females	0.386	0.413	0.432	0.439	0.448
	(0.487)	(0.492)	(0.495)	(0.496)	(0.497)
Foreign born,	0.014	0.016	0.015	0.017	0.017
advanced countries	(0.118)	(0.124)	(0.123)	(0.129)	(0.128)
Foreign born,	0.033	0.031	0.038	0.043	0.044
other countries	(0.178)	(0.175)	(0.190)	(0.203)	(0.204)
Share higher educated*	0.401	0.404	0.442	0.451	0.460
	(0.490)	(0.491)	(0.497)	(0.498)	(0.498)
Part-time	0.363	0.393	0.412	0.428	0.437
	(0.481)	(0.488)	(0.492)	(0.495)	(0.496)

Note: Standard deviations are in parentheses. *Higher educated workers are defined as those with at least higher tertiary education (HBO or university degree).

Table 6.2 shows descriptive statistics for three groups of employees: workers that were born in the Netherlands, workers that were born in advanced economies, and other foreign-born workers. The average wages of foreign workers from advanced economies are not very different from those of native workers, as is the number of hours worked. However, the standard deviation of their wages is far higher. The latter is consistent with theories that suggest that search frictions might be higher for foreign workers. Also, they are about equally likely to have obtained at least a degree in higher tertiary education.

Even though there is no statistically significant difference between the average age of natives and the foreign-born workers from advanced economies that are in our sample, they would have been somewhat younger on average had we not needed to remove foreign workers that moved to the Netherlands less than ten years ago. Foreign-born workers from advanced economies are more often female relative to natives, and they are far more likely to work in exporting firms or foreign owned firms. The latter finding is thus consistent with the hypotheses that were formulated in Section 6.2, as the knowledge of foreign workers is more likely to be valuable in these firms, while their lack of Dutch language skills could be less of a problem in firms with an international orientation.

The rightmost column of Table 6.2 shows that foreign workers that were born in low and middle-income countries are, in contrast, very different from both their native-born colleagues and those born in advanced economies. On average, they are less well educated (even within our sample, where we have already excluded workers with the lowest levels of education), and earn far lower wages. Similar to foreign workers from advanced countries (albeit to a somewhat lesser extent), they do work more often in foreign owned or exporting firms.

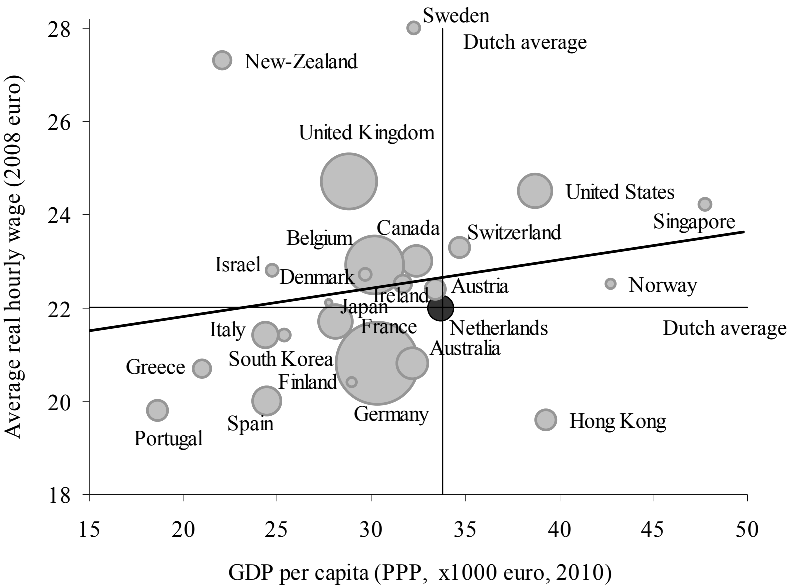
Table 6.2. Descriptive statistics by origin group, 2000–2008

	Native Dutch employees	Foreign born, advanced countries	Foreign born, other countries
# Observations	391,504	6,671	15,884
Real hourly wage	22.02	22.28	19.62
	(10.86)	(13.07)	(9.79)
Real annual wage	38,188	38,557	34,616***
	(23,432)	(27,618)	(20,465)
Hours worked	1,695	1,685	1,742***
	(436)	(439)	(399)
Age	43.06	43.49***	43.69***
	(8.92)	(8.49)	(8.71)
Females	0.426	0.502***	0.465***
	(0.495)	(0.500)	(0.499)
Share higher educated	0.438	0.444	0.379***
	(0.496)	(0.497)	(0.485)
Part-time	0.413	0.446***	0.379***
	(0.492)	(0.497)	(0.485)
Export share	0.243	0.306***	0.293***
	(0.336)	(0.361)	(0.358)
Employed at foreign firm	0.098	0.149***	0.137***
	(0.297)	(0.356)	(0.344)

Notes: Higher educated workers are defined as those with at least higher tertiary education (HBO or university degree). Significance levels of 0.05, 0.01 and 0.001 for the difference to native born workers are denoted by *, ** and ***, respectively.

Table 6.3 presents descriptive statistics by country of origin. There is considerable variation in average wages between workers from different countries of birth. Although variation is mostly explained by the low number of observations for some countries (e.g., given the small sample size and the high standard deviation of wages, some outliers are to be expected), some broad patterns can be observed from differences in average wages. First of all, workers from countries with a higher GDP per capita, tend to earn higher wages (see Figure 6.2).

Figure 6.2. GDP per capita (PPP) country of birth and wage of foreign workers



Note: The size of data points represents the number of foreign workers from each country.

There are two explanations for the positive relation between the wage foreign workers earn in the Netherlands and GDP per capita in their country of birth. First, human capital is generally lower in countries with a relatively low GDP per capita, which makes workers less productive. This seems a plausible explanation, as the correlation between the share of workers that has at least higher tertiary education and the average wage is 0.63, while the correlation between the education and GDP per capita is 0.57. A second explanation could be that the relatively low wages in the home country provide an incentive to accept job offers that pay less than what a native with comparable education and experience would earn, because it remains to be a higher wage than what would be earned in the home country. Besides wages, there are substantial (often statistically significant) differences between countries in the average age of workers, the share of individuals that work at a foreign owned firm, and export activities of the firms where workers are employed. The regression analyses in the next section will show how these variables are related to the wages and productivity of foreign workers.

Table 6.3. Descriptive statistics by country of origin

Country of origin	# Obs.	Hourly wage (average)	Hourly wage (st. dev.)	Age	Higher educated	Foreign firm	Export share
Dutch Natives	391,504	22.0	10.9	43.1	0.438	0.098	0.243
Foreign born, developed countries	6,671	22.3	13.1	43.5***	0.444	0.149***	0.306***
Foreign born, other countries	15,884	19.6***	9.8	43.7***	0.379***	0.137***	0.293***
Australia	277	20.8*	8.8	42.6	0.419	0.137	0.220
Austria	135	22.4	13.5	44.5	0.422	0.148	0.290
Belgium	978	22.9*	13.5	43.7*	0.524***	0.116	0.312*
Canada	289	23	14.6	43.4	0.405	0.125	0.325
Denmark	67	22.7	11.9	42.7	0.433	0.090	NA
Finland	30	20.4	8.8	48.2***	0.400	0.200	NA
France	335	21.7	13.7	43.6	0.472	0.119	0.332
Germany	1,806	20.8***	10.5	43.0	0.391***	0.116*	0.275
Greece	95	20.7	10.4	41.9	0.337*	0.189*	NA
Hong Kong	132	19.6*	11.4	41.2**	0.394	0.144	0.382
Ireland	109	22.5	11.9	46.0***	0.376	0.147	NA
Israel	59	22.8	9.8	43.2	0.576*	0.119	NA
Italy	218	21.4	13.4	45.0***	0.372*	0.193***	0.407*
Japan	29	22.1	8.6	47.8**	0.621*	0.310*	NA
New-Zealand	110	27.3*	27.0	43.2	0.473	0.164	NA
Norway	44	22.5	13.7	41.8	0.614*	0.091	NA
Portugal	135	19.8*	11.8	41.9	0.252***	0.252***	0.271
Singapore	48	24.2	14.3	40.4*	0.646**	0.146	NA
South Korea	51	21.4	9.6	33.4***	0.451	0.216*	NA
Spain	254	20.0***	9.3	43.1	0.287***	0.197***	0.441***
Sweden	62	28.0**	17.0	45.0	0.613**	0.129	NA
Switzerland	129	23.3	15.6	41.9	0.512	0.116	NA
United Kingdom	896	24.7***	15.3	45.4***	0.472*	0.228***	0.322**
United States	319	24.5**	14.1	43.7	0.589***	0.154**	0.278

Notes: Data are only presented if the number of observations is at least 25. Higher educated workers are defined as those with at least higher tertiary education (HBO or university degree). Significance levels of 0.05, 0.01 and 0.001 for the difference to Dutch born workers are denoted by *, ** and ***, respectively.

The descriptive statistics presented earlier in this section showed that even though natives and workers born in other advanced countries are rather comparable on average, there are substantial differences across workers born in different countries. Table 6.4 compares average wages and the share of different types of education. The share of workers with a university degree is considerably higher for foreign workers that were born in advanced countries (27 percent), than for Dutch workers (15 percent). For other types of education there are also substantial differences. However, these differences are likely to have been affected by differences in educational systems. While foreign-born employees that have finished higher tertiary education earn about the same wage as natives within most types of education, lower educated foreign workers earn relatively less (though the lowest level is an exception to this). The reason that the average wage across all education levels is equal thus results from the fact that foreign workers are somewhat higher educated.

Table 6.4. Stylized facts by level of education

	Dutch Natives		Foreign workers from advanced countries		Ratios	
	hourly wage (1)	%-share (2)	hourly wage (3)	%-share (4)	(3/1)	(4/2)
Lower tertiary education (MBO 2+3)	17.59	20.23	17.84	24.40***	1.01	1.21***
Lower tertiary education (MBO 4)	19.08	26.93	18.36***	15.72***	0.96***	0.58***
Higher secondary education (HAVO+VWO)	20.61	9.08	19.36**	15.45***	0.94**	1.70***
Higher tertiary education (HBO+BA)	23.92	29.13	23.45	21.93***	0.98	0.75***
Higher tertiary education (MA, PhD)	30.66	14.62	30.72	22.49***	1.00	1.54***
Total	22.02	100.00	22.28	100.00	1.01	1.00

Note: Significance levels of 0.05, 0.01 and 0.001 for the difference to Dutch born workers are denoted by *, ** and ***, respectively.

Table 6.5 and Figure 6.3 present stylized facts for natives and foreign-born workers from advanced economies by 2-digit ISCO-88 occupation. While there is some heterogeneity in occupational composition, differences between natives and foreign workers show no clear pattern. When we look at wages, in contrast, an interesting pattern emerges. There is a significant positive correlation (with a coefficient of 0.33) between the average wage of native workers within an occupation and the ratio between wages of foreign workers and natives. Foreign workers earn more than natives in highly rewarded occupations, but less in lower paid occupations.

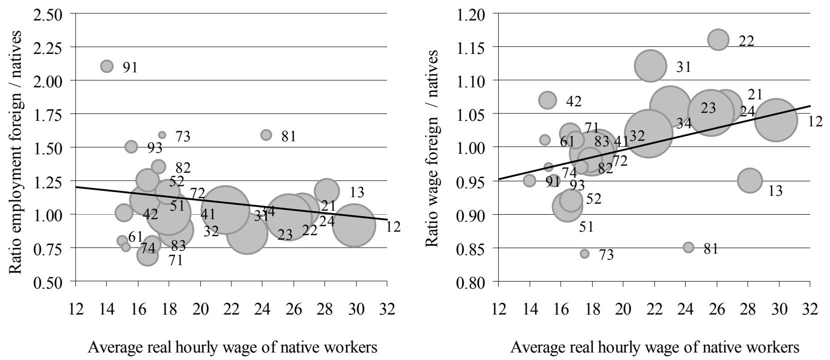
Table 6.5. Stylized facts by 2-digit ISCO-88 occupation

		Dutch Natives		Expatriates		Ratios	
		hourly wage (1)	%-share (2)	hourly wage (3)	%-share (4)	(3/1)	(4/2)
12	Corporate managers	29.88	9.20	30.99	8.40*	1.04	0.91*
13	Managers of small enterprises	28.17	3.40	26.85	4.00*	0.95	1.17*
21	Physical, mathematical and engineering science professionals	26.60	6.20	28.29*	6.40	1.06*	1.03
22	Life science and health professionals	26.15	2.60	30.29**	2.40	1.16**	0.94
23	Teaching professionals	23.06	8.60	24.46**	7.30***	1.06**	0.85***
24	Other professionals	25.70	10.80	26.87*	10.50	1.05*	0.97
31	Physical and engineering science associate professionals	21.81	5.30	24.33**	5.30	1.12**	0.99
32	Life science and health associate professionals	18.48	6.90	18.44	6.10**	1.00	0.88**
34	Other associate professionals	21.68	12.00	22.13	12.30	1.02	1.03
41	Office clerks	18.00	10.00	17.84	10.10	0.99	1.01
42	Customer services clerks	15.16	1.60	16.27	1.60	1.07	1.01
51	Personal and protective services workers	16.49	4.80	15.01***	5.30	0.91***	1.10
52	Models, salespersons and demonstrators	16.67	2.90	15.41*	3.70**	0.92*	1.25**
61	Skilled agricultural and fishery workers	15.00	0.60	15.15	0.50	1.01	0.80
71	Extraction and building trades workers	16.66	2.60	17.07	1.80***	1.02	0.69***
72	Metal, machinery and related trades workers	17.93	3.20	17.60	3.70*	0.98	1.16*
73	Precision, handicraft, craft printing and related trades workers	17.56	0.40	14.81*	0.60*	0.84*	1.59*
74	Other craft and related trades workers	15.24	0.50	14.77	0.40	0.97	0.75
81	Stationary plant and related operators	24.24	0.80	20.52***	1.20***	0.85***	1.59***
82	Machine operators and assemblers	17.33	1.10	16.78	1.50*	0.97	1.35*
83	Drivers and mobile plant operators	16.97	1.70	17.14	1.30**	1.01	0.77**
91	Sales and services elementary occupations	14.01	0.90	13.25*	1.80***	0.95*	2.10***
93	Laborers in mining, construction, manufacturing and transport	15.62	1.00	14.79	1.50***	0.95	1.50***
	Total	22.02	97.20	22.28	97.60	1.01	1.00

Notes: Data are only presented for occupations where the number of observations is at least 25. Significance levels of 0.05, 0.01 and 0.001 for the difference to Dutch born workers are denoted by *, ** and ***, respectively.

This finding could be related to search frictions, which predict that foreign workers may earn more than natives in some jobs, but are at the same time relatively likely to earn less if they do not succeed to find a good match. There are, however, also other possible explanations for this observation. For example, it could be that the Netherlands attracts below average productivity workers in the lower paid professions (for example, construction workers with two left hands), while attracting the best doctors and professors, that are more productive than natives. In this case there would be a simple selection bias. However, it is theoretically not clear why such a pattern would emerge.

Figure 6.3. Average wage natives and ratio between employment (left) and wages (right) of workers from advanced countries and natives by ISCO-88 occupation



Note: Size of circles denotes total employment within each occupation. The occupation codes correspond to those in Table 6.5.

6.4 Empirical evidence

The approach used in this chapter is similar to the methodology of Chapter 3, where augmented Mincer regressions (after Mincer, 1974) are used to estimate the effects of agglomeration on wages and productivity. We present the results of various estimations of wage regressions:

$$\log(w_{i,f,r,t}) = \alpha + X_{i,f,r,t}\beta + \gamma F_{f,t} + d_f + d_s + d_{r,t} + \varepsilon_{i,f,r,t} \quad , \qquad (6.3)$$

where the natural logarithm of the pre-tax real hourly wage w of employee i in firm f and region r in year t is explained by a constant, a matrix X with individual worker characteristics (including occupation fixed effects in most specifications), a matrix F with firm characteristics that vary over time, optional firm fixed effects d_f or industry fixed effects d_s and time × region fixed effects $d_{r,t}$, and a residual term. The inclusion of fixed effects (both time invariant and variant) is to avoid a number of estimation pitfalls. These are endogeneity on the regional level and omitted variable bias on the level of industries, firms, occupations, and regions.

From an empirical perspective, estimating the effects of diversity on the firm level has several advantages over estimating it on the regional level. The reason for this is that it is difficult to control for endogeneity on the level of regions. As exogenous instruments for diversity are rare, using instrumental variable techniques is generally not an option. The inclusion of region-specific fixed effects does not solve these estimation issues, because in that case the effect of diversity (and other variables) is mostly estimated on time variation. This does not make the estimates less vulnerable to omitted variable bias and endogeneity, because it is likely that regions with above average wage growth are becoming increasingly attractive to foreign labor. If we estimate on the level of firms on the other hand, we can control for this by including year × region-specific fixed effects. Local wage determination takes place on the level of local labor markets (rather than on the level of individual firms). Furthermore, it is unlikely that individual firms have a large impact on the average attractiveness of locations that goes beyond the attractiveness of the region (which represents the attractiveness of wages offered by all firms in the region).

Even when including firm fixed effects, however, one could argue that there remains the possibility of endogeneity on the level of the firm. E.g., if a firm has become increasingly productive over time, it may have started hiring more people, which may explain an increasing share of foreign-born workers. They are likely to have a younger workforce that was hired at a more recent time when the share of foreign-born workers in the population was higher, and foreign workers are more flexible as they do not have a strong bond with a certain location. To control for this, we include both the average job duration of workers in each firm, and the number of employees in each firm. All specifications report robust standard errors, which are clustered within firms.

Results

Table 6.6 presents estimation results for five different specifications. Specification (I) includes only time and industry fixed effects, specifications (II)–(IV) include sector, occupation and time × region fixed effects, and specification (V) includes firm, occupation and time × region fixed effects. Specifications (I) and (II) are our basis specifications. They include a dummy for foreign-born workers from advanced countries, a dummy for other foreign workers, the log of employment at the firm where the individual works, a dummy that indicates whether the firm is foreign owned or not, and the share of exports in turnover of the firm. Specifications (III)–(V) include several interaction effects for these variables. Rather than including a single dummy that indicates whether a worker is foreign born, we include interaction effects with the number of years the individual has been present in the Netherlands. As we expect that foreign workers will gradually accumulate the language and social skills of natives, we expect that the wage differential with natives will decrease over time.

We also estimate interaction effects for natives, foreign-born workers from advanced countries and (for reference) foreign-born workers from other countries with log firm size, working for a foreign firm, and exports. The theoretical section predicted that foreign workers will be relatively more productive in firms with an international orientation. We thus expect a difference in the relation of these variables with wages for workers born in different countries. For presentational convenience, we present these interaction effects separately, in Table 6.7. Specification (III) is estimated on our entire sample, specification (IV) is estimated only on workers who are employed at firms with at least 20 employees.

We find that individual worker characteristics provide a strong explanation for differences in payment. The results are robust across different specifications, and the estimated coefficients are comparable to those in Chapters 2 and 3, although the returns to education are somewhat lower in specifications (II)–(V) because of the inclusion of occupation dummies. This is because occupation is endogenous and largely dependent on education (and, for that matter, ability). Interestingly, the wage differentials between males and females and between part-time and full-time workers are reduced somewhat by the inclusion of firm fixed effects. This implies that females work in occupations and firms that pay somewhat lower wages *ceteris paribus*.

Table 6.6. Regression results

Dependent: Log real hourly wage	(I)	(II)	(III)	(IV)	(V)
# Observations	413,915	413,695	413,695	340,821	413,695
Female	–0.152***	–0.148***	–0.148***	–0.139***	–0.135***
	(49.4)	(53.6)	(53.8)	(44.8)	(43.1)
Age	0.048***	0.043***	0.044***	0.044***	0.042***
	(55.3)	(53.0)	(53.4)	(46.6)	(43.0)
Age-squared	–0.0004***	–0.0004***	–0.0004***	–0.0004***	–0.0004***
	(45.9)	(44.0)	(44.5)	(39.6)	(35.3)
Part-time	–0.031***	–0.010***	–0.010***	–0.007*	0.006*
	(10.9)	(3.8)	(3.8)	(2.5)	(2.0)
Lower tertiary education	0.082***	0.043***	0.042***	0.041***	0.041***
(MBO 4)	(39.9)	(23.6)	(23.4)	(19.7)	(21.1)
Higher secondary education	0.113***	0.069***	0.070***	0.070***	0.063***
(HAVO + VWO)	(41.1)	(27.4)	(27.7)	(24.6)	(23.0)
Higher tertiary education	0.272***	0.164***	0.164***	0.165***	0.155***
(HBO + BA)	(84.8)	(54.4)	(54.4)	(48.5)	(41.4)
Higher tertiary education	0.459***	0.331***	0.331***	0.335***	0.311***
(MA + PhD)	(103.2)	(79.2)	(79.4)	(72.1)	(63.4)
Foreign-born worker,	–0.023***	–0.008***			
from advanced country	(4.4)	(1.6)			
Other foreign worker	–0.135***	–0.086***		*Interaction effects*	
	(38.0)	(27.0)			
Log employment firm	0.005***	0.006***		*with country of birth are in*	
	(3.4)	(4.3)			
Foreign firm	0.056***	0.050***		*Table 6.7*	
	(8.6)	(8.6)			
Share of export	0.045***	0.044***			
in turnover	(5.2)	(5.5)			
Log average tenure firm	0.069***	0.071***	0.071***	0.079***	0.032***
	(15.1)	(18.3)	(18.3)	(15.5)	(7.6)
Expat and foreign firm	0.103*	0.075	0.052	0.045	0.004
are from same country	(2.4)	(1.6)	(1.1)	(0.8)	(0.1)
At least one expat in firm	0.083***	0.073***	0.073***	0.096***	0.052***
	(8.2)	(7.7)	(7.8)	(8.1)	(6.4)
Log share expats in firm	0.017***	0.016***	0.016***	0.021***	0.011***
	(5.9)	(6.0)	(6.0)	(7.0)	(5.7)
Log diversity expats in firm	0.013***	0.0004	0.0004	0.007*	0.002
	(3.5)	(0.1)	(0.1)	(2.1)	(0.6)
Year dummies	Yes	No	No	No	No
Sector dummies	Yes	Yes	Yes	Yes	No
Occupation dummies	No	Yes	Yes	Yes	Yes
Year × municipality fixed effects	No	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	Yes
R^2	0.39	0.45	0.46	0.46	0.38

Notes: (I)–(III) and (V) are estimated on all firms, (IV) only on firms with more than 20 employees. Omitted category is lower tertiary education (MBO 2+3). *t*-values are in parentheses. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

Foreign-born workers from advanced economies earn slightly lower wages than natives in our first specification. Once we include fixed effects for occupations in specification (II), however, the difference completely disappears.[51] This implies that their lower wage in specification (I) is explained by their overrepresentation in lower paid occupations. The interaction effects with the number of years a foreign worker has been living in the Netherlands (that are estimated in specifications (III)–(V), and presented in Table 6.7) show that the difference is somewhere around 4 to 5 percent, and more or less constant over time. The difference is somewhat lower, however, for workers that have been living in the Netherlands for more than 30 years. The latter is most likely explained by selection effects: the more successful foreign workers are more likely to remain working. If it were the result of increasingly better Dutch language skills and the accumulation of social capital, we would expect a decreasing wage differential for workers that have been a resident for 10–30 years as well. Foreign workers that were born in middle and lower income countries earn far lower wages than both natives and foreign workers from advanced countries. The difference is about 10 percent on average. Furthermore, the wage difference decreases almost linearly over time.

Larger firms pay relatively more. This may be explained by efficiency wage theory (Akerlof, 1982). There are, however, substantial interaction effects between firm characteristics and country of birth on wages. As Table 6.7 shows, doubling the number of employees in the firm where an individual works is associated with a 0.5 percent increase in wages of natives and foreign workers from lower and middle-income countries. This figure is between 1.0 and 1.2 percent for foreign workers from advanced countries. Working for a foreign firm also has a substantially different effect on workers born in different countries. Dutch natives earn between 2.4 (in specification (V), where firm fixed effects are included) and 5.1 percent more in foreign firms. For foreign-born workers from advanced economies, this varies from as high as 8.6 percent (specification III) to 3.2 percent (specification V).

Although the results for some specifications seem to suggest that foreign-born workers earn more in a foreign firm if they come from the same country as the owner of the firm, this result is not robust across specifications. As foreign

[51] When estimating specification (II) with only year dummies, or with separate year and municipality dummies, rather than dummies for year × municipality combinations, the estimated coefficient for foreign workers from advanced countries is more or less the same.

workers from advanced countries are relatively overrepresented in larger firms and foreign firms, the positive association between working in these firms and their wages may explain why the wage differential is about zero in specification (II) while it is (statistically significant) negative in specifications (III) to (V). This implies that while foreign workers born in advanced countries earn about the same wage as natives on average, they earn less when they work in small or Dutch owned firms, but somewhat more than natives in large firms that are foreign owned. Clearly, this is consistent with the hypothesis that foreign workers may be expected to earn more in the type of firms that benefit from highly educated foreign workers.

In contrast, the effect of working in an exporting firm on wages is not consistent with the theories that were presented. While natives and workers from middle and lower income countries earn significantly higher wages in exporting firms (although this effect has become insignificant in specification (V)), this is not the case for foreign workers from advanced countries. This could imply that differences between different types of firms in the (loss of) effectiveness of foreign labor due to language differences etc. are relatively more important compared to potential knowledge spillovers. Clearly, if the higher productivity of foreign workers from advanced countries would be due to their valuable knowledge that natives lack, there is no reason why this knowledge would suddenly *reduce* their productivity in exporting firms. We suspect that the estimated (and statistically significant) difference in the effect of working for an exporting firm in specifications (III) and (IV) was in fact due to unobserved heterogeneity, as it completely disappears when firm fixed effects are included.

All specifications find a statistically significant relationship between the presence of foreign workers from advanced countries and the wages of natives in the same firms. Having at least one foreign worker is associated with a 5.2 to 9.6 percent higher wage (depending on the specification). Furthermore, doubling the share of foreign workers from advanced countries increases expected wages by another 1.1 to 2.1 percent. In larger firms, there is thus a stronger relationship between the presence of foreign workers and the wages of natives. In contrast, the effect of diversity within the group of foreign knowledge workers does not seem to matter much. Once more, this makes no sense from the perspective of “value of diversity” kind of explanations. It is, however, also possible that the statistical insignificance of the estimated effect of diversity is explained by the relatively low variation of diversity within firms.

Even though the evidence presented in Table 6.7 provides rather strong evidence for the existence of a relationship between the productivity level within firms and the presence of foreign workers from advanced economies, we must thus conclude that it is not yet entirely clear whether the higher productivity of those other workers was *caused* by the presence these foreign workers or not.

Table 6.7. Results – interactions with country of birth (3 classes)

Dependent: Log real hourly wage	(III) Native	Expat	Other foreign	(IV) Native	Expat	Other foreign	(V) Native	Expat	Other foreign
10–15 years in NL		–0.045*	–0.139***		–0.046	–0.141***		–0.032	–0.105***
		(2.3)	(12.6)		(1.8)	(9.7)		(1.4)	(6.9)
15–20 years in NL		–0.053**	–0.121***		–0.044	–0.119***		–0.052	–0.087***
		(2.9)	(9.8)		(1.9)	(7.4)		(2.5)	(5.2)
20–25 years in NL		–0.064***	–0.077***		–0.051*	–0.085***		–0.049*	–0.064***
		(3.8)	(6.3)		(2.3)	(5.4)		(2.4)	(4.0)
25–30 years in NL		–0.058***	–0.056***		–0.047*	–0.056***		–0.051**	–0.041**
		(3.7)	(5.3)		(2.2)	(4.2)		(2.6)	(3.0)
≥ 30 years in NL		–0.030*	–0.035***		–0.023	–0.042**		–0.029	–0.034*
		(2.1)	(3.3)		(1.1)	(3.0)		(1.6)	(2.4)
Log firm size	0.005***	0.012***	0.004	0.006***	0.011***	0.006*	0.006***	0.010***	0.005
	(4.2)	(4.7)	(1.9)	(4.0)	(3.5)	(2.1)	(4.3)	(3.5)	(1.8)
Foreign firm	0.051***	0.086***	0.005	0.042***	0.077***	–0.005	0.024***	0.032*	–0.028**
	(8.9)	(5.6)	(0.5)	(7.2)	(4.8)	(0.5)	(4.4)	(2.1)	(2.9)
Share of export in turnover firm	0.043*** (5.5)	0.017 (0.7)	0.063*** (4.0)	0.031*** (3.7)	–0.003 (0.1)	0.054*** (3.3)	–0.008 (1.3)	–0.030 (1.2)	–0.0003 (0.0)

Note: *t*-statistics (in absolute values) are reported in parentheses. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

To further analyze the relation between the presence of foreign workers from advanced economies on the wages of natives, we have extended models (III) and (IV) with interaction effects between level of education of natives and the dummy that indicates whether at least one foreign worker from an advanced country is present in the firm, the log share of these workers, and the log share of diversity among these foreign workers.

The results presented in Table 6.8 show substantial heterogeneity among workers with different levels of education. While the wages of native workers with at most lower tertiary education are almost completely unrelated to the share of foreign workers in the firm (or this relation might be even slightly negative), this relation becomes increasingly more positive as we move to the higher levels of education. Consistently among all levels of education, the effect is more positive when estimated on a sample of larger firms. In larger firms, wages of native workers with a university degree are expected to be as much as 16 percent higher when at least one of their colleagues was born in an advanced country other than the Netherlands. Doubling their share is associated with another 3.5 percent increase of the wages of natives with a university degree. Again, diversity among foreign-born workers has no effect at all. The interpretation of these results is not straightforward. However, the absence of a diversity effect seems to be inconsistent with the view that knowledge spillovers explain higher wages in firms where foreign workers are present.

Table 6.8. Interactions between the effect of foreign-born workers from advanced countries on the wages of other workers in the firm by level of education

Dependent: Log real hourly wage	Similar to (III), all firms			Similar to (IV), >20 empl.		
	At least one foreign worker[a] in firm	Log share foreign workers[a] in firm	Log diversity foreign workers [a] in firm	At least one foreign worker[a] in firm	Log share foreign workers[a] in firm	Log diversity foreign workers [a] in firm
Lower tertiary education	–0.011	–0.006*	–0.009	–0.010	–0.003	–0.006
(MBO 2+4)	(1.1)	(2.2)	(1.7)	(0.8)	(1.1)	(1.0)
Lower tertiary education	0.048***	0.009***	–0.002	0.068***	0.014***	0.004
(MBO 4)	(4.9)	(3.9)	(0.3)	(5.4)	(5.0)	(0.7)
Higher secondary education	0.077***	0.013***	0.007	0.099***	0.018***	0.015
(HAVO + VWO)	(5.0)	(3.4)	(0.8)	(5.3)	(4.1)	(1.8)
Higher tertiary education	0.112***	0.026***	0.009	0.136***	0.030***	0.014*
(HBO + BA)	(7.9)	(7.7)	(1.3)	(8.3)	(8.0)	(2.1)
Higher tertiary education	0.126***	0.028***	0.001	0.158***	0.035***	0.010
(MA + PhD)	(4.8)	(4.8)	(0.1)	(5.3)	(4.4)	(0.9)

Notes: The effects of the presence of foreign knowledge workers on the wages of other employees in the firm with different levels of education are estimated by extending models (III) and (IV) with interaction terms. Other parameter estimates are qualitatively the same as the estimates of the respective base models. *t*-statistics (in absolute values) are reported in parentheses. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively. [a]Foreign workers that were born in advanced countries.

As we have seen in Section 6.3, foreign knowledge workers from advanced economies are still a rather heterogeneous group in terms of average wages. Our econometric specification allows us to include separate dummies for foreign-born workers from different countries as opposed to a single combined dummy. Table

6.9 shows the estimates of these dummies – again for all countries with at least 25 observations, using specification (III) as a basis. The wage differentials between foreign workers that were born in advanced economies and natives are almost never statistically significant. There are no countries that supply citizens that earn a significantly higher wage (e.g. that are *ceteris paribus* more productive) than native Dutch workers. There are a few countries, however, whose citizens earn considerable lower wage relative to otherwise comparable Dutch natives (in terms of observed individual characteristics, type of occupation, industry, and region). These countries are mostly located in southern Europe. However, the main message of the low significance of the parameters for separate countries is that differences in the productivity of foreign workers are mostly explained by differences in observed worker characteristics such as age, education, occupation, and the type of firms where they work. The country where a foreign worker came from does not matter much.

Table 6.9. Dummies foreign-born workers by country of origin

Country of origin	Coefficient	*t*-statistic	Country of origin *(continued)*	Coefficient	*t*-statistic
Portugal	–0.120	(3.9)	Canada	–0.041	(1.4)
Hong Kong	–0.130	(3.6)	Finland	–0.107	(1.3)
Italy	–0.096	(3.2)	United Kingdom	–0.032	(1.3)
Spain	–0.077	(2.5)	Belgium	–0.026	(1.1)
France	–0.069	(2.4)	Switzerland	–0.042	(0.9)
Greece	–0.087	(2.2)	Norway	–0.031	(0.5)
Israel	–0.096	(1.9)	Singapore	–0.023	(0.4)
Germany	–0.039	(1.9)	Ireland	–0.017	(0.4)
Japan	–0.131	(1.8)	New Zealand	0.013	(0.2)
Australia	–0.047	(1.7)	Denmark	0.028	(0.6)
Austria	–0.065	(1.6)	Sweden	0.032	(0.6)
United States	–0.050	(1.6)	South Korea	0.059	(1.0)

Notes: *t*-statistics are in absolute values. Omitted category: native workers. Significance levels of 0.05, 0.01 and 0.001 are denoted by *, ** and ***, respectively.

We have estimated several additional specifications. For example, we included interaction effects between the level of education of foreign workers and the wage differential to natives, as well as interaction effects with occupation. However, that did not yield any substantial (i.e., statistically significant) results. Furthermore, we estimated many different specifications on subsamples (excluding part-time workers, including only employees in firms with at least 100 employees), different combinations of fixed effects, and gross annual wages rather than hourly wages. The findings presented in this section are rather robust across different specifications.

6.5 Conclusion

The presence of foreign workers – particularly high skilled – is often associated with externalities that result in higher productivity. The questions addressed in this chapter are whether there is a difference between the productivity of high skilled foreign workers and similar natives, and whether the presence of these foreign workers is related to the productivity of native workers.

Our results show that the presence of foreign workers is likely to have a positive effect on productivity in some firms and occupations (where heterogeneous knowledge is valuable), but that their lack of knowledge about language and local culture may reduce their productivity in many other professions. This may imply a more complex labor market match for foreign workers. The finding of Chapter 5 that foreign workers from advanced countries have an unemployment duration that is almost twice as long compared to natives after having been fired, is consistent with this theory.

Our empirical evidence shows that the difference between the wages of foreign-born workers from advanced countries and the wages of comparable natives is rather small. In native firms, and in foreign owned firms, they earn between 3 to 5 percent lower hourly wages. When working in foreign firms, however, this effect disappears. As foreign workers from advanced countries also earn a relatively high wage premium in larger firms, they earn a *ceteris paribus* higher average wage compared to natives in firms that are both large and foreign owned. This is consistent with the view that it is important (and more difficult) to find a good match. In some types of firms, foreign workers (from advanced countries) earn more than natives, in other firms they earn less.

Foreign workers from lower and middle-income countries earn lower wages across all types of firms. Furthermore, while the wage differential between natives and foreign workers from advanced countries remains rather constant as they have been living in the Netherlands for a longer time, the differential between natives and foreign workers from other countries gradually decreases. This implies that the lack of language and social skills is relatively more problematic for workers that migrated from lesser-developed countries, who start at a relatively large productivity disadvantage. In contrast with the so-called value of diversity hypotheses, we do not find a stronger effect of working in an exporting firm on the wages of foreign workers compared to natives. There is no clear reason why the knowledge and international orientation of foreign workers would increase their productivity in foreign owned firms, but not in exporting firms.

We also estimate the relationship between the presence of foreign-born workers from advanced countries and the wages of natives within the same firm. By including various fixed effects (both time invariant and time variant), we attempt to avoid a number of estimation issues. We find a robust positive association between the presence of high skilled foreign workers and the wages of natives. This effect is relatively larger for higher skilled natives (while the effect is negligible for lower educated workers), and it is larger for natives working in larger firms. In contrast to the presence of foreign workers, diversity among the foreign workers that are present within firms is almost completely unrelated from the wages of natives. Again, this finding seems to be inconsistent with the view that the positive association between the presence of foreign workers and the productivity of other workers results from knowledge spillovers. If knowledge spillovers would be the explanation, it would be reasonable to expect that more diversity – and thus more heterogeneous knowledge within the firm – would result in larger externalities.

While our empirical evidence rather convincingly shows that foreign-born workers from advanced countries are more likely to work in the type of firms where highly educated natives are relatively productive, it cannot be ruled out that this relationship is the result of something other than the positive externalities from the presence of foreign workers. Future research will need to increase our understanding about what explains the positive relation between firm level productivity and the presence of skilled foreign workers.

7 CONCLUSION

Looking back at the previous five chapters, we find little evidence in support of negative effects of increased international and regional division of labor, while several chapters find evidence pointing in the opposite direction. There is a long tradition in the economic literature – starting with Smith, Ricardo and Mill – that emphasizes the benefits *for the average citizen* of the increased division of labor that is made possible by agglomeration and free trade. Less attention, however, was devoted to the transitional or distributional effects that these trends could have for different groups of workers – not the least because of a lack of means. The micro data that are used in this thesis allowed us to address this issue.

Wage inequality

In retrospect, the start of this thesis already set the tone for the chapters to come. Chapter 2 showed that between 2000 and 2008 – despite some drastic changes in the economic landscape – aggregate wage inequality in the Netherlands changed little. In 2000, computers and the use of the internet had just started the conquests of our offices. By 2008, new information and telecommunication technologies had brought considerable change in many professions.

During the same period, the share of imports from the BRIC countries in total Dutch imports increased from just 5 percent in 2000 to 13 percent in 2008. Even though these trends changed both the domestic and the international division of labor, the 90^{th} to 10^{th} percentile wage differential increased by only 3 percent. However, at the same time the findings showed that the flatness of the aggregate distribution hides the dynamics for different groups on the labor market. While Chapter 2 attributed this mostly to the composition of the labor market, we also observed a slight increase in the return to education (resulting in higher inequality because high skilled employees have relatively high incomes). The chapter thus showed that there could be some truth in theories predicting that technological progress and globalization are relatively more beneficial for higher skilled workers, but its effect is not large.

From a policy perspective, this has some important implications. If we had found wage inequality to be significantly increasing, there would at least be *something* low-wage workers could be protected against. Though it still would not be clear whether that *something* was globalization, agglomeration, or maybe something else entirely, and although it would be uncertain whether the government could intervene without causing additional disturbances, there would at least be a potential for government intervention. However, if there is nothing to protect against, the only thing we can expect from policy measures are the disturbances they might or might not cause.

Agglomeration economies

In Chapter 3, we shifted our attention from wage inequality in general to the regional dimension of inequality: wage differences between regions. In this chapter, we find that firms in larger agglomerations pay a wage premium to workers, after correcting for observed worker characteristics. Using population density of 1840 to instrument for current density, we find that doubling the employment density of a NUTS-3 area (which approximates the size of a local labor market) is associated with a 4.8 percent higher productivity. Furthermore, we find a positive effect of specialization. Doubling the relative share of an industry in a region is related to a 2.9 percent higher wage level. The amount of specialization and agglomeration that is offered by cities is thus associated with considerable productivity advantages for workers.

This has some important implications for policies that aim to regulate the dispersion of people across space, investment in infrastructure, as well as policies that aim at reducing commuting. The lesson to be learned from Chapter 3 is that the location where an individual works matters a great deal. If we pick a random individual from the countryside, and move him or her to Amsterdam or one of the other larger Dutch cities, Chapter 3 shows that we may expect a wage or productivity premium in excess of 10 percent. Having workers employed at the location where they are most productive is not only beneficial to themselves, but it also increases the budget we have to pursue other valuable goals.

Housing market regulations increase the difficulty for individuals to work closer to a productive job. In fact, the most productive cities in the Netherlands are among the municipalities with the most regulated housing markets, and are characterized by a high share of social renting houses that are occupied by individuals to whom the productivity advantages of the cities where they live do not matter much. The individuals that would have lived there if the allocation of housing would have been left to the market, are now faced with the option of either commuting a longer distance or working at a less productive location.

Commuting

It is not difficult to see how increasing the costs of commuting further reduces the incentives of workers to work at the most productive locations. Because the decisions of individuals to work in a job with a certain productivity level (or maybe not work at all) have implications for tax revenues and social security expenses, the outcomes of these decisions result in externalities that go far beyond the individual.

Chapter 4, which analyses heterogeneity in commuting patterns between workers with different levels of education, finds that highly educated workers commute further than lower educated, both in terms of time and distance. This is often explained by labor market and housing market rigidities that are relatively high for higher educated workers. Compared to lower educated workers, higher educated workers are also far more likely to commute towards the larger agglomerations and the more productive regions, which implies that the productive advantages offered by densely populated areas are particularly large for higher educated workers.

Housing market regulations have on the one hand reduced the supply of the kind of housing that is in demand by higher income households in some of the largest Dutch cities, while on the other hand taxes have resulted in relatively high transaction costs of buying a new house (although these costs have been considerably reduced in recent years). As higher educated individuals are more likely to own rather than rent a house, this affects them relatively strong. On the labor market, search frictions are likely to be larger for higher educated workers, because they are more specialized. The probability of finding an optimal match close to the current residence of a worker is therefore relatively low for a higher educated worker.

Highly educated workers are thus particularly affected by the trade-off between accepting a less productive job (if they do not find a good match close to their home location), incurring high costs of buying a house closer to a productive job, or commuting longer distances. Due to the externalities associated with using the available human capital in a country as productively as is possible, it makes no sense from a policy perspective to *ceteris paribus* discourage commuting. Rather, the findings of the Chapters 3 and 4 suggest that substantial externalities (in terms of worker productivity) are associated with having housing markets that allow workers to live and work at the location where they are the most productive, and to reduce commuting costs such that workers are able to work at a location where they are relatively more productive while living somewhere else. If commuting is not an option, the way to go from a policy perspective is thus to make housing markets more flexible: particularly markets for housing that is attractive to high skilled workers in the largest and most productive cities.

This does not mean that all housing market regulation, taxation of commuting, or open space preservation policies should be completely abandoned – the advantages of these policies to the wellbeing of people could generate externalities that are beyond the scope of this dissertation – but rather that is it important that the inefficiencies that result from such policies are sufficiently taken into consideration. Further research may be needed to identify to what extent commuting is associated with more people working in productive jobs.

Unemployment, trade, offshoring and multinationals

In Chapter 5, we analyze the effects of three different dimensions of globalization on unemployment: exporting behavior of firms, working for a foreign owned firm, and offshorability of occupations. We find that variation in unemployment incidence is largely explained by personal characteristics. For example, females have a *ceteris paribus* almost fifty percent higher probability of getting fired, as have foreign workers from advanced countries, while foreign workers from lower and middle-income countries are more than twice as likely to be fired. Older workers, in contrast, have a lower probability of getting fired. Once unemployed, however, it takes a longer time for older workers to find a job again. The transition of females back to a job is similar to that of males. Foreign workers do not only face a higher risk of becoming unemployed, it takes also longer for them to find a new job. Contrary to popular belief, education does not matter much for both the risk of getting unemployed and finding a new job. While there is a very strong relation between level of education and wages, this relation is largely absent for unemployment.

Of all firm and job characteristics that were taken into account, only firm size has a substantial effect on unemployment. Workers employed at larger firms are less likely to become unemployed. Exports, working for a foreign firm, or offshorability of jobs are not related to higher unemployment incidence. In fact, our results associate offshorability of jobs to *less* rather than *more* unemployment. The findings thus imply that offshoring is unlikely to have a negative effect on unemployment incidence and duration.

In view of the consensus about the positive long-term effects of increased international specialization, even if globalization would have short term negative effects for some groups on the labor market, it would make no sense to shelter domestic workers from an economic perspective. A far more efficient solution would be to redistribute some of the gains from those who benefit from globalization to those who lose. However, the findings of both Chapter 2 and 5 indicate that – even in terms of short-term transition effects – we have little to fear from increased international specialization. In fact, given its history as a center of international trade and its position as a gateway to Europe, the trend of increased internationalization offers the possibility to further specialize in the creation of value through orchestrating international value chains.

From a policy perspective, this means that it is unlikely to be helpful in any way to take measures when individual jobs are lost to other countries. If a foreign firm downsizes its Dutch activities, this is likely to be part of normal business dynamics. Even though this may have negative effects in terms of wages or unemployment for those who got fired, many hundreds of thousands of individuals find new jobs each year in the Netherlands. As the Netherlands is rather successful in attracting and retaining foreign firms (for example, the share of employees that works for a foreign owned firm is increasing), it is not unlikely that more foreign jobs are lost in other countries and relocated to the Netherlands than the other way around. Government intervention aimed at retaining employment at these firms is likely to result in rent seeking behavior of firms, and misallocation of resources as these help programs reduce the incentive to use employees and capital into more productive activities.

Rather than protecting jobs, adapting some elements of the Danish *flexicurity* system, which combines a relatively low level of employment protection with generous unemployment benefits and active labor market policies, could be an option for the Netherlands (De Groot et al., 2006; OECD, 2012). Active labor market policies – such as training schemes – could improve the transition to a new job of workers who are fired. At the same time, a more flexible labor market will speed up the transition towards more productive activities.

As was noted in the introduction, unemployment is not the outcome of the number of jobs that are destroyed, but rather the outcome of labor market clearing. One of the most important determinants of (long-term) cross-country differences in unemployment is the quality of labor market institutions. Besides preventing labor markets from becoming overly rigid, and getting the incentives to work right, a useful policy goal should be to prevent school dropouts and encourage adolescents to at least achieve higher secondary education (HAVO or VWO) or the intermediate levels of tertiary education (MBO4). While having more individuals with higher tertiary education – particularly university graduates – is likely to generate substantial externalities in terms of productivity, it does not matter much for unemployment.

Minimum wage arrangements and social transfers have a relatively strong impact on the incentives to work for the lowest educated workers (particularly those with only primary education). There are possibilities to improve these incentives somewhat, for example, by arranging social benefits in such a way that the decision to work enables individuals to increase their consumption bundle – including all benefits in kind – by at least a few hundred euros. However, some disincentives are probably unavoidable given the desire to provide minimum standards of living to all. In view of that desire, it is the more important to encourage individuals to acquire a minimum level of education.

Foreign workers

Chapter 6 shows that foreign workers who were born in advanced countries are on average equally productive as natives, while at the same time they are not equally productive in *all* firms. After controlling for an extensive set of worker characteristics, including education and occupation, we find that they are slightly less productive in smaller firms and Dutch owned firms, but relatively more productive than natives in large and foreign owned firms. In contrast, foreign workers from lower and middle-income countries earn substantially lower wages across all firms.

The finding that there are differences in observed wages between natives and similar foreign workers may simply reflect productivity differences due to unobserved heterogeneity (in which case they are not that similar after all). However, it is also likely that foreign workers are less productive in many occupations and firms because of their lack of language skills. In the opposite direction, there are theoretical reasons why there might be externalities from having a heterogeneous work force to some firms. The finding that foreign workers from advanced countries earn somewhat more than natives in large and foreign owned firms, while slightly less in small and Dutch owned firms cannot be fully accounted for by unobserved worker heterogeneity. It is not clear, however, whether foreign workers are relatively more productive in larger and foreign firms because of the value of their knowledge and skills for these firms, or because it is less of a problem that they (for example) do not speak Dutch.

If the presence of high skilled foreign workers would result in externalities through knowledge spillovers, this could result in higher productivity and wages of natives. Indeed, we find rather strong evidence for the existence of a positive relation between the share of foreign workers from advanced countries and the wages of natives in these firms. This is particularly the case for high skilled natives. Even though there could thus be a truth in theories predicting that the presence of high skilled foreign workers results in externalities due to the available of more heterogeneous knowledge, some of the evidence we found was inconsistent with this view. For example, we find that working in an exporting firm is in fact more positive for natives than it is for foreign workers from advanced countries. Furthermore, we find that a diverse composition of the group of foreign workers in firms does not matter for the wages of natives. This is again inconsistent with the "value of diversity" hypothesis, as more heterogeneous knowledge implies more opportunity for knowledge spillovers.

Future research

Even though the use of micro data offers unprecedented possibilities to describe the dynamics that underlie trends in aggregate wage inequality that were observed in Chapter 2, it does not provide a full-fledged explanation for those observed trends. Future research can use the findings of the present study to further theorize, and ultimately integrate theory and empirical evidence on the determinants of wages. A further question of interest is what explains cross-country differences in (trends in) wage inequality.

Chapter 3 studies agglomeration economies in relative isolation, albeit explicitly taking sorting processes into account. A valuable topic for further research is analyzing agglomeration economies, amenities, housing prices, and the decisions of individuals about their residence, where they work, and their commuting behavior in an integrated manner. This way, agglomeration economies (Chapter 3) and commuting behavior (Chapter 4) could be analyzed using an integrated framework. In addition to this, more research is needed to the specific channels through which agglomeration externalities work. For example, it remains unclear whether it is the work location or the residence location of individuals that matters.

Another topic that should be addressed by future research is the importance of knowledge spillovers for regional productivity. Such spillovers are not only one of the explanations behind the productivity advantages of cities, they also have implications for the wages of workers with different characteristics. As regions differ substantially in the composition of the work force, it is important to know how this composition is related to spillover effects. For example, if lower educated workers would benefit from the presence of higher educated workers, this would have implications for regional wage inequality.

Chapter 4 focused mostly on the productivity advantages offered by cities as a driving force behind commuting behavior. Amenities could, however, also be an important determinant of the location behavior of individuals (De Groot et al., 2010). Future work can address how trends in the spatial sorting of individuals are related to amenities offered by cities. A further topic that is of interest is the effect of (costs of) commuting on employment and the productivity level of employees.

While this dissertation addresses both agglomeration and globalization, more research is needed to analyze how these two processes are interrelated. For example, the revival of cities during the last decades remains – to a large extent – unexplained. Furthermore, it remains unclear whether future advancements in transaction and transportation costs will result in *more* or rather in *less* agglomeration.

While Chapter 5 shows that highly educated foreign-born workers from advanced countries are more likely to work in the type of firms where highly educated natives are relatively productive, it remains possible that this relation is mostly the result of something else than the positive externalities from the presence of foreign workers. Future research will need to increase our understanding about what explains the positive relation between firm level productivity and the presence of skilled foreign workers.

Because of the limited access to micro data in other countries, studies that compare countries using comparable micro data – whether it is on inequality, commuting behavior, or unemployment – are relatively scarce. At the same time, it is precisely this type of data that can help to explain the large differences between countries in, for example, trends in wage inequality or commuting distance. As the methodology of data collection has been to a large extent harmonized within the European Union, the solution to this problem boils down to improving accessibility of data.

APPENDIX A. NUTS-3 CLASSIFICATION

There are 40 NUTS-3 regions in the Netherlands (known in the Netherlands as COROP regions). The borders of NUTS-3 regions respect the borders of provinces. Municipalities are never divided into multiple NUTS-3 regions. Because the boundaries of a NUTS-3 region only change when two municipalities merge that are in different regions, the classification is rather stable over time. Even though NUTS-3 regions are not defined as local labor market areas, they are a reasonable approximation of local labor markets in most cases.

NEDERLANDSTALIGE SAMENVATTING (SUMMARY IN DUTCH)

Agglomeratie, globalisering en regionale arbeidsmarkten

Inzichten op basis van Nederlandse microdata

Deze dissertatie onderzoekt de gevolgen van agglomeratie en globalisering voor regionale arbeidsmarkten in Nederland. Ze bestaat uit één algemeen hoofdstuk over loonongelijkheid (hoofdstuk 2), twee hoofdstukken die zich richten op agglomeratie (hoofdstukken 3 en 4), en twee hoofdstukken waarin aan globalisering gerelateerd onderzoek centraal staat (hoofdstukken 5 en 6).

Binnen de economische literatuur worden agglomeratie en globalisering traditioneel geassocieerd met een toename van arbeidsdeling, die resulteert in hogere productiviteit – en daarmee uiteindelijk welvaart – voor de gemiddelde werknemer. Dichtbevolkte regio's laten meer specialisatie toe, doordat de omvang van relevante afzetmarkten groter is. Globalisering, met de daaraan verbonden internationale arbeidsdeling, maakt verdere stijgingen van productiviteit mogelijk doordat landen zich in toenemende mate kunnen specialiseren naar hun comparatieve kostenvoordelen. Door hun goede verbindingen met de buitenwereld lijkt de trend van globalisering het belang van steden op het wereldtoneel versterkt te hebben.

De jaren 2000 tot en met 2008 waar de analyses in dit proefschrift betrekking op hebben waren een tijd waarin zich veel veranderingen voordeden. Het decennium na 2000 werd gekenmerkt door grote dynamiek op het gebied van globalisering en technologische vooruitgang. Zo steeg het aandeel van de BRIC landen in de Nederlandse invoer van 5 procent in 2000 naar 13 procent in 2008. Tegelijkertijd veroverde de computer onze werkplaatsen, waardoor het gemak waarmee gegevens – op een globale schaal – kunnen worden uitgewisseld drastisch is toegenomen. Binnen veel professies is de manier waarop gewerkt wordt hierdoor aanzienlijk gewijzigd.

Hoewel maatschappelijke onrust – met name over globalisering – zich in het bijzonder toespitst op specifieke subgroepen op de arbeidsmarkt, zoals laagopgeleiden en oudere werknemers, zijn juist deze verdelingseffecten lange tijd onderbelicht gebleven doordat de beschikbaarheid van data met een voldoende detailniveau zeer beperkt was. De microdata die aan de empirische analyses in dit proefschrift ten grondslag liggen stellen ons in staat om een bijdrage te leveren aan het bestuderen van dit vraagstuk.

Het gebruik van microdata met daarin de kenmerken van werknemers en de bedrijven waarin zij werkzaam zijn is één van de elementen waarin deze dissertatie zich onderscheidt. Traditioneel wordt bij onderzoek naar macro-economische onderwerpen zoals agglomeratie en globalisering voornamelijk gebruik gemaakt van geaggregeerde data, niet in de laatste plaats omdat betere data lange tijd niet beschikbaar waren. De laatste decennia is het zwaartepunt in zowel de theoretische als de empirische literatuur steeds verder in de richting van een micro-economische benadering verschoven. Een belangrijk inzicht dat hieruit is voortgekomen, is dat inzichten in heterogeniteit van regio's, bedrijven, en werknemers essentieel zijn om de complexiteit van economische vraagstukken adequaat te adresseren (Van Bergeijk e.a., 2011).

Vanuit beleidsoogpunt zijn 'one size fits all' oplossingen eerder uitzondering dan regel. Niet alleen kunnen de gevolgen van fenomenen zoals agglomeratie en globalisering zeer uiteenlopend zijn voor verschillende bevolkingsgroepen, het niet in ogenschouw nemen van heterogeniteit van actoren kan leiden tot inaccurate conclusies. Zo laat hoofdstuk 3 in navolging van het werk van Combes e.a. (2008a) zien dat de correlatie tussen agglomeratie en geaggregeerde productiviteit in belangrijke mate wordt verklaard door verschillen in de samenstelling van de lokale beroepsbevolking, en niet uitsluitend door de relatie tussen economische dichtheid en productiviteit.

Loonongelijkheid

De studie start in hoofdstuk 2 met het in kaart brengen van recente trends in loonongelijkheid. Hoewel zich gedurende de onderzochte periode (2000–2008) een aantal drastische veranderingen voordeden in het economische landschap, bleef de geaggregeerde loonongelijkheid in Nederland relatief constant: het loonverschil tussen het 90e en het 10e percentiel uit de loondistributie nam toe met ongeveer 3 procent over de gehele periode. Tegelijkertijd laat hoofdstuk 2 echter zien dat deze relatieve stabiliteit op geaggregeerd niveau een aanzienlijke onderliggende dynamiek verbergt voor verschillende groepen werknemers. Zo is het belang van opleidingsniveau voor de beloning toegenomen. Lonen van hoogopgeleide werknemers zijn relatief snel gestegen, wat *ceteris paribus* tot een toename van ongelijkheid heeft geleid. Het hoofdstuk laat daarmee zien dat er een kern van waarheid kan zitten in theorieën die voorspellen dat technologische vooruitgang en globalisering relatief voordelig zijn voor hoogopgeleide werknemers, maar dat het onwaarschijnlijk is dat deze verschillen in effecten groot zijn.

Agglomeratie effecten

Hoofdstuk 3 verschuift de aandacht van inkomensongelijkheid in zijn algemeenheid naar de ruimtelijke dimensie van ongelijkheid. Een belangrijk deel van loonverschillen tussen regio's wordt verklaard door verschillen in samenstelling van de beroepsbevolking. Zo werken hoogopgeleiden relatief vaak in de grote steden. Hoewel de geografische omvang van Nederland beperkt is, blijken er na correctie voor geobserveerde heterogeniteit van werknemers substantiële loonverschillen tussen regio's te bestaan. We vinden dat een verdubbeling van het aantal werknemers in een COROP regio samengaat met een 4,8 procent hogere productiviteit, waarbij reële uurlonen worden gebruikt als productiviteitsmaat. Hierbij gebruiken we de bevolkingsdichtheid kort voor het begin van de industriële revolutie (1840) als instrument voor de huidige dichtheid. Het verdubbelen van het relatieve aandeel van een sector in de lokale economie – een maat voor specialisatie – resulteert in een 2,9 procent hogere productiviteit.

Het hoofdstuk laat zien dat de locatie waar een werknemer werkt van grote invloed is op de productiviteit. Wanneer een werknemer met gegeven kenmerken van het platteland naar één van de grote steden verhuist is een loonstijging van ongeveer 10 procent te verwachten. Vanuit beleidsoogpunt is het dan ook belangrijk dat er rekening wordt gehouden met de productiviteitseffecten van barrières die verhinderen dat werknemers werken op de plaats waar zij het meest productief zijn.

Forensengedrag

Niet alleen in het locatiegedrag van werknemers zijn aanzienlijke verschillen zichtbaar tussen hoger- en lager opgeleide werknemers. Hoofdstuk 4 laat zien dat opleidingsniveau ook een belangrijke verklarende factor is voor geobserveerd forensengedrag. Hoogopgeleide werknemers forensen verder dan hun lager opgeleide collega's, zowel in termen van reisafstand als reistijd. In de literatuur wordt dit vaak verklaard door relatief grote zoekfricties voor hoger opgeleiden op zowel de woningmarkt als de arbeidsmarkt. Terwijl lager opgeleide werknemers relatief ver van hun woonlocatie werken indien ze een relatief hoog loon verdienen, zijn de reistijd en reisafstand van hoger opgeleiden relatief hoog (ook na correctie voor inkomensverschillen). Ook forensen hoger opgeleide werknemers vaker in de richting van grotere steden, en steden die gekenmerkt worden door een relatief hoog productiviteitsniveau, wat impliceert dat de voordelen van agglomeratie relatief groot zijn voor hoogopgeleiden. Naast verschillen in de omvang en richting van forensenstromen, zijn er ook verschillen in de gebruikte vervoersmodaliteit. Hoogopgeleiden maken relatief vaker gebruik van de trein, en fietsen vaker naar hun werk.

Werkloosheid

In hoofdstuk 5 wordt de aandacht verschoven van de regionale dimensie van arbeidsdeling naar internationale handel. Met behulp van een unieke dataset is de koppeling gelegd tussen werkloosheidsuitkeringen, kenmerken van personen, en kenmerken van de laatste baan die werknemers hadden voordat ze werden ontslagen, en de baan na werkloosheid (indien die er is). Op basis van deze dataset is onderzocht in welke mate een drietal dimensies van globalisering – internationale handel, de mate waarin beroepen te offshoren zijn, en het werken voor een onderneming in buitenlands eigendom – samenhangen met de kans op werkloosheid en de kans op een baan na werkloosheid.

De belangrijkste verklaringen voor werkloosheid zijn te vinden in persoonskenmerken. Zo ligt de ontslagkans van vrouwen *ceteris paribus* bijna vijftig procent hoger ten opzichte van mannen, net als de ontslagkans van buitenlandse werknemers die in westerse landen zijn geboren, terwijl buitenlandse werknemers uit niet-westerse landen zelfs twee maal zo vaak ontslagen worden als in Nederland geboren werknemers. Oudere werknemers hebben daarentegen juist een relatief lage kans om ontslagen te worden, maar als ze eenmaal ontslagen worden hebben ze een relatief lage kans om een nieuwe baan te vinden. Mannen en vrouwen vinden ongeveer even snel een nieuwe baan, terwijl in het buitenland geboren werknemers niet alleen relatief vaak ontslagen worden maar ook minder snel een nieuwe baan vinden. In tegenstelling tot de hoogte van lonen, hangt de kans op werkloosheid slechts in beperkte mate samen met opleidingsniveau. Alleen werknemers met de laagste opleidingsniveaus – in het bijzonder wanneer ze de middelbare school niet hebben afgerond – hebben een relatief grote kans op werkloosheid.

Van alle bedrijfs- en baankenmerken die in het onderzoek zijn meegenomen heeft alleen de omvang van het bedrijf een (statistisch) significante relatie met de kans op werkloosheid. Werknemers die in grote bedrijven werken hebben een relatief grote kans om ontslagen te worden. Exportactiviteiten, of een bedrijf al dan niet in buitenlands eigendom is, en de mate waarin de baan van een werknemer te offshoren is blijken nauwelijks gerelateerd te zijn aan de kans op werkloosheid. Offshorability wordt zelfs geassocieerd met relatief lagere werkloosheid. Mogelijk is dit te verklaren doordat het job-matching proces relatief minder gecompliceerd is voor mensen met beroepen die gemakkelijk te outsourcen zijn. Zowel de bevindingen van hoofdstuk 2 als die van hoofdstuk 5 impliceren dat de negatieve transitie effecten van globalisering relatief beperkt van omvang zijn.

Buitenlandse werknemers

Hoofdstuk 6 onderzoekt in welke mate er een verband is tussen de aanwezigheid van hoogopgeleide buitenlandse werknemers in bedrijven en productiviteit. Buitenlandse werknemers beschikken mogelijk over kennis die hun Nederlandse collega's niet hebben, bijvoorbeeld over buitenlandse afzetmarkten. Het is echter ook mogelijk dat de aanwezigheid van buitenlandse werknemers de productiviteit (zowel van de buitenlandse werknemers zelf als van hun collega's) juist verlaagt, bijvoorbeeld door verschillen in taal en cultuur.

Na correctie voor een groot aantal kenmerken van zowel werknemers als bedrijven blijkt dat hoogopgeleide buitenlandse werknemers uit westerse landen ongeveer even productief zijn als in Nederland geboren werknemers met vergelijkbare kenmerken. Tegelijkertijd laat het echter zien dat de productiviteit niet in alle bedrijven even groot is: in kleine bedrijven en ondernemingen in Nederlands eigendom ligt de productiviteit iets lager, terwijl de productiviteit van hoogopgeleide buitenlandse werknemers in grote bedrijven en in bedrijven in buitenlands eigendom juist iets hoger is. In tegenstelling tot werknemers uit westerse landen verdienen hoogopgeleide buitenlandse werknemers die geboren zijn in niet-westerse landen een relatief laag loon in alle typen bedrijven.

De aanwezigheid van buitenlandse werknemers in bedrijven blijkt ook van belang voor de productiviteit van de andere werknemers in het bedrijf. Hoogopgeleiden verdienen een relatief hoog salaris in bedrijven met een hoog aandeel van buitenlandse werknemers. Voor lager opgeleide werknemers is er nauwelijks een effect. Het is echter niet duidelijk of dit productiviteitsverschil te verklaren is door de waarde van de kennis van buitenlandse werknemers. Een deel van de bevindingen is daarmee namelijk inconsistent: zo verdienen buitenlandse werknemers relatief minder in exporterende ondernemingen (terwijl eventuele buitenlandse kennis ook daar van belang zou moeten zijn), en vinden we geen effect van diversiteit binnen de in bedrijven aanwezige buitenlandse werknemers op de productiviteit, terwijl meer heterogeniteit meer mogelijkheden tot kennis spillovers zou moeten bieden.

Besluit

Dit proefschrift heeft laten zien dat microdata belangrijke inzichten op kunnen leveren in de dynamiek die schuil gaat achter cijfers op geaggregeerd niveau. De economische wetenschap staat aan het begin van een periode met veelbelovend onderzoek, waarin individuele werknemers, bedrijven en regio's in toenemende mate centraal zullen staan. De inzichten die dit oplevert zijn niet alleen van wetenschappelijk belang, maar kunnen ook helpen bij het ontwerpen van beleid dat toegespitst is op de veelzijdigheid en diversiteit van de economische realiteit.

Hoewel de economische waarde van zowel binnenlandse als internationale arbeidsdeling al eeuwen lang erkend wordt binnen de economische wetenschap, bestaan er nog altijd restricties die het vrije verkeer van personen en het internationale handelsverkeer beperken. De resultaten van dit proefschrift vormen een toevoeging aan het bewijs dat agglomeratie en globalisering resulteren in een hogere productiviteit, zonder noemenswaardige negatieve transitie- en herverdelingseffecten te veroorzaken.

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