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Labour Markets in Space

Essays on commuting and labour market pooling

Proefschrift voorgedragen tot het behalen van de graad van Doctor in de Economische Wetenschappen

door

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In loving memory of my parents, Victor Torfs & Alexandra Deheyder

Doctoral committee

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[1] Granted, with a break, a visit to the EIB and a premature departure to the IPTS.
[2] Being the stubborn, slow learner that I am.
[3] Mostly. *Mostly.*
[4] And maybe a little bit of intellectual vanity, admit it!
[5] Although I'm not entirely sure whether Joep feels this is actually a good thing!

Greet. I cannot thank you enough for your support over all these years. From a simple[6] 'Hello' in the morning, to the comforting words when times got tough, your presence made my stay at Vives so much more pleasant. Even now, from 2000km away, I can still count on you if I need a favour! The 'two words' do not do justice the extent of my appreciation for your kindness, but here they are nevertheless: thank you!

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[6]Yet consistently enthusiastic!

[7]I saw your feet slipping through the door opening!

[8]You know, 'dogs', those things that fly around in the park?!

[9]Or me.

[10]= Joep.

[11]You quite a bit faster than I, but let's leave that for the footnote here.

[12]If I ever gave you the impression I wasn't really listening to what you were saying, by all means, this was also the case.

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Mum, Dad. Thanks for letting me find my own way in life, while watching on the sidelines, always being ready with advice. Thanks for letting me make my own choices, my own mistakes, over, and over, and over again. Whatever happened, I knew I could always go home and find you there with open arms, with love and support. It brought me where I am today and where I will go tomorrow. You didn't stick around to see me finish this. Otherwise, I could have told you how I owe this all to you. All of this. All that was, is, and will be. I just got lucky to have had the best parents in the world. That's it.

Wouter Torfs
Leuven, July 2015

[13] Unless you find a job at the OECD before I do. You are warned.
[14] I forgive you for giving up after page 60.

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Labour Markets in Space

Space has a highly tangible effect on our daily labour market activities and decisions. Its impact manifests itself through a variety of channels, of which commuting is arguably the most tangible. Commuting is costly. In part, because it takes time. A lot of time. And time is money. On average, a Belgian worker spends one hour a day getting to and from work (Verhetsel et al., 2007). The time cost of commuting is an opportunity cost, intrinsically related to a worker's wage. Van Ommeren & Fosgerau (2009) demonstrate that the marginal cost associated with one hour of commuting amounts to 17 Euro. Off-the-back-of-my-envelope,[15] this totals to 24.7 billion Euro for the entire Belgian economy in 2015, nearly 5 percent of expected 2015 GDP! And this does not consider the fixed part of the time costs, nor other fixed costs that are unrelated to the duration of the commuting journey. Admittedly, these back-off-the-envelope calculations are all rather raw, but they illustrate nicely the drastic impact of space on the labour market in particular and the economy in general.

This dissertation consists of four distinct chapters. The analysis in Chapter 1 borrows a concept from natural sciences to identify and quantify the different spatial component of the commuting cost, with a particular emphasis on regional border effects, a topic particularly relevant in the Belgian context. In Chapter 2, I discuss how congestion externalities, such as rising commuting costs, can be

[15]Van Ommeren & Fosgerau (2009)'s analysis used 2002-data for the Netherlands, but given income differences between Belgium and the Netherlands are minor, it is safe to assume Belgians value their time similarly. Assuming an average annual inflation of 2 percent over 13 years, this amounts to 22 Euro anno 2015. Total commuting costs are evaluated at their marginal costs, for 4 500 000 workers who commute on average one hour a day for 250 days per year.

reconciled with the increasing rate of urbanisation observed in reality. Chapter 3 combines the two central concepts of the previous chapters, commuting costs and labour market pooling effects, and analyses their combined impact on the labour market outcome of workers of different skill levels in an urban economics framework. Finally, Chapter 4 describes a tool to visualise the geographic extent of local labour markets and applies it to the Belgian municipalities.

The idea for *Chapter 1* originated from a little map I have had lying around my university desk somewhere, for what must have been my entire scholarly career (figure 1). I came across it for the first time when I was writing my master thesis on regional unemployment disparities, back in 2007, even before I was enrolled in the doctoral program.[16] The map illustrates the spatial distribution of unemployment in Belgium at the municipality level. I deliberately omitted the markers of the regional borders. I challenge the reader to take a pencil and try to trace out the border separating the Belgian NUTS1 regions, Brussels, Flanders and Wallonia.[17] While within-country differences in regional unemployment rates are not uncommon, the stark contrast in the labour market outcomes of adjacent municipalities fascinated me. This led to the idea to try to analyze the impact of spatial frictions imposed by the language border on Belgian regional labour market outcomes. No sooner said than done, this gave rise to the analysis set out in Chapter 1. I use a gravity equation framework to quantify the impact of regional borders on the spatial distribution of commuter flows. The term 'gravity equation' undoubtedly sounds familiar to all but those that did not make it through their fourth year of high school. It has its roots in what must be one of the most influential scientific publications in human history, Newton's *Philosophiæ Naturalis Principia Mathematica*. Wikipedia quotes Newton's law of universal gravitation as follows: 'Any two bodies in the universe attract each other with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between them'. Economists have applied analogies to Newton's gravitational theorem

[16] I believe it was Damiaan Persyn who first showed it to me. He was my thesis supervisor at the time and became a co-author of this chapter later.

[17] In chapter 1, section 1.1 you can find the version with regional border marks to check how many municipalities you misallocated!

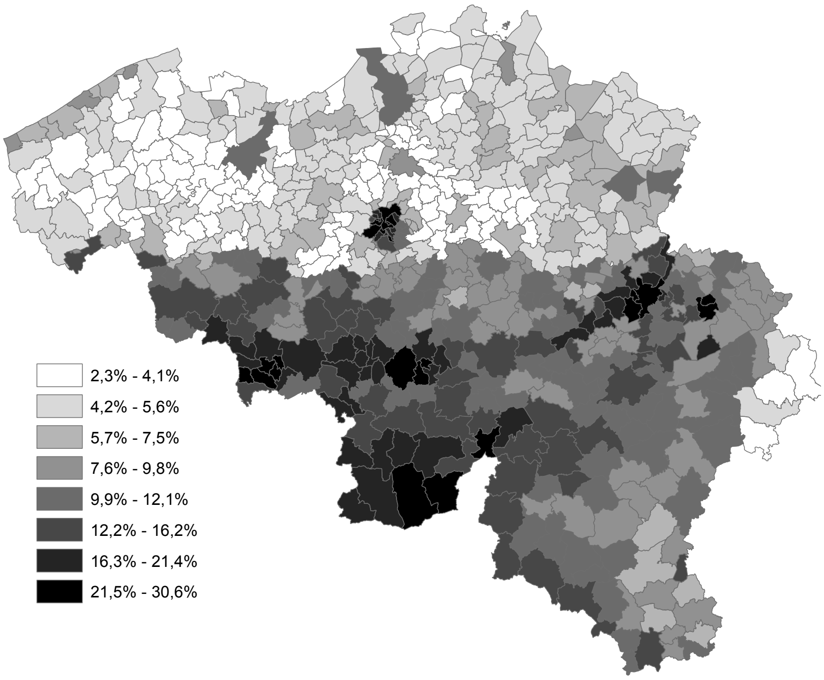


Figure 1: Unemployment rates for Belgian municipalities in 2008

to explain economic flows running in between two economic entities, most often in a spatial context. The flows can be just about anything: shopping trips, telephone calls, but most importantly in the context of this chapter: trade flows and commuters. Newton's gravitational law for commuter flows between locations would model the number of commuters going from A to B as a function of the distance travelled, and two proxies for the size of both locations. While some might argue the analogy is far-fetched, this chapter demonstrates how to derive a Newton-type gravity equation from a tractable labour market model. The approach builds on the work of J. Anderson & Van Wincoop (2003), who originally proposed this framework in the context of international trade theory. Interestingly, the resulting gravity equation for trade flows shows some remarkable similarities with the doubly constrained gravity equation developed by A. G. Wilson (1967), a workhorse model from spatial interaction theory. This chapter is the first to explicitly bridge the gap between these two rich gravity traditions. Similar to the gravity-trade literature, spatial interaction theory deals with economic flows between locations in relation to local supply and demand, yet both strands have been co-existing mostly parallel to one another for several decades with little or no cross-references linking them. Linking the two can provide fertile ground for future advances in either literature. Gravity equations in spatial interaction models have mostly been set up without micro-foundations and have rather relied on analogies from statistical mechanics. This contrasts with the trade literature, in which gravity equations are built from economic models where demand and supply are derived from optimising behaviour of economic agents. Interaction theory has been much more focussed on the role of the so-called constraints imposed on the empirical model, something which has been largely ignored by trade theorists. In J. Anderson & Van Wincoop (2003)'s model, for example, the constraints enter naturally through the derivation of labour demand and a 'spatial equilibrium condition'. The choice of constraints is non-trivial, as they enforce a relationship between the size of locations in the spatial system and the flows running between them. The doubly-constrained framework for example avoids that doubling the number of workers in the system leads to a quadrupling of the total number of worker flows. It implies that if the number of workers and jobs in the economy doubles, the total number of commuters[18] in the economy also doubles. This makes sense in the context of commuting. In the case of a trade model however, this exact correspondence between the size measures of trading partners (GDP) and the total production of the economy under consideration might break down due to certain factors, such as increasing returns to scale in production, for example. I take the gravity model to the data, using a Belgian municipality-level commuting trip matrix and quantify the deterrent effect of regional borders on the commuting behaviour of Belgian workers.

The entire analysis of Chapter 1 revolves around the adverse impact of transport costs on labour market commuting decisions. High levels of commuting costs are typically a by-product of the spatial concentration of economic activity. Progressing urbanisation in Western countries, and beyond, have led to record levels of road congestion. In addition, urban pollution, towering real estate

[18]The total number of commuters is simply the total amount of job-worker linkages.

prices and rising crime levels add to the unpleasantness of urban life. This begs the question what drives people to flock together in these congested agglomerated areas in the first place. Back in the nineteenth century, Marshall (1890) listed three sources of positive externalities brought about by the geographic concentration of economic activity: input sharing, knowledge spillovers, and labour market pooling. The first category certainly holds intuitive appeal. Given the advances in modern day transport infrastructure, it does not seem likely that the availability of a wide variety of inputs is a significant driver of agglomeration at the city-level. The second category, unmistakably important in Marshall's time, just sounds plain silly in this day and age. That leaves us with the third category, the one that I feel is most interesting, intuitive and arguably most relevant at an urban scale. Labour market pooling refers to situations where labour market scale positively affects aggregate urban outcomes, such as productivity, wages and unemployment. *Chapter 2* surveys the literature on labour market pooling. The relationship between labour market scale and the efficiency of the matching process between firms and workers takes a prominent place throughout the exposition. On the one hand, scale can simply make it easier for workers to find a job. Therefore, some authors have argued that urban scale affects the rate at with workers and firms form matches, or the *quantity of matches*. Others have made a compelling argument why there might not be such a relationship: the wide-spread availability of potential options can make urban workers more choosy in which offer to accept.[19] In this case, the effect of labour market scale would work through the *match quality*, rather than quantity. Finally, a third channel through which labour market related mechanisms affect the attractiveness of urban areas is their *risk-sharing* capability. Large labour markets allow individual firms and workers to take shelter from the adverse effects of labour demand shocks. This chapter is structured around these three main categories. This is the first survey paper devoted entirely to labour market pooling, thoroughly linking theory to existing empirical evidence. It will provide an overview of what has been done in the field, and can serve as a source of inspiration for scholars who are looking to further explore this fascinating topic.

[19] And vice versa for firms.

Chapter 3 examines how commuting costs impact labour market decisions of workers from different skill groups, when search activities are subject to scale effects, one of the forms of labour market pooling externalities discussed in Chapter 2.[20] In chapter 1 the commuting costs are intrinsically connected to the wage. Firms produce with a love-of-variety for workers from different locations, resulting in a geographical commuting pattern that is demand driven. In contrast, the theoretical model of Chapter 3 is built around a bipolar urban setting with labour markets that are characterised by search frictions (Coulson et al., 2001) and populated by heterogeneous agents on both sides of the market. After workers and firms match, production proceeds in pairs using a production technology with skill-complementarity in production (Shimer & Smith, 2000). Commuting costs are fixed and unrelated to earnings. The commuting decision of workers is driven by a selection effect and is the outcome of the interaction between this fixed mobility costs, labour market pooling effects and skill complementaries in production.

Chapter 4 visualizes the Belgian regional labour market using the Travel-To-Work-Area (TTWA) methodology of Bond & Coombes (2007). Traditionally, administratively delimited regions traditionally form the basis for data collection and the economic analysis of labour markets. Their borders are often drawn arbitrarily or rest on a purely historic basis. Consequently, there is no reason to believe that administrative regions correspond to a labour market in any economically relevant sense. In contrast to administratively delimited labour markets, the boundaries of functional labour markets are rooted in the behavior of economic agents. The methodology of this chapter applies a mathematical algorithm to a matrix of Belgian municipality-level commuting trips to construct 11 aggregate functional local labour markets. The average size of the TTWAs is closely related to the commuting propensity of workers. A highly mobile work force implies larger and fewer functional labour markets.

The final section concludes this dissertation by reflecting on some of its policy implications.

[20]This chapter is joined work with Liqiu Zhao, assistant professor at Beijing's Renmin University.

Chapter 1

A Gravity Equation for Commuting

1.1 Introduction

Commuting is an important spatial equilibrating mechanism in the labour market. In standard closed-economy labour market models, commuting reduces disparities in regional labour market outcomes such as unemployment rates and wages, and brings aggregate welfare gains (see for example Borjas, 2001). Commuting is costly, however. One can think of obvious costs that are directly related to commuting distance, such as straightforward travel expenses or the opportunity cost of a lengthy daily commute. Additionally, there exist less tangible but nonetheless substantial costs when a worker commutes to a different region. These costs could arise from, for example, informational deficiencies, linguistic barriers or a regional cultural divide. They explain the difference between the expected commuting flows between regions based on purely economic and geographic factors, and observed commuting flows. Such 'missing interregional commuting' suggests an inefficient spatial allocation of labour, implying that welfare gains can be obtained from policies aimed at removing these barriers, for example by improving information exchange related to interregional job search, adjusting the regional skill structure, investing in language education, etc. This should be especially beneficial for countries with marked differences in regional labour market performance, as is the case for many European countries.

This chapter quantifies the effect of regional borders on commuting by means of a gravity framework and while doing so bridges the gap between the gravity traditions developed in the context of international trade on the one hand and spatial interaction modelling on the other. Our gravity equation is derived from a small spatial labour market model inspired by J. Anderson & Van Wincoop (2003), in which firms characterised by a love-of-variety production function employ workers from different locations. In the spatial interaction literature, gravity equations have mostly been set up without micro-foundations and have rather relied on analogies from statistical mechanics (see A. Wilson, 2010, for a review) or on discrete choice theory (Anas, 1983; Fotheringham, 1986). The development of gravity equations in the context of international trade has taken a different route, relying on economic models where demand and/or supply are derived from optimising behaviour of economic agents and the gravity equation describes the resulting market-clearing flow of goods. Applying the latter approach in a labour market setup results in a functional form for the gravity equation which is remarkably similar to the functional form of the doubly constrained specification often used in spatial interaction modelling, but nevertheless differs from it in some important aspects. Measures of fit suggest that our approach improves commuting flow predictions. We also argue that it enables us to more accurately identify the border effect by taking into account economic push and pull factors.

The commuting gravity equation is empirically estimated by means of a count model. Count models allow for zero as a possible outcome and avoid the biases introduced by estimating log-linearised models in the presence of heteroskedasticity (Silva & Tenreyro, 2006). The empirical application uses aggregate data on commuting flows between 580 Belgian municipalities[1] in 2008. Belgium is

[1] Nine municipalities belonging to the small German speaking community of Belgium were excluded from the analysis. This leaves 580 out of a total of 589 Belgian municipalities in the sample. Including the German community in the sample and estimating a separate border effect for this group would increase our number of directional border effects from 9 to 16. At the same time, these additional border effects would be difficult to estimate given the

an interesting case for the study at hand for a number of reasons:

Regional borders are important in Belgium. Belgium is a multilingual country, consisting of three NUTS1 regions; Flanders in the north, and Wallonia in the south are officially unilingually Dutch and French speaking regions, respectively. The central capital region of Brussels is officially bilingual, but de facto a majority of the local population speaks French (Janssens, 2008). Nevertheless, many jobs in Brussels require knowledge of both French and Dutch. Belgium is a federal state, with regional governments in each of the three NUTS1 regions. Successive reforms of the Belgian state resulted in an increasing degree of independence for the regions, for example with regards to active labour market policy. The socio-cultural divide between the regions is large. With the exception of the capital region of Brussels, there exist no cross-regional political parties which are represented in the national parliament. None of the dominant newspapers and television chains target-audience comprises all three regions.

The three Belgian regions are also characterized by strong and persistent differences in economic performance. The capital region of Brussels is unmistakably the centre of Belgian economic activity, hosting 17 percent of total Belgian payroll employment. Despite being Belgium's most important economic hub, the Brussels unemployment rate is the highest in the country. This can also be seen in Figure 1.1, which shows unemployment rates for 2008 at the municipal level and illustrates the stark contrast between the labour market performance of Brussels, where unemployment reached 16 percent, and Flanders, where unemployment was only 3.9 percent. At 10.1 percent, the Walloon unemployment rate was also significantly higher than in Flanders. These regional differences in labour market performance arose in the aftermath of the seventies oil-crises and the decline of traditional steel and coal industries, and have persisted ever since (Torfs, 2008).[2] It is noteworthy how the linguistic and regional borders

small number of municipalities, the small size of their labour markets and their remoteness from Flanders and Brussels . Moreover, these German municipalities do not constitute a legal geographical entity with the same level of competences as the Walloon, Flemish and Brussels regions.

[2] Remarkable is also that the exact location of the historically important coal basin in Wallonia can still be clearly recognised, running East-West and parallel to the language border, although

in Belgium can be clearly recognized on this map of municipal unemployment rates. Municipalities in Brussels and Wallonia have consistently higher unemployment rates compared to their Flemish counterparts located just a few kilometres away.

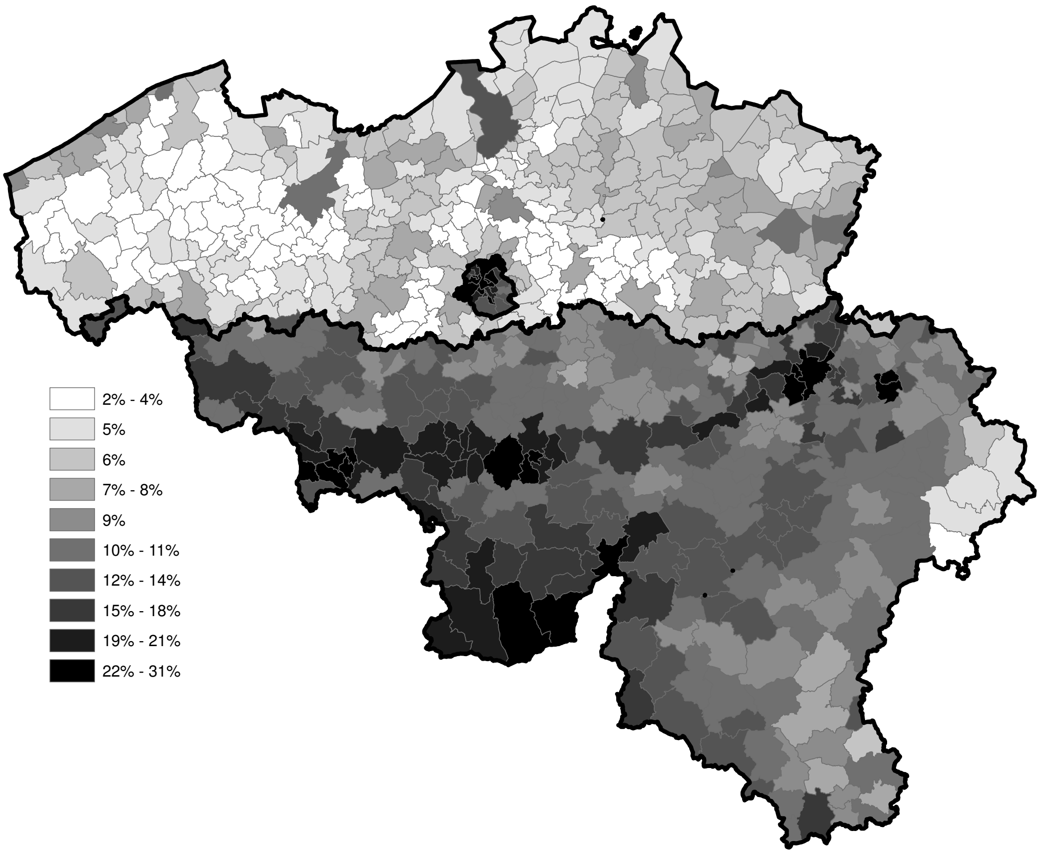


Figure 1.1: Unemployment rates for Belgian municipalities in 2008

Figure 1.2 uncovers the salient spatial patterns of commuting flows in Belgium, aggregating flows at the district level.[3] Only inter-district flows containing more than 3000 workers are shown and larger commuting flows are represented by thicker lines. Also here, the role of the central capital region of Brussels as the nation's most important employment centre becomes clear from the web of commuting lines surrounding it. The northern city of Antwerp and the western

the last mine in this area closed in 1984.

[3]A district or 'arrondissement' is the second smallest level of administrative regions in Belgium of which there are 43 in total.

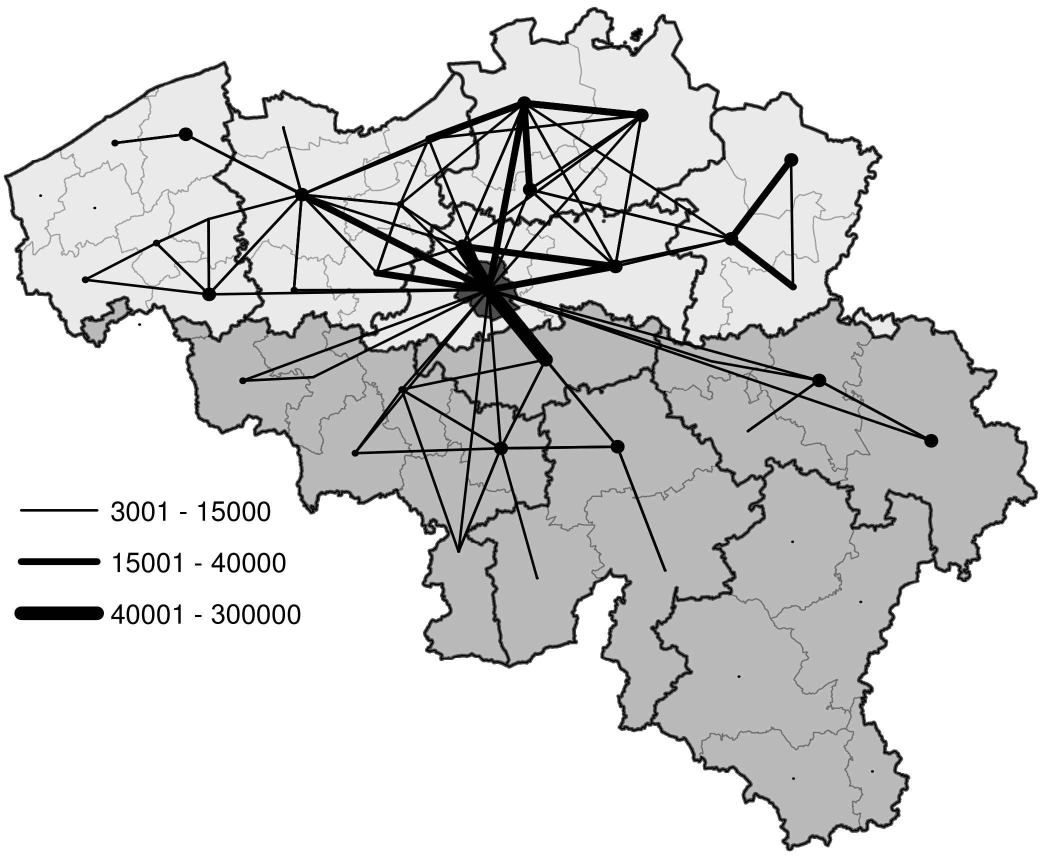


Figure 1.2: The main commuting flows in Belgium

city of Ghent play an important role for the northern region of Flanders. In the southern region of Wallonia, most commuting takes place between and around the cities of the axis Mons-Charleroi-Liège. Notably, there is not one district-level commuting flow running between the northern region of Flanders and the southern region of Wallonia that contains more than 3000 workers. If one considers pairs of municipalities at a distance between 10 and 30 km, there are on average 7.5 times less commuters between a pair of municipalities separated by the Flemish-Walloon regional border, as compared to pairs of municipalities at similar distances, but within both regions. These findings are striking since there are no legal or administrative barriers to labour mobility across regions whatsoever.

The gravity model developed in this chapter provides a framework to analyse the determinants of the spatial structure of commuter flows that is illustrated in Figure 1.2. After controlling for factors such as the geographic distribution of workers and jobs, and the travel time by public transport and by car, it is found that regional borders remain a significant hurdle to commuting. Our findings are in line with Falck et al. (2012), who use data on historic language differences between German dialects as a proxy for contemporary cultural differences and find that these form a hurdle to migration flows. This deterrent effect of regional borders on labour mobility offers a possible explanation for the lack of correlation in regional labour market outcomes across borders as observed by Fuchs-Schündeln & Bartz (2012). Given the large disparities in local labour market performance, our results therefore suggest that a lot can be gained from policies that reduce the deterrent effects of regional borders on labour mobility, such as improving language education or promoting cross-border cultural exchange.

1.2 A micro-founded gravity equation for commuting

1.2.1 Deriving a micro-founded gravity equation for commuting

Our derivation of a gravity equation for commuting builds on J. Anderson & Van Wincoop (2003), who derive a gravity equation for international trade flows. The labour supply of a locality is assumed to be fixed and workers are residentially immobile. Commuting is the only form of labour mobility available to workers. For the sake of simplicity, assume that each locality hosts a single firm. The firm operating in locality d produces output Y_d using a CES technology with labour differentiated by locality as the sole input.

The assumption that labour is differentiated across localities seems strong. We argue that, apart from offering a convenient functional form, this assumption captures some essential spatial features of the labour market. Labour market agents come in all shapes and forms and not all varieties fit well together: a worker's skill set can differ from an employer's educational requirements, a worker's career prospects can differ from those on offer or a worker's personality might simply not fit a firm's corporate culture. Preferably, workers and employers in search for a perfect partner would want to avoid having to bear large commuting costs and therefore will search for a suitable match nearby. But in very heterogeneous labour markets, the chances of finding the right match locally are slim. Firms and workers could wait until random shocks free up a suitable partner nearby, but will often find that the opportunity costs of waiting outweighs the commuting cost of matching with a partner at more distant locations. If matches are broken randomly over time and tangible or intangible costs to moving residence are high, we would end up in a situation where firms source workers from different localities, which is captured by our model. The value of remote workers might simply lie in their availability at the time of the vacancy posting. A similar dynamic matching process is described by Hausmann et al. (2013), where firms that locate in a region in which they are an industry pioneer face uncertainty about the relevant characteristics of the local workforce. They consequently choose to hire non-local workers that possess the required industry experience. Their empirical findings suggest that these firms do form some suboptimal matches with local workers, but expand their geographic recruiting distance for key-workers. This is analogous with the spatial commuting pattern generated by our model. Rosen (1978) and Dupuy (2012) discuss in greater detail some formal derivations of aggregate CES production function using microfoundations that rely on worker and job heterogeneity and matching.

More formally, write C_{od} for the amount of labour from locality o used by the firm in locality d. The production function is given by

$$Y_d = \left(\sum_{o=1}^{R} (A_o C_{od})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

where the parameter A_o reflects differences in the productivity of the local workforce. The parameter $\sigma > 1$ is the elasticity of substitution between workers from different localities.

A firm from locality d which minimizes costs conditional on some exogenous output level has the following demand for locality o's labour:

$$C_{od} = w_{od}^{-\sigma} \left(\frac{1}{A_o \Omega_d} \right)^{1-\sigma} \sum_{o=1}^{R} w_{od} C_{od}, \tag{1.1}$$

where w_{od} is the wage earned by workers commuting from o to d, and

$$\Omega_d = \left(\sum_{o=1}^{R} \left(\frac{w_{od}}{A_o} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{1.2}$$

is the wage index faced by firms in d. We will write $B_d \equiv \sum_{o=1}^{R} w_{od} C_{od}$ for firm d's total wage bill.

Commuting is costly, and hence a spatial equilibrium where all workers are indifferent to their location of work requires the firm in d to pay a higher wage w_{od} to commuting workers from o, compared to the wage w_o these workers would earn locally. We assume that commuting costs are a fixed proportion of wages and write $\tau_{od} - 1 > 0$ for the commuting cost between o and d as a fraction of w_o. A spatial equilibrium then requires $w_{od} = w_o \tau_{od}$. Note that τ_{od} can be interpreted as an implicit wasteful ad-valorem tax on commuting. This functional form implies that commuting costs do not contain a fixed component. This formulation simplifies the analysis significantly[4].

Next, write E_o for the total earnings of all workers living in locality o

$$E_o \equiv \sum_{d=1}^{R} w_{od} C_{od}. \tag{1.3}$$

Substituting equation (1.1) into (1.3) and using $w_{od} = w_o \tau_{od}$ allows to write

[4]As I illustrated in the introduction of this dissertation, opportunity costs are a non-negligible part of total commuting costs.

local wages w_o as:

$$\left(\frac{w_o}{A_o}\right)^{1-\sigma} = \frac{E_o}{\sum_{d=1}^{R}\left(\frac{\tau_{od}}{\Omega_d}\right)^{(1-\sigma)} W_d}. \tag{1.4}$$

This in turn can be substituted into equation (1.1) to get:

$$w_{od}C_{od} = \frac{E_o}{\sum_{d=1}^{R}\left(\frac{\tau_{od}}{\Omega_d}\right)^{(1-\sigma)} W_d}\left(\frac{\tau_{od}}{\Omega_d}\right)^{1-\sigma} W_d, \tag{1.5}$$

Next, define Y^T as the total wage bill paid (and earned) in the economy, and define $b_d = W_d/Y^T$ and $e_o = E_o/Y^T$, which are the shares of d's wagebill and o's earnings, respectively, such that equation (1.5) becomes:

$$w_{od}C_{od} = \frac{E_o W_d}{Y^T}\left(\frac{\tau_{od}}{\Pi_o \Omega_d}\right)^{1-\sigma}, \tag{1.6}$$

with

$$\Pi'_o \equiv \Pi_o^{(1-\sigma)} = \left(\sum_{d=1}^{R}\left(\frac{\tau_{od}}{\Omega_d}\right)^{(1-\sigma)} b_d\right). \tag{1.7}$$

After substituting the expression for $(A_o/w_o)^{(1-\sigma)}$ from equation (1.4) into equation (1.2), Ω_d can be written as:

$$\Omega'_d \equiv \Omega_d^{(1-\sigma)} = \left(\sum_{o=1}^{R}\left(\frac{\tau_{od}}{\Pi_o}\right)^{(1-\sigma)} e_o\right) \tag{1.8}$$

Equations (1.6) to (1.8) are the labour market equivalents of the J. Anderson & Van Wincoop (2003) gravity model for trade flows. To express commuter flows in quantities, rather than monetary flows as customary in the international trade literature, we rewrite equation (1.6) in terms of number of workers, by using the fact that $w_{od} = w_o\tau_{od}$ and therefore $E_o = \sum_{d=1}^{R} w_{od}C_{od} = w_o \sum_{d=1}^{R} \tau_{od}C_{od}$:

$$C_{od} = \frac{\overline{E}_o W_d}{Y^T}\tau_{od}^{-\sigma}\left(\frac{1}{\Pi'_o \Omega'_d}\right) \tag{1.9}$$

where $\overline{E}_o = \sum_{d=1}^{R} \tau_{od} C_{od}$ is the new adjusted mass variable for the locality of origin.

Equation (1.9) is our final gravity equation, derived from a spatial labour market model. Together with equations (1.7) and (1.8) it represents the system of equations describing commuting flows. The origin mass variable equals the sum of all bilateral commuter flows originating from that locality, weighing each flow by its bilateral commuting costs. The mass variable of the locality of destination is simply the total wage bill in that locality.

In line with J. Anderson & Van Wincoop (2003), the gravity equation contains an origin-specific term, Π'_o, and a destination specific term, Ω'_d. These terms are similar to the factors which J. Anderson & Van Wincoop (2003) label ‘multilateral resistance terms’ (or MR-terms) in the context of international trade and serve as control variable for the economic surroundings of the locality. Both depend on all bilateral commuting costs in the economy and on the distribution of economic activity around the origin and destination locality. Intuitively, the flow of commuters between o and d depends not only on the bilateral commuting costs and the economic variables of both municipalities, but also on their surroundings. The MR-terms thus contain all alternatives for workers in locality o or firms in locality d. Controlling for Ω'_d and Π'_o incorporates the entire spatial structure of the economy into the equation. As emphasized by J. Anderson & Van Wincoop (2003), ignoring the MR-terms leads to biased parameter estimates.

1.2.2 Trade literature versus Spatial interaction theory

Gravity equations have a long tradition in fields other than international trade theory, most notably in the field of spatial interaction modelling. Often, these gravity equations are not formally derived from underlying behavioural assumptions or theory. International trade has been an exception in this respect. J. E. Anderson (1979) provided the theoretical foundations that largely served as a basis for the development of gravity equations in the international trade literature. This evolution has occurred largely parallel to the developments taking place in spatial interaction modelling. However, there are some striking similarities between the relatively recent J. Anderson & Van Wincoop (2003) model and some older spatial interaction models, more precisely the Wilson doubly constrained model.

A naive gravity equation for commuting could start with the assumption that commuter flow F_{od} between an origin o and destination d can be modelled as a multiplicative function of (1) the number of workers in the origin o ($N_o = \sum_d F_{od}$), (2) the number of jobs in the destination d ($J_d = \sum_o F_{od}$), and (3) a factor (ϕ_{od}) reflecting the effect of distance, often an exponential or power function of geographical distance.

$$F_{od} = N_o J_d \phi_{od} \tag{1.10}$$

This specification suffers from two important problems. First, it only takes into account the characteristics of the origin and destination region and ignores the influence of third regions on the predicted flow between o and d. Second, doubling the mass variables would quadruple the predicted flows in the system.

The doubly constrained spatial interaction model provides one way of dealing with these concerns by adding two additional terms Q_o and R_d to the gravity equation. These terms constrain the model such that the predicted outflows $N_o = \sum_d F_{od}$ and inflows $J_d = \sum_o F_{od}$ in every locality remain constant. It is straightforward to show that the constraints hold when the gravity equation and the two balancing factors are defined as follows:

$$F_{od} = N_o J_d Q_o R_d \phi_{od}$$

$$\text{with} \quad Q_o = \left(\sum_d J_d R_d \phi_{od} \right)^{-1} \quad \text{and} \quad R_d = \left(\sum_o N_o Q_o \phi_{od} \right)^{-1}. \tag{1.11}$$

Although Q_o and R_d introduce the influence of third regions in the model in an intuitively appealing way, it remains debated whether these factors do this in a way which correctly reflects economic push and pull forces originating from third regions (see for example Fotheringham, 1983). In the end, their aim and construction is to uphold the constraints, and nothing more. This critique applies to our model and the trade-gravity literature as well. There exist interesting other approaches such as the model of Alonso (1978) in which the degree to which the flow totals are constant is flexible, with the models (1.10) and (1.11) as two extreme special cases. With some exceptions (such as Bröcker, 1989), the model of Alonso has largely been ignored in the trade-gravity literature. In a way this is remarkable as it seems realistic that total trade flows are not constant and would increase in response to trade liberalisation (which should be reflected in border effect estimates).

The doubly constrained gravity model can be derived from entropy maximisation (or information minimisation) as in A. G. Wilson (1967). Anas (1983) provides a link between this doubly constrained gravity equation and a discrete choice framework. We will refer to this model as Wilson's doubly constrained gravity equation A. G. Wilson (1967). Even though J. Anderson & Van Wincoop (2003) do not explicitly refer to their model as being constrained, they (and we) implicitly incorporate both a supply and a demand side constraint. A fundamental difference is that in our model the constraints pertain to monetary aggregates, contrary to Wilson's model, whose constraints pertain to aggregate commuter flows. On the supply side, instead of constraining the total number of outgoing commuters (the number of resident workers in a locality), we constrain the total workers' earnings in each locality to remain fixed. On the demand side, Wilson's model constrains the total number of incoming commuters (number of jobs), whereas we constrain our model such that the outgoing wage payments in each locality (the total wagebill) always equals their initially observed value. These monetary constraints enter our model naturally through the derivation of the labour demand framework by substituting for the local wage levels, w_o, so that our gravity equation captures differences in the local average productivity level of workers, A_o. Our approach highlights that constraints don't need pertain to the unit of the dependent variable: despite the fact that we consider commuter flows, from an economic perspective, it seems intuitive to keep the total costs (wagebill) of the firm in any destination region fixed when considering changes in commuting costs, rather than the number of in-commuters.

The predictive ability of commuting models is traditionally judged on their ability to replicate the trip distribution matrix with measures such as the root mean squared error (RMSE) (see Knudsen & Fotheringham, 1986). Although the focus of Wilson's doubly-constrained model is on commuting flows and imposes constraints in the unit of the dependent variable (total inflow and outflow of workers), we show that the RMSE and the Akaike Information Criterion (AIC) of our model is actually smaller. This confirms our prior intuition that the monetary constraints are a sensible choice in this context. In addition to a superior model fit, monetary constraints are more appropriate to control for the role of wages as a spatial equilibrating mechanism between local labour markets as they take into account how firms value different workers and how local labour productivity differences affect the spatial commuting patterns. Failing to control for the local wage level can lead to biased estimates of the border effect if spatial productivity is not randomly distributed with respect to the border location.

1.3 Estimation strategy

A log-linearized version of the gravity equation (1.9) could be estimated by OLS[5]. But as argued by Silva & Tenreyro (2006) this approach is problematic for two reasons: first, Jensen's inequality implies that, in the presence of heteroskedasticity, log-linear transformations will cause the error term to become correlated with the covariates.[6] Second, by log-transforming equation (1.9), all observations with a commuter flow equal to zero drop out of the analysis. This is the case for about 65 percent of all observations in our sample. This

[5]For an insightful discussion on the evolution of estimation techniques of gravity equations in the trade literature, see Burger et al. (2009).

[6]Flowerdew & Aitkin (1982) describe how the expected value of the logarithm of a random variable depends on its variance. So, in the presence of heteroskedasticity, where the variance of the error term depends on the covariates, its logarithm depends on the regressors, hence violating the consistency condition of OLS, leading to biased estimation. See also Silva & Tenreyro (2006).

type of censoring leads to sample selection bias. To overcome both problems, we treat commuter flows as count data. Count models explicitly allow for zero as a possible (and possibly likely) outcome and do not suffer from bias in the presence of heteroskedasticity. We use a negative binomial model which allows the variation of the count variable to exceed its mean (overdispersion).[7]

Assume that commuting costs are a log-linear function of geographical distance ($dist_{od}$) and a dummy capturing the effect of regional borders (B_{od}), such that

$$\tau_{od} = {dist_{od}}^{\alpha_1} e^{\alpha_2 B_{od}} \qquad \text{or} \qquad \ln \tau_{od} = \alpha_1 \ln dist_{od} + \alpha_2 B_{od}. \tag{1.12}$$

For within-locality commuting, the 'internal distance' $dist_{ii}$ is assumed to be directly proportional to the square root of the area of each municipality, and calculated according to the formula $dist_{ii} = (2/3)\sqrt{area_i/\pi}$, as in Head & Mayer (2000).

The stochastic negative binomial model for the gravity equation (1.9) is given by:

$$\begin{aligned} C_{od} &\sim Poisson(\exp(\eta_{od} + \nu_{od})) \\ e^{\nu_{od}} &\sim Gamma(1/\gamma, \gamma) \\ \eta_{od} &= -\ln Y^T + \ln \overline{E}_o + \ln W_d - \sigma\alpha_1 \ln dist_{od} - \sigma\alpha_2 B_{od} \\ &\quad + \ln \Pi'_o + \ln \Omega'_d \end{aligned} \tag{1.13}$$

where γ is the overdispersion parameter, $\overline{E}_o = \sum_{d=1}^{R} \tau_{od} C_{od}$ and $W_d = \sum_{o=1}^{R} w_{od} C_{od}$. The error term ν_{od} contains transitory shocks to bilateral commuting flows and is assumed to be uncorrelated with the regressors. Equation (1.13) is then estimated and solved subject to the set of non-linear constraints (1.8) and (1.7).

To solve this non-linear system of equations, we apply a nonlinear version of the Gauss-Seidel method.[8] Using some initial guess for the vector Π'_o and

[7] The critique of Bosquet & Boulhol (2010) on the use of the negative binomial model does not apply in this context as our dependent variable, the number of commuters, is scale independent.

[8] A similar method is also discussed in Head et al. (2013). For a more general description of nonlinear Gauss-Seidel methods, see Vrahatis et al. (2003)

the parameters α_1 and α_2 governing the commuting costs, we calculate a first approximation for Ω'_d. Using these values Ω'_d, we in turn calculate an improved guess for Π'_o. Iteration proceeds between updating Ω'_d and Π'_o for given α_1 and α_2 until convergence is achieved. Equation (1.13) is subsequently estimated using maximum likelihood, providing updated values for the commuting costs parameters α_1 and α_2, after which new values for Ω'_d and Π'_o are iteratively calculated. This entire process is repeated until α_1 and α_2 converge. Since σ cannot be identified without knowledge of the specific elements of τ_{od}, an assumption on σ is required to calculate the MR-terms. The analysis proceeds using $\sigma = 2$.[9] As the MR-terms are stochastic in nature, we use a bootstrap method to calculate standard errors on the coefficients in all tables using 200 replications.

The resulting coefficient on the border dummy $-\sigma\alpha_2$ does not correspond to the percentage change in commuting due to the presence of the border as in a standard regression. The ceteris-paribus condition is violated because other variables in the model change depending on the absence or presence of a border (see J. Anderson & Van Wincoop (2003) and Feenstra, 2004). Values for the MR-terms have to be recalculated to conduct comparative static analyses. As in J. Anderson & Van Wincoop (2003) we consider only the direct effect of varying the border effect on Π'_o and Ω'_d and ignore changes in the shares e_o and b_d as well as the mass variables.

Define the border effect X_{od} as the percentage difference between a commuter flow C_{od} between two localities o and d which are separated by a border ($B_{od} = 1$), and the commuter flow C^*_{od} under the hypothetical scenario in which the effect of a set of borders B_{ij} is set to zero. From equation (1.9) and (1.12) it follows that

$$X_{od} = \frac{C_{od} - C^*_{od}}{C^*_{od}} = \frac{(\Pi'_o \Omega'_d)}{(\Pi^*_o \Omega^*_d)} e^{-\sigma\alpha_2} - 1, \tag{1.14}$$

where Π^*_o and $\Omega^*{}_d$ are the recalculated multilateral resistance terms, setting

[9]Varying the value of σ to other (extreme) values of sigma reported in the relevant literature, leaves the results qualitatively unaltered. We refer to section 1.4.2 for a discussion of the sensitivity of the border effect to the chosen value of σ.

some $B_{ij} = 0$. Obviously, the border effect X_{od} is only defined for localities that are separated by a border.

The fact that some of the explanatory variables in our estimation equation are not deterministic implies that the regular standard errors of the coefficients may be downward biased. All reported standard errors are therefore bootstrapped using 200 replications, including those of derived statistics such as the border effects reported in section 1.4.

1.4 The effect of regional borders on commuting

1.4.1 Data description

Highly disaggregated data on the number of daily commuters between 580 Belgian municipalities[10] was obtained from the Belgian National Social Security Office (NSSO) for the year 2008. This administrative source covers the total Belgian population of payroll employment, but excludes the self-employed. Seventy-six percent of the Belgian payroll workers work in a different municipality than the one they live in. Sixteen percent of them work in a different NUTS1 region. Our unit of analysis is the number of commuters between pairs of municipalities. Including within-municipality commuting flows, our dataset consists of 336 400 datapoints (containing 3 274 709 workers). Of these pairs 217 721 or about 65 percent do not have any commuting between them. The largest (great-circle) distance one can travel (280km) within Belgium's boundaries is between the sea-side municipality of Koksijde and Aubange, a municipality near the Luxembourgh border. The non-zero commuter flow covering

[10]Nine municipalities belonging to the small German speaking community of Belgium were excluded from the analysis. This leaves 580 out of a total of 589 Belgian municipalities in the sample. Estimating a separate border effect for this group would increase our number of directional border effects from 9 to 16. At the same time, these additional border effects would be exceedingly difficult to estimate given the small number of municipalities, the small size of their labour markets and their remoteness from Flanders and Brussels. Moreover, these German municipalities do not constitute a legal geographical entity with the same level of competences as the Walloon, Flemish and Brussels regions.

the largest great-circle distance runs between the municipalities of Koksijde and Waimes, located 247km away from each other. Arguably, the relatively small difference between the furthest non-zero commuter flow and the maximum commutable distance implies that all our municipality pairs in the sample are within a commutable distance from one another. The vast majority of commutes takes place within much smaller distances: in our sample, the median commuter bridges 9.3km and the average distance commuted is 21.3km. Seventy-five percent of all commutes take place within 24km.

To analyze commuter flows, travel time is likely to be more relevant to commuters than simple great-circle distance, since it controls for factors such as the quality of transport infrastructure. The analysis includes three different measures of inter-municipality distance. A first proxy is the geographical distance (dist_{od}) between the town halls of both municipalities. Additionally, we consider travel time by car (car_{od}), obtained through the Google Maps API, and travel time by public transport (pubtrans_{od}), obtained from the website of the main Belgian train operator, NMBS.[11]

A substantial part (782 927 workers or 23.9 percent) of Belgian commutes takes place within municipality borders. We proxy intra-municipality travel times using the following methodology: first, a log-log specification is used to regress travel time on distance using data on short-distance *inter*municipality commuting. This provides an estimate for the relationship between travel time and distance. Using this relationship, the within-municipality travel times were then predicted, starting from the internal distance measure $\text{dist}_{ii} = (2/3)\sqrt{\text{area}_i/\pi}$. The resulting average within-municipality commuting distance is 2.52km, with an associated average commuting time of 17.8 minutes by public transportation or 6.9 minutes by car. Our results do not change much when we use other proxies for internal distance and travel time or simply exclude within-municipality commuting from the analysis altogether.

The data also contains the average wage paid by the firms in a municipality. We

[11] Public transport times refers to the shortest travel time to get to the destination at 8.30am on a Tuesday morning, combining all forms of public transport such as train, bus and underground. The data on travel times reflect the situation in June 2011.

use it to calculate the total wage bill in each municipality, which serves as the mass variable of destination. The origin mass variable, in contrast, has to be calculated iteratively in the estimation procedure as described in section 1.3.

1.4.2 Estimation results, base specification

This section proceeds with the estimation of the gravity equation represented by equation (1.13). All the empirical specifications include an origin-specific constant term for each of the three regions. This is equivalent to assuming the commuting cost vector contains a region-of-origin specific component. An alternative interpretation follows from the perspective of defining the desired control group, since a separate constant term for each region controls for regional differences in the average size of outgoing inter-municipality commuting flows. By including origin-specific constant terms, we evaluate the size of cross-border commuting flows by comparing them to commuting flows within the same region-of-origin.

We first estimate the border effect using one single dummy variable that indicates whether the commuter flow between two municipality pairs crosses one of the regional borders between Brussels, Flanders and Wallonia. This implies that Table 1.1 assumes commuting costs to be symmetric for all border crossing. Which border is crossed, or the direction wherein, is not taken into account. This symmetry assumption will be relaxed later on. The border effects are reported in the lower half of Table 1.1. They are calculated using the comparative static formula (equation (1.14)), which compares the cross-border flows with all borders intact, relative to the hypothetical cross border flows, where a single border effect is set to zero ($B_{od} = 0$) in Π_o^* and Ω_d^*. The border effects in Table 1.1 differ between border crossings only because of differences in the counterfactual MR-terms. Column (1) of Table 1.1 shows the result of estimating a specification which corresponds to model (1.13), except for the fact that the coefficients on the variables are not constrained to their theoretical values. Proxies for commuting costs are the geographic distance between the

	(1)	(2)	(3)
$\ln \overline{E}_o$	1.022***	1.021***	1
	(0.0267)	(0.0174)	
$\ln W_d$	1.138***	1.075***	1
	(0.0192)	(0.0194)	
$\ln dist_{od}$	−1.951***		
	(0.0280)		
$\ln car_{od}$		−2.663***	−2.555***
		(0.0989)	(0.117)
$\ln pubtrans_{od}$		−0.530***	−0.679***
		(0.107)	(0.132)
B_{od}	−0.941***	−0.547***	−0.432***
	(0.0631)	(0.0477)	(0.0412)
$\ln \Pi'_o$	−0.856***	−0.898***	−1
	(0.0625)	(0.0367)	
$\ln \Omega'_d$	−1.174***	−1.150***	−1
	(0.204)	(0.133)	
Border effects, X_{od}			
$X_{od}(o \in FL, d \in WL)$	−0.486***	−0.326***	−0.300***
	(0.0238)	(0.0232)	(0.0247)
$X_{od}(o \in FL, d \in BR)$	−0.456***	−0.301***	−0.278***
	(0.0192)	(0.0221)	(0.0233)
$X_{od}(o \in WL, d \in FL)$	−0.481***	−0.321***	−0.296***
	(0.0278)	(0.0260)	(0.0268)
$X_{od}(o \in WL, d \in BR)$	−0.518***	−0.349***	−0.323***
	(0.0183)	(0.0235)	(0.0250)
$X_{od}(o \in BR, d \in FL)$	−0.559***	−0.371***	−0.343***
	(0.0347)	(0.0312)	(0.0321)
$X_{od}(o \in BR, d \in WL)$	−0.588***	−0.401***	−0.371***
	(0.0263)	(0.0267)	(0.0288)
Measures of fit			
RMSE	2474	1434	1023
AIC	2.437	2.346	2.359
N	336400	336400	336400

Bootstrapped standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.1: Estimating the gravity equation for commuting, with a single border-crossing dummy B_{od} indicating any inter-regional border crossing. Column 1 controls for the simple distance measure. Column 2 controls for the two commuting time measures. Column 3 restricts the coefficients on the mass variables and MR-terms to 1 and -1, respectively. The border specific estimates are calculated using the comparative static formula (1.14). The notation $X_{od}(o \in XX, d \in YY)_{od}$ indicates the effect of the existence of the regional border between region XX and YY on commuting between them. Note that the border effects differ between border crossings only because of discrepancies in the MR-terms.

H_o	Chi^2	p-value
$\beta_{\overline{E}_o} = 1$	0.08	0.7716
$\beta_{W_d} = 1$	12.53	0.0004
$\beta_{\Pi'_o} = -1$	6.22	0.0126
$\beta_{\Omega'_d} = -1$	0.90	0.3421

Table 1.2: Results of 4 separate t-tests on the coefficient restrictions imposed by the theory, for the estimation results of column 2 in Table 1.1.

town halls of both municipalities, $\ln dist_{od}$ and the border dummy, B_{od}. The coefficients on the mass variables are estimated close to unity, as predicted by theory. The coefficients on the MR terms deviate somewhat further from their predicted value of -1, but are still within a reasonable range. The effect of distance is clearly negative, as expected. The large and negative coefficient on B_{od} shows that, after controlling for distance and the mass and multilateral resistance of the origin and destination, regional borders act as a barrier to commuters.

Column (2) replaces the simple distance measure by two distance variables which are more relevant to commuters, travel time by car (car_{od}) and public transport ($pubtrans_{od}$). Both variables are included in logs. The time it takes to commute between two municipalities by car is clearly the most important determinant of the two. A 10 percent increase in travel time by car, reduces the commuter flow by 27 percent, whereas for travel time by public transport, this is only 5.3 percent. Comparing the results in column (1) to column (2) reveals that after controlling for the two alternative distance measures, the absolute value of the coefficient on the border dummy decreases. This means that part of the regional border effect captured in column (1) can actually be explained by poor interregional transport infrastructure connecting municipalities across regional borders. In addition, the drop in the associated RMSE shows that the model's fit improves. To make the estimation fully consistent with theory, the coefficient on the mass variables and MR terms should be equal to 1 and -1, respectively. Table 1.2 shows the result of separate t-tests on the four coefficients estimated in column (2) of Table 1.1. It cannot be rejected that the coefficients on the origin's mass variable and the destination's MR-term equal their theoretically consistent values. For the other two coefficients, however, this hypothesis is rejected. This is not entirely surprising, given the large sample size. As a robustness check, we solved the model imposing all four restrictions (column (3) of Table 1.1). The results remain qualitatively unchanged with a reduction in the estimate of the coefficient on the border dummy from -0.547 to -0.432.

As in J. Anderson & Van Wincoop (2003), we need to assume a value for the elasticity of substitution σ to solve our model. The results in Table 1.1 assume an elasticity of substitution equal to 2. Whether this is a reasonable assumption depends on the nature of the mechanism that is driving the firms' spatial love-of-variety. To the extent that the spatial substitution pattern of workers is driven by differences in the average skill mix of municipalities, a well-chosen value of σ should reflect the degree of substitutability between worker groups with a different educational background. In this context, the relevant literature reports values ranging from 1.1 to as much as 7.5 (see Card & Lemieux, 2001, in the context of educational groups). Firms' love of variety, as argued in section 1.2, could also be driven by the intertemporal dynamics of the labour market, in combination with heterogeneous workers characteristics/vacancy requirements. In this context, we know of no studies that provide estimates of σ. A sensitivity analysis (based on the unrestricted specification, reported in column (2) of Table 1.1) shows that our main conclusions hold, regardless of the value of σ.[12] Solving the model with $\sigma = 1.1$, the lowest value reported by Card & Lemieux (2001) results in a border coefficient of -0.534, only marginally lower than -0.547. Increasing the elasticity of substitution to $\sigma = 7.5$, results in a border coefficient of -0.787. That the cost of the border increases as the spatial substitutability of workers increases (ceteris paribus) is expected. We continue our analysis with a value of 2, a value in the lower range of elasticities reported in the literature, which provides a conservative estimate of the border effect.

[12]This is in line with the findings of J. Anderson & Van Wincoop (2003).

	(1)	(2)
$\ln N_o$	1.001***	1
	(0.0260)	
$\ln J_d$	1.003***	1
	(0.0151)	
$\ln car_{od}$	−2.465***	−2.438***
	(0.0916)	(0.124)
$\ln pubtrans_{od}$	−0.559***	−0.732***
	(0.102)	(0.135)
B_{od}	−0.802***	−0.827***
	(0.0532)	(0.0677)
$\ln Q_o$	0.659***	1
	(0.0394)	
$\ln O_d$	0.705***	1
	(0.0632)	
Measures of fit		
RMSE	1720	3346
AIC	2.365	2.426
N	336400	336400

Bootstrapped standard errors * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.3: Wilson's doubly-constrained model described by equation (1.11). Column 1: unrestricted estimation. Column 2: restricted estimation. The variables Q_o and R_d are the 'balancing factors', which correspond to J. Anderson & Van Wincoop (2003)'s multilateral resistance terms Π_o' and Ω_d'.

1.4.3 Estimation results, comparison with doubly-constrained model

Table 1.3 shows the results when estimating the classic doubly-constrained model from equation (1.11). The specification is similar to the model presented by equation (1.13), but instead of constraining the destination's wagebill and the origin's total earning to their observed values, the total number of jobs and total number of workers are constrained, respectively. Table 1.3 reports both the unrestricted (column 1) and the restricted (column 2) version of the model. Comparing the unrestricted models (column (2) Table 1.1 vs column (1) Table

1.3) reveals that the results are quite similar, apart from the coefficient on the border dummy whose absolute value is estimated at 0.802, substantially higher in Wilson's double-restricted model. As argued before, this could be caused by failing to control for the role of wages in the gravity equation: if productivity is not randomly distributed with respect to the location of regional borders, this could lead to biased estimation of the border effect. Tables 1.1 and 1.3 also report the RMSE and the AIC to assess the fit of the models. The RMSE reported for the restricted Wilson model (3346) is higher than the one for the restricted specification in column (3) of Table 1.1 (1023), which suggests that the CES-based model is better at predicting the observed commuting flows. This conclusion carries over to the unrestricted models (column (3) of Table 1.1 versus column (2) of Table 1.3). Also using the AIC, the specifications in Table 1.1 are preferred over the classic doubly constrained model, although the difference is only minor between the unrestricted models.

1.4.4 Estimation results, relaxing assumptions on commuting costs

Gravity equations (1), (2) and (3) in Table 1.1 are similar to those commonly used in the context of international trade. We will now alter these specifications to better match the specific features of a typical labour market.

Previously, the border effect was assumed to be homogeneous: it was equal for all regional borders and independent from the direction in which those borders were crossed. This assumption is untenable in the context of interregional commuting. As an example, regional asymmetries in the knowledge of the country's other official language would lead to asymmetries in the effect of the different border crossings. We therefore replace the single border dummy with 6 border indicators, one for each of the possible border crossings between the three NUTS-1 level regions in Belgium. There might also be omitted region-specific factors which affect commuting behaviour, such as regional culture, policy, or differential preferences of commuters regarding modes of transportation.

Failing to control for such factors will lead the coefficients on the directional border crossing dummies to be biased as they will pick up this region-specific distance-decay heterogeneity (see also Melo et al., 2011; Fotheringham, 1983, for further discussion on spatial variation in the distance decay parameter). We therefore introduce a second element of heterogeneity in the commuting cost vector and allow the effect of travel time by car and train to differ between regions. Table 1.4 presents the estimation results.

Column (1) again shows a specification where the coefficients on the mass and MR variables are not constrained to their theoretically consistent value. Colum (2) imposes these restrictions. All six border effects remain qualitatively unchanged after imposing the restrictions. The results of the formal tests of these restrictions are reported in table 1.5 and are similar to our findings in table 1.2.

The bottom part of Table 1.4 reports the comparative statics (using equation 1.14). As before, we hypothetically remove each individual border separately. The result reported for the Brussels-Flanders border crossing therefore corresponds to the percentage change in commuting across the Brussels-Flanders border in the case where only this specific border would be eliminated, but all other borders would still be intact. As expected, allowing for differential coefficients on the respective border crossings increases the discrepancies between the border effects substantially.

The results reveal that the averages reported in Table 1.1 were masking the presence of both negative and positive border effects. Three of the border crossings turn out to have a positive effect on interregional commuter flows, but only the flows with destination Brussels are significantly different from zero. Instead of being deterred, the commuters are actually attracted by the Brussels Capital region. This positive border effect is likely to be caused by the special capital status of the Brussels region. Since it is the public administrative centre of Belgium, Brussels hosts a great deal of Belgian public employment: not only the federal administrative institutions are located there, but also the Flemish public administration is headquartered on Brussels territory. Arguably, there

	(1)	(2)
$\ln \overline{E}_o$	1.024^{***}	1
	(0.0152)	
$\ln W_d$	1.037^{***}	1
	(0.0158)	
$\ln car_{od} \times I(o \in BR)$	-2.296^{***}	-2.196^{***}
	(0.179)	(0.197)
$\ln car_{od} \times I(o \in FL)$	-2.799^{***}	-2.746^{***}
	(0.103)	(0.115)
$\ln car_{od} \times I(o \in WL)$	-2.542^{***}	-2.464^{***}
	(0.0826)	(0.0895)
$\ln pubtrans_{od} \times I(o \in BR)$	-0.471^{*}	-0.561^{*}
	(0.220)	(0.240)
$\ln pubtrans_{od} \times I(o \in FL)$	-0.375^{***}	-0.436^{***}
	(0.104)	(0.114)
$\ln pubtrans_{od} \times I(o \in WL)$	-0.523^{***}	-0.627^{***}
	(0.0824)	(0.0909)
$\ln \Pi'_o$	-0.847^{***}	-1
	(0.0287)	
$\ln \Omega'_d$	-1.107^{***}	-1
	(0.0890)	
Estimates of the coefficients on the border dummies , B_{od}		
$B_{od}(o \in FL, d \in WL)$	-0.472^{***}	-0.462^{***}
	(0.124)	(0.110)
$B_{od}(o \in FL, d \in BR)$	0.306^{*}	0.283^{**}
	(0.133)	(0.0910)
$B_{od}(o \in WL, d \in FL)$	-1.082^{***}	-1.035^{***}
	(0.109)	(0.0950)
$B_{od}(o \in WL, d \in BR)$	0.319^{*}	0.304^{**}
	(0.155)	(0.102)
$B_{od}(o \in BR, d \in FL)$	-0.640^{*}	-0.621^{*}
	(0.274)	(0.264)
$B_{od}(o \in BR, d \in WL)$	0.245	0.238
	(0.273)	(0.247)
Border effects, X_{od}		
$X_{od}(o \in FL, d \in WL)$	-0.294^{***}	-0.289^{***}
	(0.0637)	(0.0577)
$X_{od}(o \in FL, d \in BR)$	0.229^{*}	0.210^{**}
	(0.108)	(0.0740)
$X_{od}(o \in WL, d \in FL)$	-0.540^{***}	-0.524^{***}
	(0.0336)	(0.0322)
$X_{od}(o \in WL, d \in BR)$	0.283	0.268^{**}
	(0.156)	(0.102)
$X_{od}(o \in BR, d \in FL)$	-0.401^{**}	-0.392^{**}
	(0.145)	(0.140)
$X_{od}(o \in BR, d \in WL)$	0.245	0.238
	(0.360)	(0.318)
Measures of fit		
RMSE	574	458
AIC	2.320	2.320
N	336400	336400

Bootstrapped standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.4: Estimating the gravity equation for commuting, with a separate directional border-crossing dummy for each regional-border crossing. Column 1: unrestricted estimation. Column 2: restricted estimation. The dummy variables $B_{od}(o \in xx, d \in yy)$ indicate the respective directional interregional border crossings, where BR stands for Brussels, FL for Flanders and WL for Wallonia.

H_o	Chi^2	p-value
$\beta_{\overline{E}_o} = 1$	0.34	0.5585
$\beta_{W_d} = 1$	3.46	0.0628
$\beta_{\Pi'_o} = -1$	21.48	0.0000
$\beta_{\Omega'_d} = -1$	0.76	0.3827

Table 1.5: Results of the tests on the coefficient restrictions imposed by the theory. The tests are based on the results of column 2 (Table 1.4)

could also be a prestige premium attached to working (or running a business) in the capital region. In addition, the cultural divide between Brussels and the other two regions is less likely to be an obstacle for incoming commuter flows as its capital status and history causes the inhabitants of both regions to feel connected to Brussels. Linguistic differences are also less of a concern for this border crossing, since the bilingual status of Brussels implies both Dutch and French speakers have many opportunities on the Brussels labour market. This special role for Brussels in the Belgian interregional commuting flows was already visible in Figure 1.2. Another possible cause of this positive border effect would be a higher cost of living (including housing) in a city, forcing workers to relocate in neighbouring regions and commute. Unfortunately our current framework does not allow to consider residential choice. Although we believe omitted housing prices may be important in explaining the positive border effects towards Brussels, this is much less likely the case for the other border crossings.

The positive border effect (24.8 percent) of the Brussels-Wallonia border might appear to be contra-intuitive. Although the effect is insignificant, it suggests that the commuter flows running from Brussels to Wallonia is found to be larger than what would be expected based on observables such as distance or commuting time. A possible explanation is the peculiar geography of Brussels as a predominantly French-speaking enclave within Flanders territory with workers from Brussels, predominantly French-speaking, having difficulties accessing jobs requiring knowledge of Dutch in the surrounding Flemish municipalities.

The remaining three border are negative and were driving the negative homo-

	Brussels	Flanders	Wallonia
French	75%	95%	100%
Dutch	59%	100%	19%
French & Dutch	51%	57%	17%

Table 1.6: Language knowledge in Belgium (source: Ginsburgh & Weber, 2006)

geneous border effect. The border crossing from Wallonia to Flanders exerts the largest negative effect and reduces commuter flows by 53.5 percent. The reverse border crossing is somewhat smaller and amounts to -29.3 percent. Also the Brussels-Flanders border crossing reduces commuter flows, by 39.7 percent. Probable causes of these negative border effects are deficiencies in language knowledge, the extent of which differs between regions. Table 1.6 provides some insight into the language factor(see Ginsburgh & Weber, 2006). The data confirm indeed that the knowledge of the second country language may be driving the differential border effects. About 19 percent of Walloons consider themselves proficient Dutch speakers, whereas the percentage of Flemish who consider themselves proficient French speakers is 59 percent. Ironically, the survey reveals that the percentage of bilingual speakers is higher in Flanders than in the officially bilingual region of Brussels.

1.5 The effect of borders on wages

The local labor market equilibrium in our model depends on local supply and demand, surrounding supply and demand, as well as the spatial structure of commuting costs. The local equilibrium wage summarizes in one single value the relative attractiveness of a municipality. Equation (1.4) provides us with an explicit expression for the equilibrium wage in municipality o:

$$\frac{w_o}{A_o} = \left(\frac{E_o}{\sum_{d=1}^{R} \left(\frac{\tau_{od}}{\Omega_d} \right)^{(1-\sigma)} W_d} \right)^{\frac{1}{1-\sigma}}.$$

Through (1.4), we can graphically illustrate the equilibrium effect of borders. It should be stressed that since we only take into account direct changes in transport costs, our analysis is partial in nature. Consider a decrease in bilateral commuting costs between o and other localities. The improvement in o's accessibility will increase the demand for its labour, putting an upward pressure on the local wage w_o. This effect will be more pronounced if o is surrounded by municipalities with strong labour demand. We have shown how regional borders impose spatial rigidities, so removing them will change the spatial pattern of commuting costs. This will impact the spatial attractiveness of all locations and therefore alter the local equilibrium wage levels. From equation (1.4) follows straightforwardly that the change in the local equilibrium wage w_o can be written as:

$$\frac{w_o^* - w_o}{w_o} = \left(\frac{\sum_{d=1}^{R} \left(\frac{\tau_{od}^*}{\Omega_d^*} \right)^{(1-\sigma)} W_d}{\sum_{d=1}^{R} \left(\frac{\tau_{od}}{\Omega_d} \right)^{(1-\sigma)} W_d} \right)^{\frac{1}{\sigma-1}} - 1, \tag{1.15}$$

where τ_{od}^* represents the adjusted commuting cost vector where some border effects are eliminated.

Figure 1.3 plots the percentage increase in the equilibrium wages w_o under the hypothetical scenario in which borders would have no impact on commuting. It applies the estimation results of column (3) in table 1.5 to equation (1.15), with all the border effects in commuting cost vector τ^* set to zero. The pattern that emerges coincides with our prior expectations, and a number of interesting conclusions can be drawn. The results confirm the findings of table 1.5. The map shows significant regional heterogeneity in the impact on the local wage. The impact of removing the borders is felt strongest in the Walloon municipalities and ranges from 3 percent to as much as 33 percent. For Flanders, the average impact is much smaller: the estimated increase in w_o ranges from 0.4 percent to 7.2 percent for most municipalities. From a demand perspective, the elimination of the borders will increase wages in all regions, as decreasing costs raises demand for cross border workers. Since the WL⇒FL border effect was stronger than the FL⇒WL border effect, this increase will be more pronounced

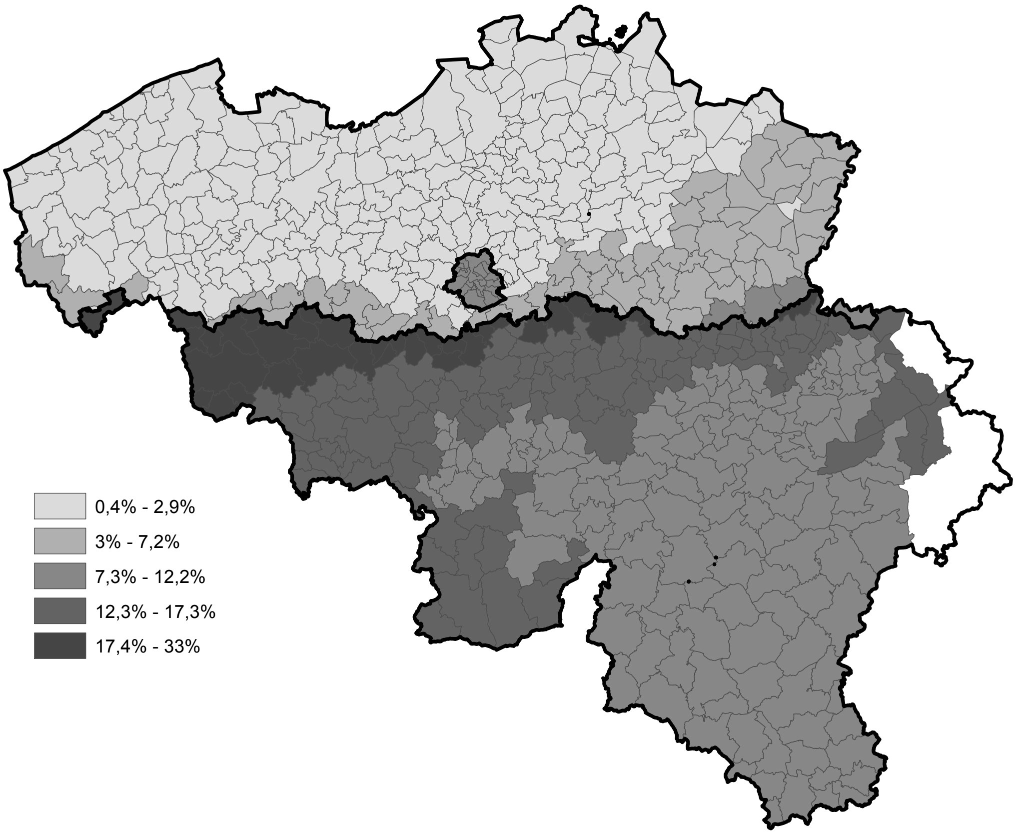
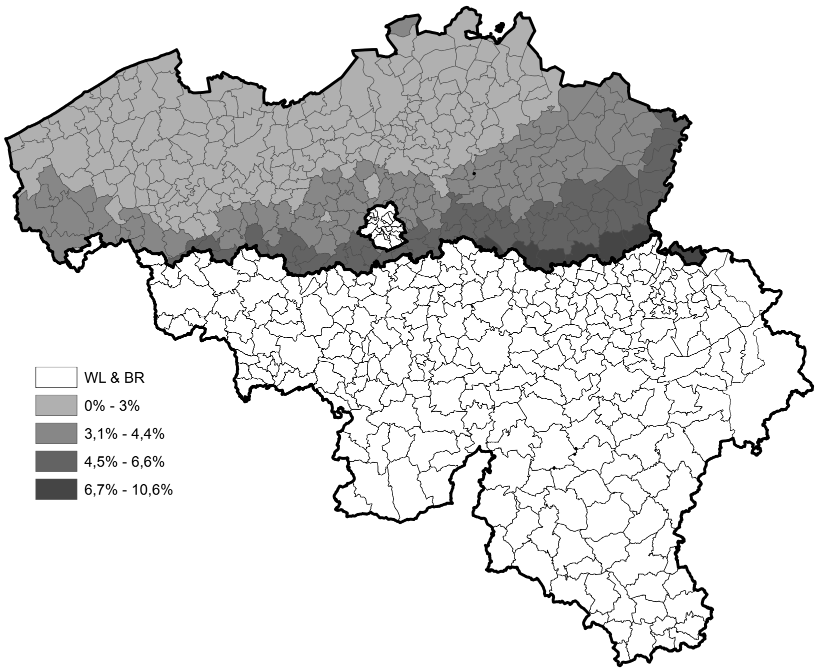


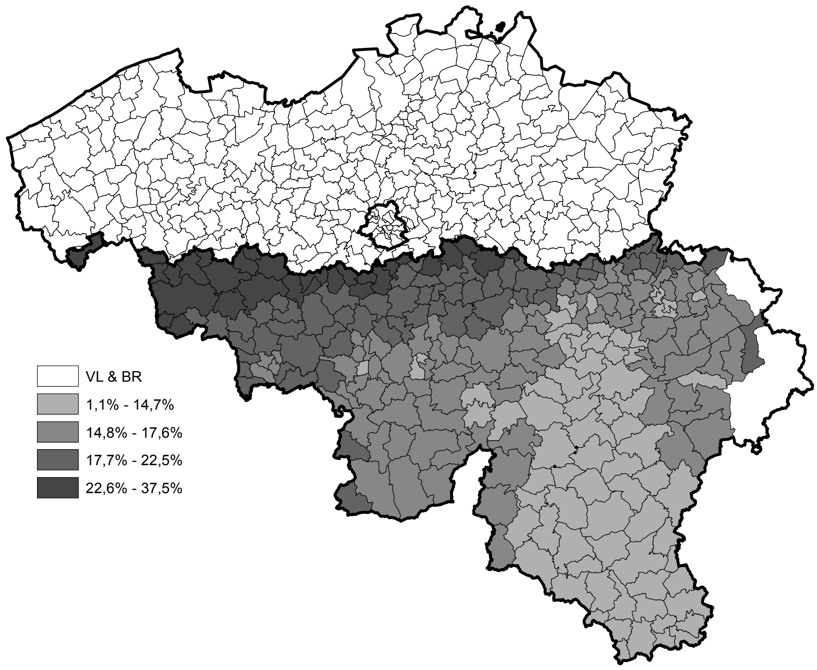
Figure 1.3: The predicted wage-effect of removing regional borders.

in the Wallonian region. This differential effect is enhanced by the fact that employment opportunities are on average relatively abundant in the Flemish municipalities.

Perhaps most interesting is the spatial pattern that emerges within the regions. Municipalities nearby the border are obviously most affected by the spatial border rigidities. But the effect is not uniform across all border municipalities. To illustrate more clearly the within-region heterogeneity in the impact of the border effect, figure 1.4 decomposes the Flanders-Wallonia regional border result into two distinct directional effects.



(a) The effect of eliminating the FL-WL border on Flemish municipalities



(b) The effect of eliminating the WL-FL border on Walloon municipalities

Figure 1.4: Directional border effects and municipal equilibrium wages

The upper panel of 1.4 shows the impact of eliminating the FL-WL border on equilibrium municipality wages in Flanders. In the province of Limburg, in the east of Flanders, the wage impact of the border removal infiltrates deep into the hinterland. For the province of West-Flanders, in the west, this is not the case and the effect attenuates rapidly with distance from the border. Compared to Limburg, which has a history of heavy industry and mining activities, employment opportunities are relatively abundant in West-Flanders (Torfs, 2008). Figure 1.4b shows how the effect of removing the WL-FL border carries deep into the Walloon hinterland, all the way up through the province of Hainaut up to the French border. The industrial economic structure of Hainaut has never fully recovered from the adverse shocks resulting from the seventies' oil crises. Its proximity to the prosperous province of West-Flanders further adds to the already pronounced effect. The part of Wallonia south of Brussels is less affected by the removal of the border effects, as it has markedly better employment opportunities, both locally and in nearby Brussels. Comparing figure 1.1 with figure 1.3 shows that the model is able to replicate existing unemployment patterns. In a way, this is remarkable since it only takes into account the distribution of economic *activity* and does not consider unemployment levels explicitly. In conclusion, the wage exercise nicely illustrates the spatial structure of the cost imposed by regional borders and the driving mechanisms of the model. Unfortunately, its the partial equilibrium structure enders it inappropriate for a fully fledged welfare analysis.

1.6 Conclusion

In this chapter, we derived a gravity equation for commuting from a simple spatial labour market model and used it to identify the deterrent effect of regional borders on commuting flows. The model assumes that firms produce with a love of variety for workers from different locations. We see our model as a reduced form of more complex labour market models with heterogeneous labour markets. Our approach builds on the work of J. Anderson & Van Wincoop

(2003), who propose a similar model to explain international trade flows. The development of gravity equations in the trade literature have taken place largely parallel to the development of gravity equations in spatial interaction modelling. Interestingly, our gravity equation, based on the J. Anderson & Van Wincoop (2003) trade model, shows some important similarities with the doubly constrained gravity equation, a workhorse model developed by A. Wilson (2010). We took this model as a benchmark to test the performance of our gravity equation and showed that our approach is superior in terms of predictive power and fit. We also argued that the control variables derived from our labour demand model are more appropriate in light of the identification of the border effect.

The gravity equation was estimated using a Belgian dataset on commuter flows between 580 Belgian municipalities. Belgium is an interesting country for the study of regional borders and their effect on commuting, as the country is multi-regional and multi-lingual, and even a casual look at the pattern of commuting flows reveals interesting regional patterns. We find a significant and large deterrent effect of regional borders on the size of inter-municipality commuting flows. The analysis further revealed that the border effect is highly dependent on which border is crossed, and even in which direction. This asymmetry suggests there is scope for region-specific policies that encourage interregional commuting to increase regional labour market integration. The border-removal exercise illustrated the impact of border-related spatial frictions on the local equilibrium wage and suggested that spatial imperfections caused by regional borders could could imply significant welfare losses, in particular in depressed localities located close to potential employment opportunities in a neighbouring region. To unveil and quantify the extent to which different possible causes contribute to the border effects, and their regional differences, has to be left as an interesting venue for further research.

Chapter 2

Scale Effects in the Labour Market: A Survey of the literature

2.1 Introduction

This chapter surveys the literature on scale effects in the labour market. Labour market scale effects or labour market pooling externalities were listed by (Marshall, 1890) as one of three sources driving spatial concentration of economic activity.[1] Labour market scale effects or labour market pooling externalities are efficiency gains that are rooted in the spatial concentration of labour market agents and serve as a popular explanation for the existence of cities. They arise if spatial proximity facilitates the interaction between actors on the labour market and renders labour market mechanisms more efficient. In his ground breaking manuscript *Principles of Economics*, Marshall (1890) discussed at length the productivity benefits associated with spatial agglomeration of industries. Many of his observations related to the functioning of the labour market:

[1]The other two being input sharing and knowledge spillovers

> *"Again, in all but the earliest stages of economic development a localized industry gains a great advantage from the fact that it offers a constant market for skill. [...] Employers are apt to resort to any place where they are likely to find a good choice of workers with the special skill which they require; while men seeking employment naturally go to places where there are many employers who need such skill as theirs and where therefore it is likely to find a good market."*
>
> – Alfred Marshall, *Principles of Economics*

The effect of spatial proximity on labour market efficiency can manifest itself through a variety of channels. Most of Marshall's observations relate to the process through which firms and workers meet and match. Scale effects can impact labour market matching at the extensive margin. If more labour market agents are actively searching for a partner in a given space, it is not unimaginable that the probability of finding a suitable match increases. Then scale is said to influence *matching quantity*. Scale effects can also impact matching at the intensive margin. A large labour pool makes it easier for firms to find the 'right man for the job', in particular in industries where complex production processes require a specialised set of skills. So scale can also influence *matching quality*. Marshall further describes a more subtle driver of labour market pooling externalities, noting that large labour pools offer 'a constant market for skills'. Large labour market shelter individual firms and workers from idiosyncratic shocks, as scale irons out their impact on aggregate wage fluctuations. Scale lets workers and firms *share risk*.

By describing the mechanisms through which scale could enhance the efficiency of local labour markets, Marshall pioneered a vast literature on urban agglomeration economies, which has been covered by a number of excellent survey papers. Duranton & Puga (2004) provide an excellent discussion of several theoretical micro-foundation of agglomeration economies. They classify them according to the driving mechanisms behind agglomeration externalities and distinguish between three different categories: learning, sharing and matching. Enrico (2011) provides an elaborate exposition about local labour markets in equilibrium, which includes a discussion on the effects of agglomeration. Rosenthal & Strange (2004) discuss both scope and sources of agglomeration externalities, but only briefly cover the topic of labour market pooling. Puga (2010) follow the classification proposed by Duranton & Puga (2004) and link it with a selection of empirical studies. They conclude that empirical evidence of matching is still lacking. More recently, Combes & Gobillon (2014) addressed this void with a survey on the empirics of agglomeration.

This paper adds to this literature a survey that is entirely dedicated to the discussion of scale effects in the labour market. It is specifically aimed at strengthening the link between theory and empirics. The exposition is structured around three main sections. The first two deal with the efficiency of the labour market matching process and discuss the relationship between labour market scale on the one hand, and matching quantity and quality on the other. The third section covers the risk-sharing aspect of labour market pooling.

2.2 Labour market scale & Matching quantity

2.2.1 Random search and the aggregate matching function

Labour market scale can speed up the rate at which agents meet and match. A popular tool for testing for scale effects in the matching rate is the empirical matching function, a concept grounded in the work of Nobel price winners Diamond (1982b); Mortensen (1982) and Pissarides (1985). In the Diamond, Mortensen and Pissarides-model (DMP hereafter), labour market are characterised by search frictions, arising from different sources, like worker and firm heterogeneity, imperfect information or costs of transportation (Pissarides, 2011). An aggregate matching function summarises the complex labour market search process by relating the number of matches M_r that form over a certain period in a certain region r to the number of open vacancies V_r and individuals searching for a job U_r:

$$M_r = A_r M\left(v_r V_r, u_r U_r, X_r\right) = A_r \left(v_r V_r\right)^{\alpha} \left(u_r U_r\right)^{\beta} X_r^{\gamma}, \tag{2.1}$$

where A_r measures the efficiency of overall matching process and X_r is a vector of control variables affecting the matching rate.[2] The supplementary terms u_r and v_r are agents' search intensities, so that the combined terms $v_r V_r$ and $u_r U_r$ are to be interpreted in terms of efficiency units.

The matching function is assumed to be increasing in both arguments, $\alpha, \beta > 0$. This means that for a given number of searchers on one side of the market, a new searching entrant on the opposite side will increase their chances of locating a partner (thick market externality). If $\alpha - 1, \beta - 1 < 0$, an additional searcher on a given side of the market will reduce the probability of locating a partner for all its competitors (congestion externality). If the number of searchers on both sides of the market increases and both effects cancel each other out, the probability of matching remains constant regardless of the number of actively searching agents. The search technology is then said to be characterised by constant returns to scale (CRS) ($\alpha + \beta = 1$), which is often interpreted as evidence against matching-related labour market pooling externalities. Search related scale effects in the labour market would imply that an increase in the number of unmatched agents leads to a disproportionate increase in the number of matches. This idea certainly has intuitive appeal. One would reasonably expect that, within a given area, search grows more efficient with the number of labour market participants actively engaged in search activities. This should then be reflected in the estimates of the coefficients on vacancies and unemployed workers, with an estimated scale elasticity larger than one, $\alpha + \beta > 1$.[3]

Empirically estimating the returns to scale coefficient is interesting in its own right, but it also has theoretical relevance. Diamond (1982a) for example, shows that an increasing returns to scale (IRS) matching process gives rise to multiple

[2] Time subscript were omitted for the sake of notation.

[3] That does not necessarily need to be the case for scale effects to exist is discussed at length in section 2.3

equilibria. In response to search being more efficient in large markets, agents could reduce their search efforts without affecting their matching probability. On the other hand, the thick market externalities could induce them so search harder, to fully reap the benefits of the scale effects, open up the possibility of two equilibria: one with low search effort and high unemployment, and one with high search effort and low unemployment (Petrongolo & Pissarides, 2001). To avoid the complexity of dual equilibria, macro-economic models often maintain the assumption of CRS for reasons of tractability. However, correctly modelling the scale coefficient of the matching function is important since it has non-trivial implications for policy, as it will affect for example the optimal unemployment benefit scheme (Schuster, 2012). Fortunately, M. Ellison et al. (2014) argue that the conditions required for equilibrium stability with an IRS matching function are more straightforward than is often assumed and simply requires that there are decreasing return to vacancy creation.

2.2.2 Empirical estimates of the scale elasticity

A constant returns to scale matching function is often taken as some kind of empirical regularity. Although the empirical literature does provide a substantial amount of evidence on CRS,[4] a non-negligible number of studies reports significant evidence of IRS in the matching process. An overview of these studies will provide a better understanding of what causes some studies to reject CRS in favour of IRS.

First, evidence on IRS seems to be more common in studies that estimate the matching function using a trans-log (TL) specification. Guilkey et al. (1983) show that a TL function is most suitable to provide consistent estimates of the returns to scale parameter, which could explain why a considerable amount of empirical studies reports evidence on IRS. Warren (1996) estimates an aggregate matching function for the United States and finds a scale coefficient of 1.332, indicating significant IRS effects. Yashiv (2000) estimates a TL matching

[4] see for example Petrongolo (2001) for an explicit test of the CRS-hypothesis and Petrongolo & Pissarides (2001) for an overview.

	Geo	Freq	Time	$\epsilon^{\alpha+\beta}$
Translog specification				
Kangasharju et al. (2005)	Finland	monthly	'91-'02	1.1-1.6
Warren (1996)	US	monthly	'69-'73	1.31
Yashiv (2000)	Israel	monthly	'75-'89	1.3
Inclusion employed search				
Baker et al. (1996)	Canada	monthly	'87-'88	1.546
Broersma & Van Ours (1999)	Netherlands	quarterly	'88-'94	1.30
Jolivet (2009)	U.S.	monthly	'03-'06	1.114
Aggregation issues				
P. M. Anderson & Burgess (2000)	U.S.	monthly	'78-'84	1.515- 1.541
Fahr & Sunde (2001)	West-Germany	yearly	'80-'95	1.206
Ibourk et al. (2004)	France	monthly	'90-'95	n/a
Ilmakunnas & Pesola (2003)	Finland	yearly	'88-'97	1.164-1.324
Profit & Sperlich (2004)	Czech Republic	monthly	'92-'96	n/a

Table 2.1: Empirical evidence on increasing returns to scale in the aggregate matching function

function for the Israeli labour market and finds convincing evidence for IRS, with scale elasticities in a similar range as those reported by Warren (1996). Kangasharju et al. (2005) explicitly compare a Cobb-Douglas (CD) to a TL specification. While they fail to reject the hypothesis of CRS for the CD function, the TL version exhibits IRS. The scale elasticity varies between 1.1 and 1.6.

Second, misspecification of the matching function can cause the scale coefficient to be underestimated. Baker et al. (1996) and Broersma & Van Ours (1999) stress the importance of having a correct correspondence between the flow variable on the left-hand side (matches) and the stock variable on the right-hand side (job searchers). For example, if on-the-job search is relatively important in the matching process, omitting them from the stock of job searchers will underestimate the true returns to scale in the matching process. Baker et al. (1996) finds increasing returns in the matching process on the Canadian labour market. They report a scale elasticity of 1.4. Broersma & Van Ours (1999) find a scale elasticity of 1.3 for the Netherlands. Although Jolivet (2009) does not find significant scale effects, he does show how ignoring on-the-job search downward biases the scale coefficient.

A third argument is put forward by Coles & Smith (1996), who link the common finding of CRS in the matching function to data aggregation issues. They argue that when spatial aggregation exceeds the geographical level relevant for local labour markets, returns to scale estimates are biased towards CRS. The intuition is simple: duplicating entirely segregated markets N times will lead the matching rate to increase by a factor N. Their spatial example carries over straightforwardly to other dimensions of aggregation, at the level of occupation or education, for example. In Blanchard et al. (1989), Robert Hall provides a similar argument: even if cross-sectional estimates exhibit constant returns to scale, there might still be scale effects for highly specialized workers. Coles & Smith (1996) test their hypothesis of spatial aggregation bias by estimating cross-sectional matching functions for the United Kingdom at the level of Travel-To-Work-Areas, which are considered to be functional labour markets. While they fail to reject the CRS hypothesis, they do find a positive effect of density on the matching rate, indicating that spatial concentration is not irrelevant in the matching process. Other studies based on disaggregated data did find evidence for IRS. P. M. Anderson & Burgess (2000) use a panel of state-level unemployment and vacancy data for the United States. Depending on the specification of the regression equation, the regional matching functions are found to exhibit IRS. Ilmakunnas & Pesola (2003) estimate a fixed effects model on a disaggregated panel of regional vacancy and unemployment data for Finland. Their reported scale coefficient varies between 1.32 and 1.6. Similarly, Munich et al. (1999) and Ibourk et al. (2004) both find IRS using spatially disaggregated data. Fahr & Sunde (2001) find evidence for IRS in the West-German matching process by estimating occupation-specific matching functions. Significant scale effects are found for crafts and technical occupations. Burdett et al. (1994) show how temporal aggregation can lead to downward biased estimation of the scale coefficient, if vacancies and unemployment follow a mean reverting process.

Other studies have examined the impact of agglomeration on efficiency of the matching process through the efficiency term A_r in equation (2.1). Hynninen & Lahtonen (2007) compare A_r across regions, controlling for differences in job seekers' heterogeneity and find that density increases matching efficiency. Ibourk et al. (2004), for France, also find positive effects of density on the rate of matching, as well as Gan & Li (2004), who report similar evidence for the academic job market. Di Addario (2011) is able to isolate the effect of changes in search intensity u_r from the impact of labour market density. The distinction is important because it is not unlikely that job search behaviour differs in dense regions. For example, if a worker is located in a dense labour market where job-search is more efficient, he can adjust his search effort accordingly. Then the effects of density on search efficiency are clouded by the downward adjustment of search intensity. Or maybe urban dwellers, facing tougher competition, intensify their job search activities. Di Addario (2011) uses the Italian Labor Force Survey micro-data to distinguish between these two factors. She finds that search intensity does not seem to be affected by density and the job finding rate is significantly higher in agglomerated regions. This indicates that higher urban matching efficiency is driven by scale effects, rather than changes in searchers' behaviour.

In sum, the empirical literature provides a mixed picture on the existence of scale effects in the labour market. I covered three explanations that address the observation that a lot of studies fail to find evidence for IRS in the aggregate matching function. They were of methodological nature and mostly related to misspecification or measurement issues. Even if evidence of scale effects is uncovered, the black-box nature of the matching function does not provide any insight into the mechanisms that are driving these scale effects. A number of studies have attempted to model the micro-foundation underlying the aggregate matching function. In spite the inconclusive evidence on the scale coefficient, most micro-foundations aim to replicate an aggregate matching function characterised by CRS (see for example Lagos, 2000; Shimer, 2007; Stevens, 2007; Ebrahimy & Shimer, 2010). Section 2.2.3 considers some of the models that have been proposed in the literature that attempt to micro-found an aggregate matching function characterised by IRS.

2.2.3 Micro-foundations for a DMP IRS matching function

Calvó-Armengol & Zenou (2005) model informal job search channels, where employed workers who run into information about open vacancies disseminate this throughout their social network. They argue that the scale of one's social network has an ambiguous effect on the probability of matching. On the one hand, larger networks facilitate the dissemination of information on job opportunities. On the other hand, workers fail to coordinate their job search efforts. This increase the probability that information about a certain vacancy is passed on to multiple job-searchers. Beyond a certain threshold, the congestion effects start to dominate. So even though their resulting aggregate matching function implies IRS, there is a non-monotonic relationship between the size of the network and the job-finding probability. Cahuc & Fontaine (2009) build further on this topic and discuss the stability and efficiency of the possible equilibria in a model with job search behaviour and social networks. They show how a decentralized equilibrium can be inefficient, leaving room for conditional unemployment benefits to improve upon welfare.

The importance of social networks in job-search behaviour has been confirmed regularly in the empirical literature. Wahba & Zenou (2005) examine the transmission of job information through social networks using the Egypt Labor Market Survey. They find a strong link between density and the probability that informal contacts were a central aspect of the job search strategy. In addition, the probability of getting a job through friends or family declines once the size of the local network surpasses a certain threshold, which is in line with the theory of Calvó-Armengol & Zenou (2005). Based on US employer-employee data, Schmutte (2015) also shows the importance of local networks in job search behaviour. His analysis shows that the labour market outcome of individuals depends on the job fortunes of their neighbours. Hawranek & Schanne (2014) analyze the relationship between referral effects and residential location for the Rhine-Ruhr urban area in Germany. They find that the probability of two individuals working together increases substantially if they live in the same neighbourhood. The relevance of social network in workers' search strategy has been confirmed by a considerable amount of empirical studies, providing support for the modelling mechanism used in Calvó-Armengol & Zenou (2005) that led to the aggregate IRS matching function.

Lester (2010) also micro-founds an aggregate matching function characterized by IRS. He develops a directed search model in which firms post wages and workers, being faced with coordination frictions, adjust their search strategy accordingly. In his model, workers decide which jobs to apply for. While doing so, they face a trade-off between a high-paying position and a large number of competing applicants on the one hand, or a modest salary but less competitors on the other. Offering high wages might be costly to firms, but it attracts more potential candidates. This increases the possibility of finding a suitable candidate. Crucially, the author distinguishes between vacancy creation along the extensive and intensive margin, as firms can decide whether to create one (extensive margin) either two (intensive margin) vacancies. Scale effects enter the model through the intensive margin. When firms decide to open multiple vacancies, matches increase not only because of the mere opening of new vacancies, but also because the matching process becomes more efficient. The reason why this is the case is intuitive. Workers do not coordinate their search actions so whenever there is more than one firm offering a vacancy, there will always exist some probability that one firm receives no applicants (see also Hawkins, 2013, who argues that labour market become 'less stochastic' for larger firms). If in the limit all vacancies are posted by one single firms, coordination frictions disappear and the search process become perfectly efficient. His model is consistent with the observation that large firms are more actively creating jobs in expansions while small firms create more jobs in recessions. Lester (2010)'s micro-foundations therefore provide an explanation why the efficiency of the matching process is often found to be pro-cyclical (Klinger & Rothe, 2012). Similarly, given that firms are larger in agglomerated areas (Manning, 2010), his model can explain why the efficiency of the matching function is positively related to the density of economic activity (see Hynninen & Lahtonen, 2007; Di Addario, 2011, among others).

2.2.4 The stock-flow approach to matching

Coles & Smith (1998) propose an alternative matching mechanism, consistent with the notion of labour market scale effects. They model the labour market as if it were a market place, so matching is no longer random. Worker heterogeneity is not explicitly modeled, but rather implicitly assumed, as was the case in the standard DPM-model.[5] Contrary to the DMP-framework, all information about unmatched workers and firms is centralized in a trading place, so that search is no longer costly. In each period, agents entering into the pool of unmatched agents immediately observe all their potential partners. If there is a suitable partner, they immediately match and exit their unmatched state. This process is called stock-flow matching, as in each period the only matches that occur are among unmatched agents and new entrants. If a worker exits employment and does not immediately find a new match, he enters into the unemployment pool and has to wait for a new vacancy to open up with which he is able to form a viable match. The stock-flow framework is consistent with the observation of long-term unemployment spells and vacancies that are difficult to fill. To see how scale effects enter the model, say there are V_{rt} open vacancies and U_{rt} unemployed in region r at the beginning of time period t and new vacancies and unemployed arrive at rate ρ_U and ρ_V respectively. If a worker enters the unemployment pool, he will consider all open vacancies available at that time. With probability p he matches with a specific vacancy, so that the chance of finding at least one suitable match among the stock of open vacancies is $1-(1-p)^{V_{rt}}$. Symmetry on the demand side of the labour market results in the following reduced form matching function:

$$M_{rt} = \rho_U[1-(1-p)^{V_{rt}}] + \rho_V[1-(1-p)^{U_{rt}}]. \tag{2.2}$$

[5]Depending on what are considered the source of the frictions.

The intuition behind the scale effects in equation (2.2) is relatively straightforward: the larger the pool of unmatched potential partners in the trading place, the lower the probability that none of them is a viable match. So treating local labour markets as isolated market places, stock-flow type matchings mechanisms result in labour market pooling externalities.

Coles & Smith (1998)'s stock-flow idea has been tested a number of times, mostly confirming that stock-flow matching is an important mechanism in the labour market. Coles & Smith (1998) themselves confirm the relevance of the stock-flow mechanism as they find that new inflows of vacancies become more important, the longer a worker is unemployed. Coles & Petrongolo (2008) compare a stock-flow to a random matching specification. They conclude that outside of steady state, the data is best described by a stock-flow mechanism. Other comparative studies include Sasaki (2008), who finds evidence for both random matching and stock flow matching on the Japanese labour market, and Forslund & Johansson (2007) who shows that Swedish data favour a stock-flow mechanism. Andrews et al. (2013) tests the stock-flow mechanism using micro-level data to find that the inflow of new vacancies has a significant effect on the probability of escaping unemployment. In line with the stock-flow intuition, new vacancies have a stronger impact on the matching probability than the size of the existing vacancy stock.

2.3 Labour market scale & Matching quality

The idea that labour market scale facilitates matching has been discussed at length in section 2.2. Empirical evidence on the returns to scale of the aggregate matching function is mixed and more often than not the hypothesis of CRS can not be rejected. This had let some authors to suggest that the effect of labour market scale manifests itself in the *quality* of matching, rather than the quantity. The idea that some matches are better than others incorporates the notion of heterogeneous labour market agents. The abilities and qualifications of workers vary substantially, as is the case for the skill-requirements of firms. This makes that some firm-worker pairs are meant to be, while others might not. Worker heterogeneity takes a central place in theories dealing with matching quality.

Agent heterogeneity is generally modelled in two different ways. When agent quality can not be ranked, heterogeneity is said to be non-hierarchical (section 2.3.1). In models that assume hierarchical heterogeneity (section 2.3.2) agent heterogeneity is interpreted in terms of skill (workers) or productivity (firms), which makes a ranking of agents possible. In sections 2.3.1 and 2.3.2, I will discuss the link between scale and matching quality. Wherever possible, the theories are linked to existing empirical evidence, to assess the extent to which their unique predictions or modelling mechanisms have received empirical support. It is not my intention to fully describe the equilibrium properties of the model, but rather to emphasize which modelling features give rise to labour market pooling externalities.

2.3.1 Non-hierarchical heterogeneity

Typically, non-hierarchical models do not rely directly on an IRS matching technology to introduce scale effects. Helsley & Strange (1990) for example use a Salop (1979) type mechanisms, which they apply to an urban labour market context.[6] Salop (1979) models heterogeneity in the context of monopolistic competition in the product market. Helsley & Strange (1990) apply this approach to a labour market context. Workers and firms are ex-ante heterogeneous and posses a differentiated set of skills, y and x. Agent randomly draw their type from a uniform unit-circle distribution. Output $q(x, y)$ can only be produced in pairs and the return of a match depends on its productivity. The smaller the distance $|x - y|$ between both agents' skill set, the more productive the match. The skill distance between the firm and the worker can therefore be interpreted as the cost of training required to align the worker's skills to those

[6] A similar approach was followed by Gan & Zhang (2006); Kim (1990, 1991); Brueckner et al. (2002); Amiti & Pissarides (2005); Moen & Yashiv (2014), among others.

required by the firm. Production then proceeds using the following technology:

$$q(x,Y) = \alpha\Omega(x) - \beta \sum_{Y(x)} |x - y|, \tag{2.3}$$

where α is a measure of worker productivity and $\Omega(x)$ is the number of workers employed by a firm. Firms produce with a fixed cost of production C and wages are determined through a split-the-difference bargaining process, so that wages and profits are given by:

$$w(x,Y) = \frac{1}{2}(\alpha - \beta|x - y|) \tag{2.4}$$

$$\pi(C,x,y) = \frac{1}{2}\left(\alpha\Omega(x) - \beta \sum_{Y(x)} |x - y|\right) - C, \tag{2.5}$$

Imperfect information is an essential driving force of the scale effects in Helsley & Strange (1990)'s model. Workers first need to decide where to locate. When choosing location, agents face uncertainty about the skill sets of potential local partners. They only have information on their numbers. Scale effects arise here because when facing uncertainty, locating in dense markets minimizes the expected skill-distance between a firm and a worker, which in turn maximizes the return to matching. The drivers of IRS in this model therefore show up in the expected return function for workers and firms:

$$E[w] = \frac{1}{2}\left(\alpha - \frac{\beta}{4m}\right) \tag{2.6}$$

$$E[\pi] = \frac{n}{2m} - \left(\alpha - \frac{\beta}{4m}\right) - C, \tag{2.7}$$

where m denote the number of firms in a city. From equations (2.6) and (2.7) it is easy to see that firm profits and worker wages are a function of local labour market scale: an increase in the number of firms results in a better match between workers' skills and jobs' requirements, leading to a positive relation between scale on the one hand, and productivity and wages on the other. The relation between productivity and city scale has been researched intensely and has been confirmed numerous times. It is beyond the scope of this paper to cover this empirical literature extensively, but a notable example is the study of Henderson (2003). Perhaps more relevant in the context of labour market externalities is the city-size wage premium, the existence of which has been documented repeatedly. Wheaton & Lewis (2002) for example, find that industries or occupations that are clustered offer an wage premium between 1.2 and 3.6 percent . Yankow (2006) finds an urban wage premium of 19 percent, one third of which can be attributed to agglomeration effects. He further distinguishes between an urban wage growth and wage level effect. A wage level effect implies that workers experience an immediate wage increase when relocating to a city. A wage growth effect implies that a worker's wage does not rise immediately, rather the pace at which is grows picks up.

Labour market pooling externalities are not the exclusive driver of urban productivity gains and the urban wage premium, as they can be attributed as well to most other agglomeration theories.[7] To assess the relevance of Helsley & Strange (1990)'s model, we turn to their driving agglomeration force, which relates city size to matching quality. Abel & Deitz (2015) explicitly test the hypothesis that labour market scale has a positive effect on match quality using a sample of college graduates in the United States. They construct a proxy that measures how well individuals' reported qualifications match their current occupation. In line with Helsley & Strange (1990), their concept of mismatch is 'horizontal' by nature, as they look at the college major in which a worker graduated, rather than the level or length of education. They find that college graduates in larger and thicker labour markets are more likely to hold a job that is related to their skill set. They also find better matched workers earn higher wages. Using Italian survey data Andini et al. (2013) test a wide range of hypotheses related to labour market pooling externalities, among which the positive relationship between urban scale and matching quality. They find that employers in dense markets report less difficulty finding suitable vacancy candidates.[8] In sum, Helsley & Strange (1990)'s model receives substantial em-

[7] Often referred to as 'Marshallian equivalence'.

[8] Other attempts at quantifying the relationship between scale and the quality of matching were undertaken by Berlingieri (2014) and Boualam (2014).

pirical support, as several studies report a positive relationship between labour market scale and match quality. However, Helsley & Strange (1990)'s model is only consistent with a level-effect in wages. Since it is lacking a dynamic dimension, it cannot explain the wage growth effect. Papageorgiou (2014) addresses this void by introducing dynamics in a Helsley & Strange (1990)-type model. Workers learn their occupation-specific productivity productivity only gradually over time, on-the-job. Finding the right occupation is easier in cities which host a wide variety of occupations, typically large cities.

A number of empirical studies have examined the relationship between urban scale, worker mobility and match quality. If workers are on average better matched in large labour market, one would expect they switch jobs less frequent than workers in peripheral areas. Bleakley & Lin (2012) indeed shows that on average workers switch occupations less often in thick markets. But they also show that the opposite holds true for younger workers, for whom the relationship between scale and occupational switches is positive. Wheeler (2008) also finds weak evidence that workers in dense areas are less likely to switch industries. Moreover, this relationship is conditional on the number of prior job switches a worker experienced. For workers who have held multiple jobs, the likelihood of changing industries decreases with the scale and diversity of the local market. Wheeler (2008)'s findings indicate that for early-career workers the former effect dominates, as first job changes occur more frequently in big cities. For more experienced job-hoppers, the latter effect starts to dominate. Both studies nevertheless point towards the importance of the relationship between scale effects, diversity and the job matching process. Wheeler (2006) concludes that "an important aspect of 'learning' in cities may involve individuals learning about what they do well".

2.3.2 Hierarchical heterogeneity

In contrast to non-hierarchical models, agents in hierarchical models can be ranked from low to high. Vertical differentiation implies that agents differ in terms of productivity. Urban scale in models with hierarchical heterogeneity improves matching quality through strengthening the degree of assortative matching. Assortative matching originated from the seminal work of Becker (1973), who developed a neo-classical assignment model and show that in a world where heterogeneous agents are complementary in production, the equilibrium assignment will be characterised by perfect positive assortative matching (PAM). Complementarity implies that the marginal product of the partner's type is an increasing function of one's own type. Imagine a world in which agents meet randomly. Upon meeting, they can decide to either match and produce or remain unmatched and continue searching. In the absence of search costs[9], no agent would be willing to match with a lower type, since he would be able to increase his pay-off by continuing his search for a better partner. In equilibrium, this leads to a situation where all production pairs are made up of agents with identical skills. This result breaks down if one departs from the neoclassical assumption that search is costless. After meeting a lower type partner, agents face a trade-off between a lower productivity level associated with forming a match with a lower type and incurring the cost of continued search. In equilibrium, costly search induces agents to match with suboptimal partners and perfect PAM no longer holds (Shimer & Smith, 2000).

Wheeler (2001) applies the idea of assortative matching in an urban context. In his model, workers and firms search for appropriate matches in cities where scale is negatively related to the cost of search. Types are hierarchically heterogeneous and complementary in production. The scale effects in the model are formalized by assuming firms pay some fixed search costs C which allows them to invite and meet a certain number of workers, who arrive at rate $\lambda(n)$, so that search costs per 'interviewed' worker $c(n) = C/\lambda(n)$ decrease in city size. The combination of complementarities in production and search costs result in a cut-off quality under which the firm is not willing to match with the workers and instead prefers to incur the cost associated with further search. The lower the cost of search, the closer will be the cut-off level to the firm's own quality. So, firms

[9] And all agents would meet all other agents instantaneously, so that there is no cost of foregone production.

become more selective in larger markets,[10] which leads the strength of PAM to be higher in dense regions. The predictions of his model are consistent with the Marshallian idea of labour market pooling, as wages, productivity and the return to skill are all increasing in city size. Additionally, his model predicts that wage inequality is higher in cities.

Where Wheeler (2001) models the dependence of search costs on market size explicitly, Teulings & Gautier (2004) achieve a similar result by using an IRS contact technology. Their approach builds on the seminal work of Shimer & Smith (2000), who introduce search frictions in the neo-classical assignment model of Becker (1973). As in Wheeler (2001), firms and workers are complementary in production and the decision to match is based on a trade-off between search costs and reduced productivity due to mismatch. Meetings are governed by a quadratic contact technology, which is the driving force of Marshallian labour market pooling effects in this model: urban scale increase the probability of meeting potential partners, thereby lowering search costs. Gautier & Teulings (2009) introduce an IRS contact technology in a system of cities, which allows them to explain urban inequality.

To validate the relevance of the drivers of scale effect in the Wheeler (2001) and Teulings & Gautier (2004) model, one should look for evidence relating labour market density to the strength of PAM. To measure the strength of sorting, worker and firm quality need to be identified. J. M. Abowd & Kramarz (1999) propose the use of Mincer wage equations supplemented with firm and workers fixed effect. By calculating pairwise correlations using the estimates of the fixed effects, they construct a measure of matching quality. Following this approach, Andersson et al. (2007) analyse the effect of density on the strength of assortative matching. Even though they fail to find convincing evidence of positive assortative matching, they report a significant positive effect of density on their proxy for matching quality. Eeckhout & Kircher (2011) argue that

[10] Wheeler (2001)'s mechanism also entails a congestion effect: bigger cities make search more complex. Intuitively, the effect of n on the costs of meeting *all* workers $nc(n)$ is ambiguous. On the one hand, search costs per worker decrease. On the other hand, there are more workers to meet. Wheeler (2001) assumes the former effect dominates the latter.

the fixed effects method of J. M. Abowd & Kramarz (1999) cannot be used to identify sorting. Lopes de Melo (2009) proposes an alternative wage based proxy for matching quality, where worker quality is proxied by their average wage over the sample period, and firm quality is proxied by the average wage of their workforce. Torfs & Zhao (2011) use this measure and provide evidence for labour market scale effects in Belgium. They show that labour market density positively affects matching quality, although in the presence of mobility costs this holds only for high ability workers who are able to self-select themselves into the most agglomerated area. Ehrl (2014) identifies firm quality using a TFP measure, while worker fixed effects are identified using the standard wage function approach. He finds a positive, but non-linear, effect of density on the strength of assortative matching.

2.4 Labour market scale & Risk-sharing

Sections 2.2 and 2.3 linked labour market pooling to the process of matching. This section elaborates on a different mechanism, one that -unsurprisingly- dates back to Marshall (1890). Marshall observed that cities 'offer a constant market for skill', so that large labour pools can mitigate individual risk and act as an insurance device against idiosyncratic shocks. This idea was later formalized by Krugman (1991).[11] To illustrate the risk-sharing mechanisms, this section will elaborate on the model's key equations.

Firm i's profits Π_i, given some employment level L_i, are given by:

$$\Pi_i = (A + \epsilon_i)L_i - \frac{1}{2}\gamma(L_i)^2 - wL_i, \tag{2.8}$$

where A is a general productivity parameter and γ measures the extent of decreasing returns to labour in the production technology. A crucial element of equation (2.8) is the firm-specific stochastic productivity factor ϵ_i, with support $[-\epsilon, \epsilon]$, distributed with a variance σ^2 around mean zero. Firms pay workers

[11] See also Duranton & Puga (2004) for a discussion of this model.

their marginal product w_i, which they take as given and adjust L_i accordingly, given the realization of the productivity factor ϵ_i. N firms then generate total employment L:

$$L = \sum_i^N L_i = \frac{\beta - w + \sum_i \epsilon_i}{\gamma}. \tag{2.9}$$

Expected wages follow straightforwardly:

$$E(w) = \beta - \gamma \frac{L}{N}, \tag{2.10}$$

as do expected profits,

$$E(\Pi) = \frac{[\beta - E(w)]^2 + var[\epsilon_i - w]}{2\gamma}, \tag{2.11}$$

which combined, result in the final expression for firm profits:

$$\begin{aligned} E(\Pi) &= \frac{\gamma}{2}\left(\frac{L}{N}\right)^2 \frac{var(\epsilon_i) + var(w) - 2cov(\epsilon_i, w)}{2\gamma} \\ &= \frac{\gamma}{2}\left(\frac{L}{N}\right)^2 + \left(1 - \frac{1}{N}\right)\frac{\sigma}{2\gamma}. \end{aligned}$$

Based on equation (2.12), it is easy to see how labour market pooling externalities enter into the model. First observe that profits are a convex function of the realization of the stochastic productivity factor ϵ_i, as well as of wages, but that profits decrease in the covariance between the idiosyncratic shock and wages. The basic intuition here is that when firms are subject to idiosyncratic productivity shocks, they prefer locations with a large pool of other firms. This dampens the effect of idiosyncratic shocks on local wages, since a single firm expanding employment will not have a strong impact on the local wage level.

The mechanisms underlying the risk-sharing argument of Krugman (1991) have received some direct empirical support from the literature. Overman & Puga (2010) looks at the relationship between industry concentration and a measure of labour market pooling. Their labour market pooling measure builds on the theoretical model of Krugman (1991) and it measures the idiosyncratic employment volatility faced by individual firms within a given industry, measured by firm-level employment growth deviations from industry employment growth. They relate it to the G. Ellison & Glaeser (1999) agglomeration measure of industry concentration and find that sectors experiencing more firm-idiosyncratic employment volatility are more spatially concentrated. Heuermann (2008) tests Krugman (1991)'s notion of risk sharing for Germany, but fails to find strong evidence that industries whose firms are prone to idiosyncratic shocks are spatially concentrated. However, they do find that industry concentration mitigates the effect of idiosyncratic employment shocks on wages. The latter two findings are in line with the Krugman (1991) risk-sharing theory of labour pooling. G. Ellison et al. (2010) investigate the determinants of co-agglomeration patterns and show how industries that use a similar type of labour pool tend to locate together. While their study does not provide an insight into the mechanisms driving location decisions, their conclusions are consistent with the theory of risk-sharing. Similar evidence has been provided by Gabe & Abel (2010), who examines co-agglomeration patterns of occupations to find that occupations that are often used by the same industry tend to locate near to each other.

2.5 Conclusion

The body of literature on Marshallian agglomeration externalities has been rapidly expanding over the past two decades. Marshall (1890) identified three distinct sources of labour market externalities: input sharing, knowledge spillovers and labour market pooling. This chapter focussed on the latter category and discussed some of the theories that explain concentration of economic activity through the presence of scale effects in the labour market. The discussion was structured along three main categories: matching quantity, matching quality and risk-sharing. Two of them relate to the process that governs match formation on the labour market. Scale effects in the labour market can lead to an increase in the rate at which firms and workers form matches. A positive relationship between matching quantity and labour market scale can be pragmatically modelled through the use of an aggregate matching function, linking job searchers and vacancies in a given labour market to the number or realized matches or matching rate. Whether the matching process is characterised by increasing returns to scale can be tested for empirically, by estimating the scale elasticity of aggregate matching functions. Empirical evidence for IRS is mixed. A number of reasons as to why this might be the case were discussed. Apart from some methodological issues, it is plausible that larger labour markets might not lead to more matches, but rather improve the matching quality. Section 2.3 discussed a selection of models in which larger labour markets improve the quality of matches between firms and workers. I distinguished between models that assume hierarchical and non-hierarchical heterogeneity of workers and firms. Finally, 2.4 discusses the Marshallian argument of risk-sharing, a theory later formalized by Krugman (1991) which says that firm locate in agglomerated areas to smoothen out the effect of idiosyncratic labour demand shocks on local wages.

Throughout the survey, I attempted to link the theories to existing empirical evidence. Marshallian equivalence, which implies that predictions of labour market pooling models are indistinguishable from the predictions of other agglomeration theories renders this a particularly daunting task. Therefore, attention went out not only empirical support for the predictions, but also for the mechanisms modelled to generate labour market pooling effects. The literature provides compelling evidence for labour market pooling as a driving source of agglomeration.

Chapter 3

Urban Labour Market Pooling, Sorting and Mobility Costs

3.1 Introduction

Although labour markets function more efficiently at larger scales,[1] a number of empirical studies have found that urban scale does not come to the benefit of all workers. Gould (2007) for example, shows that the urban wage premium is more pronounced for high-skilled workers and Möller & Haas (2003) fail to find any evidence for a low-skilled urban wage premium. In Bacolod et al. (2008) cities only increase wages of workers with cognitive skills. This chapter offers one explanation why low-skilled workers in urban areas do not enjoy labour market pooling benefits to the same extent as their highly skilled peers. We use an urban framework with two employment centres, search frictions on the labour market and mobility costs, and enrich it with two-sided heterogeneity on the labour market, skill complementarities in production, scale effects. We show that peripheral low-skilled workers that reside in the vicinity of agglomerated areas suffer twice. First, mobility costs restrict their job-search radius and excludes them from the agglomerative benefits of dense urban areas. Second,

[1] For an overview, see chapter 2.

because firms increasingly locate in agglomerated areas to reap the benefits of the concentration of job search activities, at the expense of the periphery. This novel finding has non-trivial policy implications, as it suggests that mobility subsidies might not be Pareto welfare improving.

Our spatial set-up consists of an urban area with two districts[2], which exogenously differ in the scale of their labour market. Workers' residential location is assumed to be fixed,[3] but firm location is endogenously determined by a free entry condition. Workers are free to search for jobs in either or both areas. Their optimal search strategy takes into account that commuting to the 'foreign' district is associated with a mobility cost, assumed to be fixed and equal across workers. The matching process on the labour market is described by an assignment mechanism subject to search frictions (Shimer & Smith, 2000), where heterogeneous workers and firms search for partners with whom to produce. Skills are complements in productions. This implies that the benefits of matching with a better agent increase with skill type. Consequently, 'birds of a feather, flock together' and low type workers match with low quality firms and high type workers match with high quality firms. This is referred to in the literature as *positive assortative matching* (PAM). In a labour market with search frictions, PAM is not perfect and agents will settle with a suboptimal partner.

Scale effects in the labour market are an important driver of the main results of this chapter. Labour market pooling as a source of agglomeration was already acknowledged by Marshall (1890) in the late nineteenth century. In his groundbraking manuscript *Principle of Economics*, he identified it as one of the three sources of agglomeration externalities. An important mechanism driving labour market pooling externalities is the process through which workers and firms meet and match. The idea that search grows more efficient with the number of labour market participants actively engaged in search activities certainly holds intuitive appeal and has received considerable support in the empirical

[2]The core-periphery structure of the model can be interpreted in the spirit of the urban economics literature, which often distinguishes between a Central Business District (CBD) and a SuBurban District (SBD).

[3]An assumption that will be relaxes in the appendix of this chapter.

literature (see chapter 2). Therefore, labour markets in this paper are subject to scale effects, which are introduced by means of an increasing returns to scale (IRS) contact technology (Teulings & Gautier, 2004). Agents will therefore find it easier to meet a suitable partner in larger labour markets.

Skill complementarities in production imply that the return to a better match is increasing in skill-type. The fixed cost of commuting will therefore give rise to a situation where only the high-skilled find it optimal to search and match in the agglomerated district. Peripheral workers at the bottom of the skill distribution will opt to search locally. Surprisingly, locating in the relative vicinity of large agglomerated areas deteriorates the labour market outcome of the least productive workers, as vacancy creation shifts from the peripheral to the agglomerated areas, to take advantage of the scale benefits associated with labour market density. We take our model to the data using a linked employer-employee dataset provided by the Belgian Crossroads Bank for Social Security, and we are able to confirm its predictions.

The remainder of the text is structured as follows: section 3.2 outlines the theoretical model and illustrates its equilibrium. Section 3.3 describes the data which is used for the empirical strategy elaborated in section 3.4. Results are reported in section 3.5. Section 3.6 concludes.

3.2 The Model

3.2.1 The Environment

General Structure

Figure 3.1 illustrates the general structure of the urban economy considered in this chapter. The urban area consists of two districts, A and B, which differ in the size of their labour force, so that $L_A > L_B$. In continuous time, heterogeneous agents search for partners in a labour market with search frictions. Production proceeds in pairs and is characterised by skill complementarity. All agents are infinitely lived and discount the future at a common rate $r > 0$. Contacts between firms[4] and workers are governed by a random contact technology. The search process is time-consuming but subject to increasing returns to scale, making search more efficient in district A. Workers in each district are free to look for jobs in either or both districts, but inter-district job search is less efficient than local search. In addition, workers who accept a job outside their residential district have to pay a fixed commuting cost. Upon meeting, workers and firms are given the choice between producing or continued search. This decision is based on a comparison between their part of the match surplus and their reservation value. A worker's reservation wage is district-specific and a function of the local contact rate and possibly also commuting costs. An optimal search strategy will concentrate all search efforts in the area associated with the highest reservation wage. The number of vacancies in each district is determined by a free entry condition. Since labour markets are the focus of the analysis, we do not model the goods market explicitly.

Labour market agents

Both sides of the labour market are populated by a continuum of agents, whose types are assumed to be log-normally distributed:

$$\log s \sim N(\mu^s, \sigma^s)$$
$$\log p \sim N(\mu^p, \sigma^p),$$

with density $l(s)$ for workers of skill type s and density $g(p)$ for firms with productivity p. Let u_i and v_i be the total number of unemployed workers and vacancies per unit of labour supply L_i in district i. Workers supply one unit of labour and each firm has one vacancy on offer. $u_i(s) = u_i l(s)$ and $v_i(s) = v_i g(p)$ are the densities of unemployed workers s and vacancies p per unit of labour supply L_i in district i. The total number of unemployed per skill type and vacancies per productivity level in each district are denoted by $u_i(s)L_i$ and

[4]In the remainder of this chapter, firms, jobs and vacancies are used interchangeably and refer to the same concept.

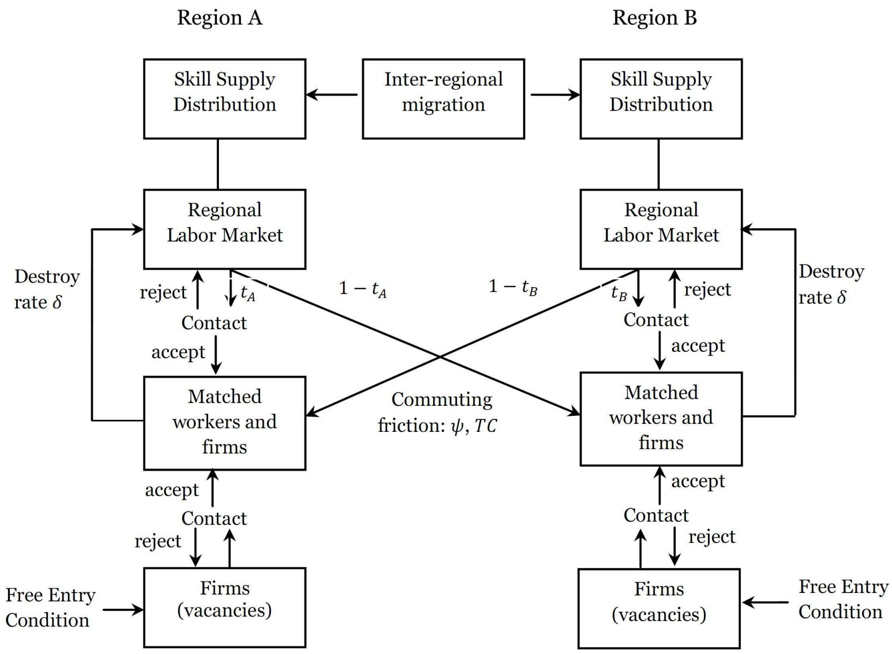


Figure 3.1: Structure of the urban economy

$v_i(s)L_i$, respectively. The unemployment rate for workers of skill type s then becomes $\frac{u_i(s)}{l(s)}$. Similarly, the vacancy rate at productivity level p is $\frac{v_i(p)}{g(p)}$.

Unemployed workers maximise their expected present value of payoffs $U_i(s)$, while vacancies in district j maximise their expected present value of payoffs $V_i(p)$. While unmatched, workers get unemployment benefits U_0 and vacancies receive nothing. Firms pay an irreversible investment f_E before entering the market. Upon entry, firms learn their productivity, which is drawn from a common distribution. The supply of vacancies in each district is determined by a free entry condition. Wages are set through Nash-bargaining as in Pissarides (1990), with $0 < \theta < 1$ being workers' bargaining power.

Production

Pairs of firms and workers produce output using production technology $f(s,p)$:

$$f(s,p) = sp. \tag{3.1}$$

The production function is supermodular (see Lu & Mc-Afee, 1996; Teulings & Gautier, 2004), which implies it is characterised by skill complementarities in production. Under supermodular production, the marginal product of an agent is increasing in the type of his partner:

$$f(s,p) - f(s,p') > f(s',p) - f(s',p'), \forall s > s', p > p' \tag{3.2}$$

or in words: the benefits of matching with a more productive firms grow larger, the higher the skill level of a worker. Skill complementarities are essential to the model because they have important implications for partner choice.[5]

Job-search technology

Each worker allocates one unit of time to job search in either or both districts. Let $t_i(s)$ and $[1 - t_i(s)]$ denote the time worker s in district i devotes to job search in districts i and j, respectively. Contacts occur randomly and there is no on-the-job search. For each type pair (s,p) there are $M_i[u(s), v(p)]$ contacts. Searching for jobs in the 'foreign' district is more time-consuming than searching for jobs locally. In addition, information dissemination of job opportunities could attenuate strongly with distance.[6] Therefore, inter-district search is less efficient than local search. This is implemented through the search efficiency indicator $0 \leq \psi \leq 1$. Over a given time interval, total contacts between job

[5] Note that if 3.2 holds, rearranging gives $f(s,p) + f(s',p') > f(s',p) + f(s,p')$, which means that total output is maximised under perfect sorting. Milgrom & Roberts (1990) provide an in-depth discussion on supermodular functions and their properties.

[6] see for example, Schmutte (2015), where information depends on the size of a worker's local network.

seekers of type s and vacancies of type p in districts A and B are then given by:

$$
\begin{aligned}
M_A[u(s), v(p)] &= \left[t_A(s)u_A(s)L_A + \psi[1-t_B(s)]u_B(s)L_B\right]v_A(p)L_A \\
M_B[u(s), v(p)] &= \left[t_B(s)u_B(s)L_B + \psi[1-t_A(s)]u_A(s)L_A\right]v_B(p)L_B
\end{aligned} \tag{3.3}
$$

The terms in large brackets represent the total number of unemployed job seekers of a given skill level s, measured in efficiency units, in the respective districts. In district A there are $t_A(s)u_A(s)L_A$ resident workers with skill level s searching for jobs locally. In addition, $[1-t_B(s)]u_B(s)L_B$ workers from B focus their search efforts in A. Their number gets discounted by a factor ψ to account for the lower inter-district search efficiency. The second term of the contact function, $v_A(p)L_A$, measures the total number of vacancies in A. Residence is predetermined and workers search for jobs from their home district. In Section A.1.1, we will relax this assumption and allow for migration.

The functional form of the contact function follows Teulings & Gautier (2004), who provide a number of arguments in favour of a quadratic contact technology. That the empirical literature often finds constant returns to scale in the matching process (for an overview, see Petrongolo & Pissarides, 2001), does not necessarily contradict this assumption. As argued by Petrongolo & Pissarides (2006), contacts should be distinguished from actual matches. If there are scale effects to search, the greater efficiency of the search process could make firms and workers more selective in their partner choice. Scale effects would then show up in the wage distribution, rather than in the matching rates.[7]

The implied contact rates are:

$$
\begin{aligned}
\rho_{iis\to p} &= t_i(s)v_i(p)L_i \\
\rho_{iip\to s} &= t_i(s)u_i(s)L_i \\
\rho_{ijs\to p} &= \psi[1-t_i(s)]v_j(p)L_j \\
\rho_{ijp\to s} &= \psi[1-t_i(s)]u_i(s)L_i,
\end{aligned} \tag{3.4}
$$

[7]Teulings & Gautier (2004)'s model simulations point out that the scale coefficient of the matching function implied by their model reduces to 1.66. While this still significantly exceeds 1, there are several empirical studies that report empirical matching functions with elasticities in the same range. For an overview, see chapter 2, section 2.2.2.

where the first subscript of ρ denotes the location of workers and the second subscript refers to the location of firms. For example, $\rho_{ABs\to p}$ denotes the rate at which unemployed workers of type s living in district A run into district B's p-type vacancies. The contact rates are subject to scale effects, a direct consequence of the quadratic contact technology. Independent of location, matches are destroyed randomly and exogenously at rate $\delta > 0$. When a match is destroyed, worker and firm re-enter the pool of searchers.

3.2.2 Equilibrium

After a firm and a worker make contact, matches are formed upon mutual agreement. For worker s in district i, the matching set $\omega_{ij}(s)$ is a time-invariant set of firms in district j, with which she is willing to match and vice versa. Symmetrically, $\omega_{ij}(p)$ is the matching set of firm p located in district i, for workers from j.

Steady state flows

In steady state, flows in and out of unemployment balance. For district A, the flow into unemployment is described by the density of employed workers, $l_A(s) - u_A(s)$, whose matches exogenously dissolve at Poisson rate δ. The flow of district A's resident workers escaping unemployment is described by $u_A(s)\int_{\omega_{AA}(s)}\rho_{AAs\to p}dp + u_A(s)\int_{\omega_{AB}(s)}\rho_{ABs\to p}dp$, of which $u_A(s)\int_{\omega_{AA}(s)}\rho_{AAs\to p}dp$ find a job locally, and $u_A(s)\int_{\omega_{AB}(s)}\rho_{ABs\to p}dp$ match with a vacancy from district B. Taken together, this gives the steady state condition, with the inflow into unemployment on the left-hand side and the outflow on the right-hand side:

$$\begin{aligned}\delta[l_A(s) - u_A(s)] &= u_A(s)\int_{\omega_{AA}(s)}\rho_{AAs\to p}dp + u_A(s)\int_{\omega_{AB}(s)}\rho_{ABs\to p}dp \\ &= t_A(s)L_A u_A(s)\int_{\omega_{AA}(s)} v_A(p)dp + \psi[1 - t_A(s)]L_B u_A(s)\int_{\omega_{AB}(s)} v_B(p)dp\end{aligned} \tag{3.5}$$

Unemployment value

$U_i(s)$ is a worker s's expected value of being unemployed and searching for a job while living in district i. When she matches with firm p in district j, she receives $W_{ij}(s|p)$, with $i,j = A,B$, so that $S_{ij}(s|p) = W_{ij}(s|p) - U_i(s)$ is her matching surplus. While unmatched, she gets unemployment benefits U_0. At flow rate $t_A(s)L_A \int_{\omega_{AA}(s)} v_A(p)dp$ she meets and matches with some $p \in \omega_{AA}(s)$ in A and enjoys a gain $S_{AA}(s|p)$, while at flow rate $\psi(1-t_A(s))L_B \int_{\omega_{AB}(s)} v_B(p)dp$ she meets and matches with some $p \in \omega_{AB}(s)$ in B and enjoys a gain $S_{AB}(s|p)$. So, the value of search for a worker s living in district A is given by the following Bellman equation:

$$\begin{aligned} rU_A(s) = U_0 + \max_{t_A(s)\in[0,1]} \Big[t_A(s)L_A \int_{\omega_{AA}(s)} & S_{AA}(s|p)v_A(p)dp \\ & + [1-t_A(s)]\psi L_B \int_{\omega_{AB}(s)} S_{AB}(s|p)v_B(p)dp \Big], \end{aligned} \tag{3.6}$$

where r is the discount rate.

Spatial search strategy

To maximise $U_i(s)$, an unemployed worker allocates her job-search time $t_i(s) = 1$ optimally between districts. Equation (3.6) implies that a worker from A searches jobs locally ($t_A = 1$) if her value from being unmatched while searching in A weakly exceeds her value while searching in B. Otherwise, she focuses her job search efforts entirely in district B. So we have that although unemployed workers can freely distribute their time endowment between districts, search activities are spatially concentrated, $t_A(s) \in \{0,1\}$:

$$t_A(s) = \begin{cases} 1 & \text{if } \mu L_A \int_{\omega_{AA}(s)} S_{AA}(s|p)v_A(p)dp \geq \psi\mu L_B \int_{\omega_{AB}(s)} S_{AB}(s|p)v_B(p)dp \\ 0 & \text{otherwise.} \end{cases} \tag{3.7}$$

Vacancy value

The value of a vacancy p in district A is written as follows:

$$rV_A(p) = L_A \int_{\omega_{AA}(p)} t_A(s)S_{AA}(p|s)u_A(s)ds + \psi L_B \int_{\omega_{BA}(p)} (1-t_B(s))S_{BA}(p|s)u_B(s)ds. \tag{3.8}$$

At flow rate $L_A \int_{\omega_{AA}(p)} t_A(s)u_A(s)ds$ a firm p in district A meets and matches with some $s \in \omega_{AA}(p)$ from district A and enjoys a gain $S_{AA}(p|s)$, while at flow rate $\psi L_B \int_{\omega_{BA}(p)}(1-t_B(s))u_B(s)ds$ it meets and matches with some $s \in \omega_{BA}(p)$ from B and enjoys a gain $S_{BA}(p|s)$.

Prior to entry, the expected net value of a vacancy in district A is $V_A - f_E$. The expected net value is driven down to zero by unrestricted entry of new vacancies. This yields the equilibrium free entry condition:

$$V_A = \int V_A(p)g(p)dp = f_E. \tag{3.9}$$

Match surplus & matching set

While matched, a worker s from district i gets payoff $\pi_{ij}(s|p)$ when matched with firm p in district j, while the firm gets $\pi_{ij}(p|s)$. The pay-offs are subject to the resource constraint $\pi_{ij}(s|p) + \pi_{ij}(p|s) \equiv f(s,p)$. At rate δ, the match is destroyed and the worker suffers a loss $S_{ij}(s|p)$. Then the value of district i's resident worker s matched with a local firm p is written as:

$$rW_{ii}(s|p) = \pi_{ii}(s|p) - \delta S_{ii}(s|p). \tag{3.10}$$

Workers living in district i that accept a job in district $j \neq i$ pay TC commuting costs,[8] so their match value becomes:

$$rW_{ij}(s|p) = \pi_{ij}(s|p) - TC - \delta S_{ij}(s|p). \tag{3.11}$$

[8]Within-district commuting is assumed to be costless.

While matched, wages are set according to a simple Nash bargaining solution with θ being the worker's bargaining power. From the bargaining problem's first order condition, we have that:

$$(1-\theta)[W_{ij}(s|p)-U_i(s)]=\theta[J_{ij}(p|s)-V_j(p)], \tag{3.12}$$

where $J_{ij}(p|s)$ is the present value for firm p in district j while matched with worker s from i. Using Equation (3.10), (3.11) and the resource constraint, we obtain the surplus of workers and firms:

$$\begin{aligned}
S_{ii}(s|p) &= \theta\left[\frac{f(s,p)-rU_i(s)-rV_i(p)}{r+\delta}\right]\\
S_{ii}(p|s) &= (1-\theta)\left[\frac{f(s,p)-rU_i(s)-rV_i(p)}{r+\delta}\right]\\
S_{ij}(s|p) &= \theta\left[\frac{f(s,p)-rU_i(s)-rV_j(p)-TC}{r+\delta}\right]\\
S_{ij}(p|s) &= (1-\theta)\left[\frac{f(s,p)-rU_i(s)-rV_j(p)-TC}{r+\delta}\right].
\end{aligned} \tag{3.13}$$

Personal surplus is the bargained share of excess matching output over the sum of unmatched values, in addition to the commuting cost in case of an inter-district match. Surplus gets discounted by the sum of the interest and destruction rate.

In equilibrium, an agent's optimal strategy is to accept any match that weakly exceeds her expected present unmatched value:

$$\begin{aligned}
S_{ij}(s|p)\geq 0 &\iff p\in\omega_{ij}(s)\\
S_{ij}(p|s)\geq 0 &\iff s\in\omega_{ij}(p).
\end{aligned} \tag{3.14}$$

Thus, the matching sets are

$$\begin{aligned}
S_{AA}(s,p)&=f(s,p)-w_A(s)-\lambda_A(p)\geq 0 \Leftrightarrow p\in\omega_{AA}(s)\Leftrightarrow s\in\omega_{AA}(p)\\
S_{AB}(s,p)&=f(s,p)-w_A(s)-\lambda_B(p)-TC\geq 0 \Leftrightarrow p\in\omega_{AB}(s)\Leftrightarrow s\in\omega_{AB}(p),
\end{aligned} \tag{3.15}$$

where $w_i(s)\equiv rU_i(s)$ is the average present value of an unmatched worker

s, which is equivalent to his reservation wage. $\lambda_i(p) \equiv rV_i(p)$ is the average present value of an unmatched vacancy p. $S_{ij}(s,p)$ is the match surplus.

Substituting (3.13) into (3.6), we obtain agents' value functions:

$$\begin{aligned} w_A(s) =& U_0 + \max_{t_A(s)\in\{0,1\}} \Big[t_A(s)\theta \frac{\mu L_A}{(r+\delta)} \int_{\omega_{AA}(s)} [f(s,p) - w_A(s) - \lambda_A(p)] v_A(p) dp + \\ & [1 - t_A(s)]\theta \frac{\psi \mu L_B}{(r+\delta)} \int_{\omega_{AB}(s)} [f(s,p) - w_A(s) - \lambda_B(p) - TC] v_B(p) dp \Big] \end{aligned} \tag{3.16}$$

$$\begin{aligned} \lambda_A(p) =& (1-\theta)\frac{\mu L_A}{(r+\delta)} \int_{\omega_{AA}(p)} [f(s,p) - w_A(s) - \lambda_A(p)] t_A(s) u_A(s) ds + \\ & (1-\theta)\frac{\psi \mu L_B}{(r+\delta)} \int_{\omega_{BA}(p)} [f(s,p) - w_B(s) - \lambda_A(p) - TC][1 - t_B(s)] u_B(s) ds \end{aligned} \tag{3.17}$$

The second term on the right-hand side of equation (3.16) is the expected value of a worker's share of the match surplus in district A and the third term is the expected surplus in B. Equation (3.16) implies that in equilibrium the expected surplus of matching is equal to the opportunity cost of search.

Definition 1. *A search equilibrium is characterised by a septuple* $(w, \lambda, V, \omega, u, v, t)$*, where* w *and* λ *solve the value equation system* (3.16) - (3.17) *given* (ω, u, v, t)*;* V *solves the free entry condition* (3.9) *given* $(w, \lambda, \omega, u, t)$*,* ω *is the matching set given* w *and* λ *based on* (3.15)*,* u *solves the steady state equation* (3.5) *given* (ω, v, t) *and* t *is the optimal spatial allocation of search time* (3.7) *given* (w, λ, ω, v)*.*

Because the wage function $w(x)$ is not available, solving the model analytically is impossible.[9] To get to a numerical solution, we proceed as follows: First, we divide the type space into 300 discrete categories. Second, we guess initial values for all endogenous objects and subsequently run through the following steps:

[9]Shimer & Smith (2000) provide a proof of existence of the equilibrium, while Teulings & Gautier (2004) apply a second-order Taylor expansion to characterize the equilibrium.

Step 1) Calculate the associated steady state unemployment rates using (3.5), the value functions using (3.16)-(3.17), the allocation of search time using (3.7) and a new matching set using (3.15).

Step 2) Repeat process (i) until the matching set remains unchanged.

Step 3) Calculate the expected firm profit using (3.9). If expected profits are larger than the sunk entry cost of a vacancy, open more vacancies and repeat step (i), (ii) and (iii) until the expected value of vacancies and the sunk entry costs equalize.

3.2.3 Illustration of the equilibrium

Worker and firm types are log-normally distributed along an interval [1, 4]. The mean $\mu^{s,p} = 0.693$ and standard deviation $\sigma^{s,p} = 0.27$ are chosen so that 95 percent of types lie within the interval's boundaries. The other parameters in the model are set as follows: the discount rate r is normalized to 1, the exogenous destroy rate $\delta = 2r$, labour market sizes $L_A = 4L_B = 2000r$, worker's bargaining power $\theta = 0.5$, commuting costs $TC = 0.4$, unemployment benefits $U_0 = 0.4$ and the sunk entry cost $f_E = 1.8$. To test whether the results are sensitive to the choice of parameters, we selected a ±25% range around the chosen values and took 1 000 random draws from the joint set of parameters. In addition, we experimented with the initial values. The results remained qualitatively unaffected.

Skill complementarities in production have important implications for the sorting of worker and firm types. In a frictionless world, no agent would be willing to match with a lower agent type. This is driven by the assumption of supermodularity of the production process. In equilibrium, perfect assortative matching is an optimum and all agents match with an identical partner. This result breaks down when search becomes costly. Agents will widen their set of acceptable partners, as they face a trade-off between suboptimal production and the cost of prolonged search. The width of that set measures the match quality.

The narrower is the matching set, the higher is the match quality. To provide a benchmark and get a feel for the model's mechanisms, we first discuss the equilibrium where inter-district job search is prohibitively inefficient ($\psi = 0$) so that the labour market in both districts operate in autarky.

Equilibrium without inter-district job search

Scale effects in search drive a wedge between the match quality in district A and district B. The first panel of Figure 3.2 illustrates how this gets reflected in the matching sets. The light-shaded area represents A's matching set, which is significantly more narrow than the matching set of B, represented by the shaded area as a whole. The bands are upward sloping because production complementarities induce positive assortative matching. The widening of the bands for higher skill-types is driven by the log-normal assumption of the type distribution. It implies relatively few high-type agents are searching for partners, which widens their matching set as they become less picky in their partner choice. The upper right panel compares reservation wages of workers in both districts. The reservation wage is higher in the large district for all skill types since the expected value of search is higher. That the difference grows larger for high type agents is a direct consequence of skill complementarities in production, which implies high types have more to gain from finding a better partner. This result will be of central importance to the commuting decision of workers (see section 3.2.3). The bottom left panel presents the values of vacancies in district A and B. Interestingly, the expected value of low type vacancies is marginally higher in B than it is in A, as the lower contact rate in B forces high type workers to accept a lower type vacancy. Higher up the type distribution however, the value of vacancies increases significantly stronger in A than in B. The bottom right panel illustrates the unemployment rate by worker types. District A's unemployment rate is lower across all skill levels. The difference is particularly large for low-skilled workers as they are more likely to be rejected by highly productive firms. Note how unemployment increases marginally for the highest worker types. This is because the opportunity costs

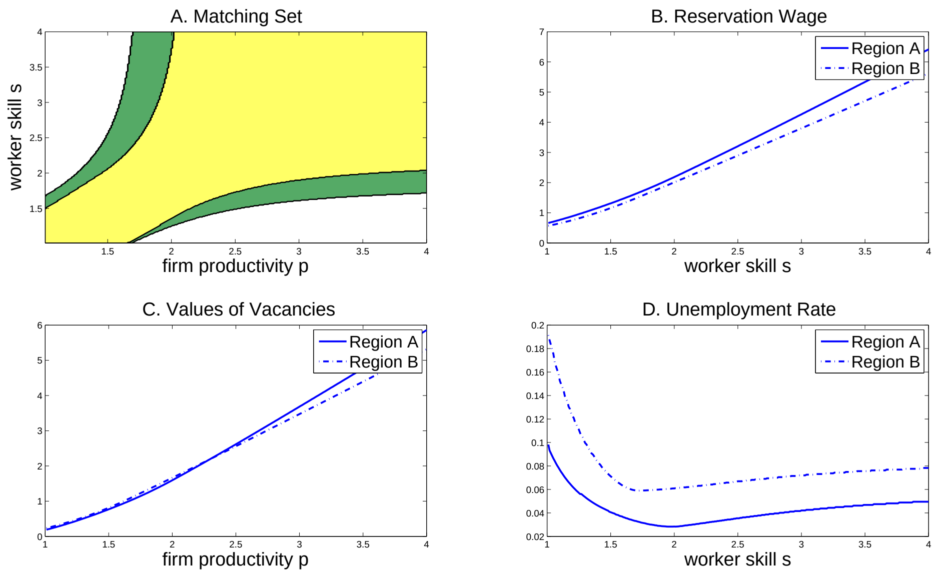


Figure 3.2: Equilibrium without inter-district job search $\psi = 0$

of matching with lower type agents becomes so high, that some of them prefer to remain unmatched.

Inter-district job-search

The commuting decision of workers is based on a comparison between the value of search (equation 3.7) in both districts. Search efforts are fully concentrated in the district in which they generate the highest return. Because of scale effects in search, resident *B* workers will have an incentive to search for jobs in district *A*, whereas resident *A* workers will only search for jobs locally. The decision balances the costs and benefits of inter-district job search. Figure 3.2 in section 3.2.3 already illustrated how the discrepancy between the reservation wages in the two districts grew larger for highly skilled workers. Supermodularity of the production process ensures skill complementarity, so that a worker's benefit of finding a better partner is increasing in her skill level. Lower inter-district job search efficiency ($\psi < 1$) and commuting costs imply that low-skilled workers will continue to concentrate their job search efforts locally. The skill cut-off

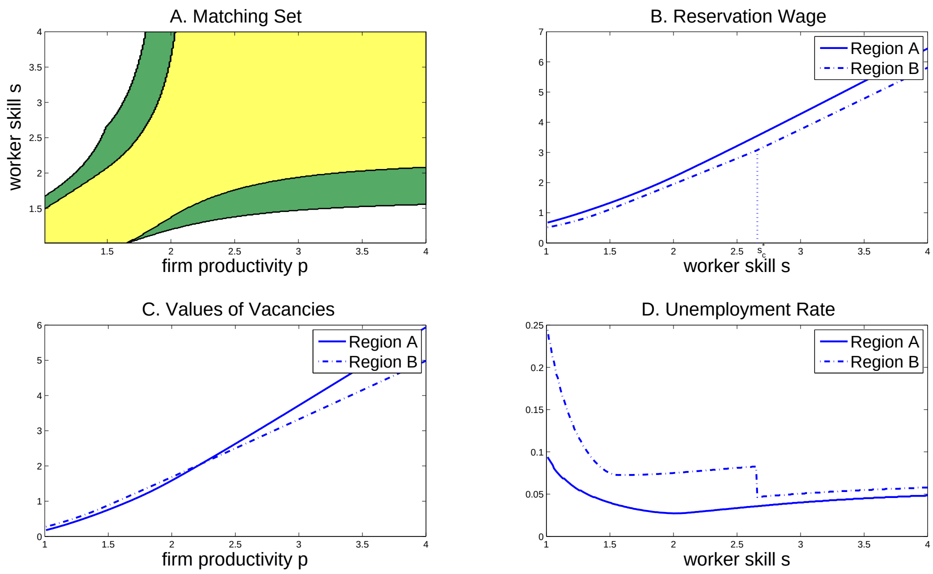


Figure 3.3: Equilibrium with inter-district job search $\psi = 0.7$

level s_c^* above which workers commute is illustrated in panel B of Figure 3.3.

Since now even more workers are focusing their search efforts in district A, more firms find it profitable to enter, further strengthening the quality of matches. The opposite occurs in district B: the outflow of high-skilled workers reduces the total number of searchers. This induces firms to widen their acceptance set, which reduces the value of vacancies and lowers the number of vacancy openings. Figure 3.4 illustrates how inter-district search increases the vacancy density in A, at the expense of district B. The relative decrease is stronger in B because of the initial size difference. Panel D of figure 3.3 shows that inter-district search activities also affect the unemployment rate . Low-skilled unemployment in B increases significantly as vacancy openings in the district decline. On the contrary, the unemployment rate of B's high-skilled workers decreases, as they find jobs in the agglomerated district.

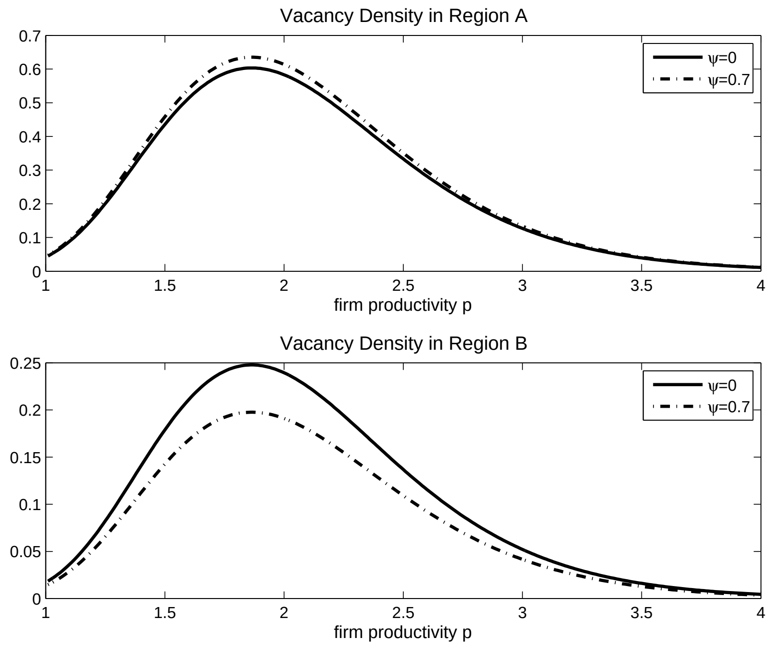


Figure 3.4: Vacancy density in region *A* and *B*

The impact of fixed mobility costs on peripheral workers

Figure 3.5 illustrates the impact of a decline in the fixed cost of commuting on the model's equilibrium. The commuting cut-off level shifts leftwards. More resident *B* workers can now afford to search for jobs in *A*. Importantly, as less workers are now concentrating their job search effort in the peripheral district, fewer firms will find it profitable to open a vacancy there. This puts a downward pressure on local contact efficiency and deteriorates the labour market outcome of low-skilled peripheral workers that are left behind. Their reservation wage declines and unemployment level rises.

Interestingly, the labour market outcome of workers depends not only on the size of the local labour market, but also on the size of the labour market in neighbouring districts. High-skilled workers in the peripheral district are better off located close to agglomerated areas, since production complementarities imply that agglomerated areas offer them 'a higher return to skill'. This enables them to afford the commuting cost, which grants them access to the neighbour-

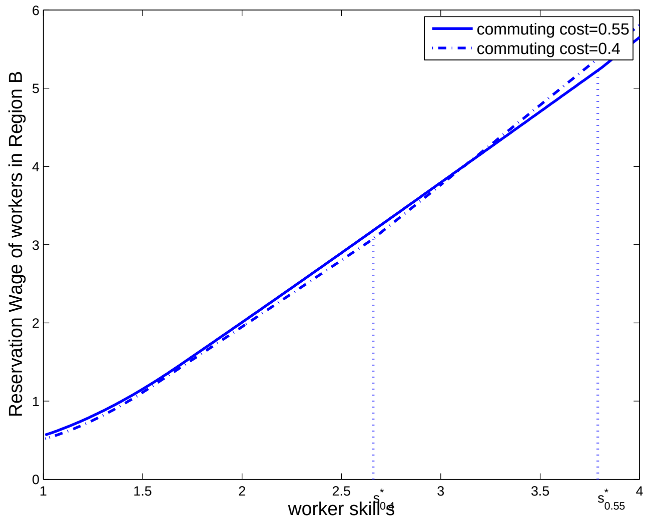


Figure 3.5: The impact of commuting costs on reservation wages in B

ing labour market. As firms realise workers concentrate their search efforts in the agglomerated areas, they decide to open vacancies there, at the expense of the peripheral district. This hurts the remaining low-skilled peripheral workers, who see their labour market prospects deteriorate. To the best of our knowledge, this novel finding has not been documented before.

The model yields two important testable predictions:

1. The vicinity of agglomerated districts *increases* the match quality of *high*-skilled workers.
2. The vicinity of agglomerated districts *reduces* the match quality of *low*-skilled workers.

Both predictions will be tested using Belgian linked employer-employee data, which are described in section 3.3.

3.2.4 Related literature

The model described in section 3.2 is essentially an urban model with a polycentric structure. It analyses the impact of fixed geographic mobility costs on workers' labour market outcome, in the presence of random search, skill complementarities in production and labour market pooling in the context of an urban area with two employment centres.

Our model is closely related to the two-district model described in Coulson et al. (2001), which shares a number of important features with the framework applied in this chapter: an urban set-up with two points in space (CBD-SBD setup), worker heterogeneity, search frictions, free entry of vacancies and mobility costs. Just as in our model, the agglomerated district exerts a pull effect on peripheral workers. This pull effect is driven by a lower entry cost of vacancies, which increases the contact rate and raises wages in the agglomerated district. Coulson et al. (2001) further assume heterogeneous commuting preferences, which in equilibrium lead to a selection of workers who commute from the peripheral to the agglomerated district. Therefore, the peripheral district's workforce will also be partitioned into a group of commuters and one of non-commuters. In our model, however, the pull effect is generated through scale effects in search, making search more efficient in the agglomerated district. In contrast to Coulson et al. (2001), we endogenise the selection effect by coupling it to productivity through skill complementarities in production. This way fixed mobility costs have a differential impact across skill-levels. Importantly, both models lead to fundamentally different policy implications. Coulson et al. (2001) show that reducing commuting costs between the two district is Pareto welfare improving.[10] A similar policy in our model would lead to a deterioration of the labour market outcome of low-skilled workers in the peripheral district, because the delocalisation of search efforts to the agglomerated area negatively impacts the strength of labour market pooling effects in the peripheral district.

Labour market pooling effects are of central importance to our analysis. They

[10]For a similar model, see Ortega (2000), who concludes as well that mobility improves the welfare of migrants, while leaving the outcome of left behind native workers' unchanged.

are introduced through a labour market assignment model where job-search is subject to scale effects, resulting in a positive relationship between labour market scale and matching quality. This relationship has been discussed and documented by several authors before us. Helsley & Strange (1990), for example, were among the first to highlight the importance of scale and matching quality in an urban context using a Salop (1979)-type model with non-hierarchical heterogeneity. In contrast, our assignment framework with search frictions builds on Shimer & Smith (2000) and is characterised by hierarchical agent heterogeneity, which is an important driver of our main results. In their model, scale effects in the search technology generate the positive relation between labour market size and matching quality.[11] Gautier & Teulings (2009) introduce this framework in a system of cities and use scale effects in search to explain differences in city size. The aim of this paper is not to explain urban scale, but rather to examine the impact of costly spatial interaction between urban district on the labour market outcome of workers.

3.3 Data

3.3.1 Data Description

The main implications of the model are tested using a unique Belgian linked employer-employee dataset (LEED), ranging from 1998 to 2008. This dataset is collected by the Crossroads Bank for Social Security in Belgium. The data covers nearly the entire Belgian population and initially consists of 35,721,027 observations, with each observation corresponding to a worker-firm-year combination. At the worker-level the data provide information on age, gender, gross daily wage (full time equivalent), location of residence and workplace, labour market status, and an indicator of whether a worker is a full- or part-time worker. At the firm-level, the data contains information on firm location, number of employees, the industry in which the firm operates and an indicator

[11] A feature made more explicit by Teulings & Gautier (2004).

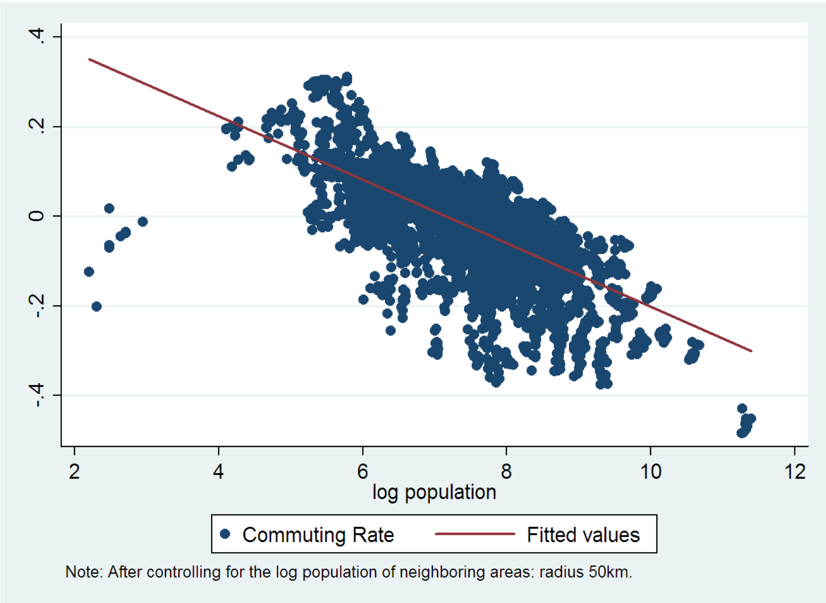
of whether a firm is a single- or multi-plant firm. Firm and worker location are reported at the level of the municipality. Municipalities are the smallest administrative regions in Belgium of which there are a total of 589. This high level of geographical disaggregation in the data allows us to construct detailed measures of labour market size. One limitation of the firm-level data is that there are no direct links between workers and establishments. However, an indicator allows us to single out single-plant firms, which together account for about 70 percent of total employment. For the remaining 30 percent of workers we do not know with certainty their location of employment.

The analysis only covers the private sector. Belgium upholds a minimum mandatory schooling age of 18 and an official mandatory retirement age of 64, so we only consider workers in the implied working age category. In case a worker holds multiple jobs, only the primary job, defined as the one paying the highest wage, is kept. Workers with wages in the bottom and top one percent of the wage distribution are omitted from the sample, as well as those earning less than the minimum wage. Section A.2 in the appendix provides a detailed description of the dataset and cleaning process. Table A.1 provides the summary statistics for the sample.

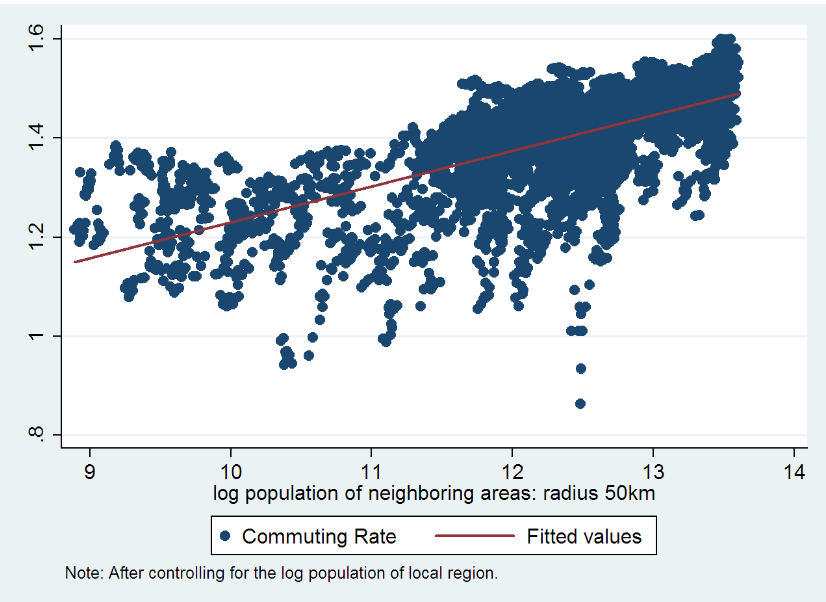
3.3.2 Graphical illustration of the model's driving mechanisms

Underlying the model's implication for the match quality of workers, two important mechanisms are at play. First, resident workers from peripheral districts are more likely to commute. Second, this decreases job openings in the peripheral district. The two scatter plots in Figure 3.6 illustrate the first mechanisms, as they show a negative correlation between the local commuting rate and local density and a positive correlation between the local commuting rate and the density of the neighbouring areas.[12] Figure 3.7 illustrates the

[12] Commuters are defined as workers who work outside their resident municipality. The commuting rate is defined as the ratio of commuters over total local population, at the municipality level.



(a) Local population (slope=-0.071, s.e.=0.002)



(b) Neighbouring population (slope=0.072, s.e.=0.0017)

Figure 3.6: Commuting rate and size of labour market

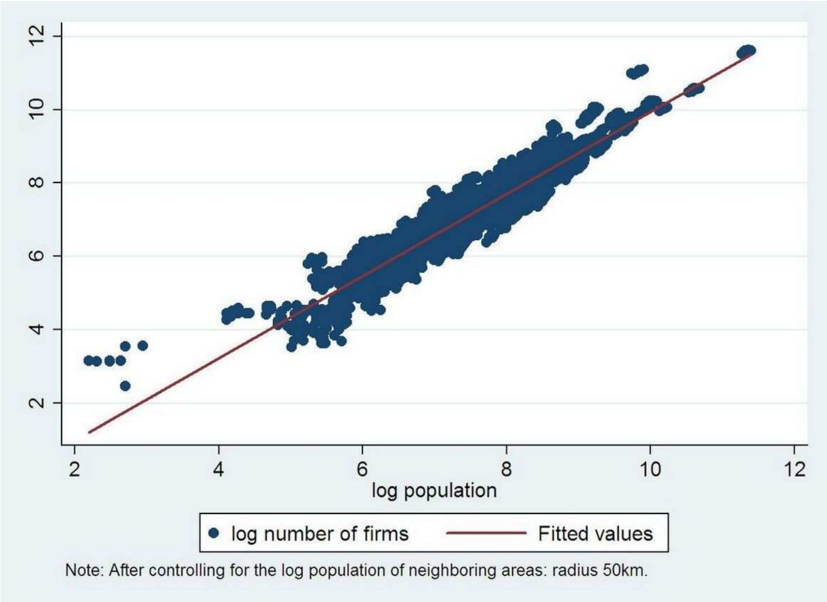
second mechanism. The left panel shows a positive correlation between local labour market density and the number of firms, whereas the right panel shows that firm count is negatively correlated with the density of the neighbouring area. Both observations illustrate the effect of labour market density on firm count through the free entry condition, which drives vacancies to agglomerated areas at the expense of the peripheral districts.

3.4 Empirical strategy

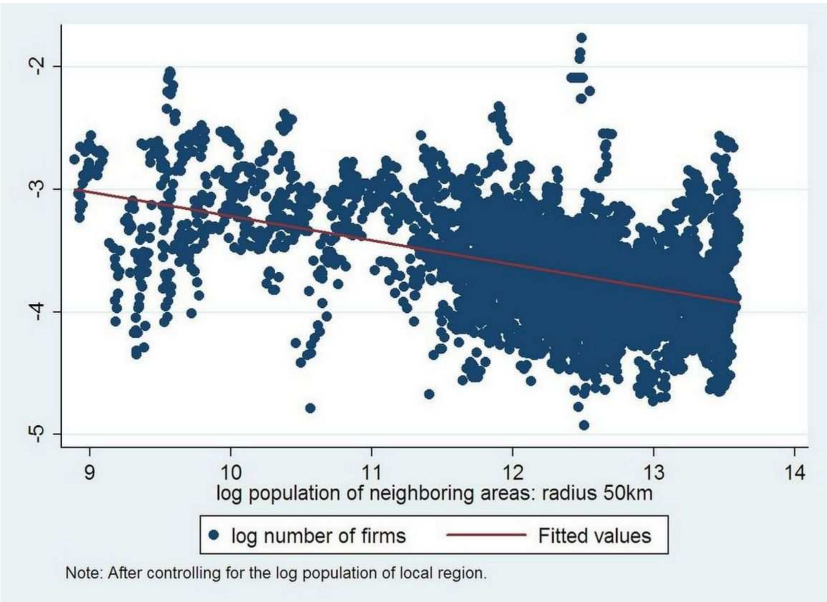
3.4.1 Measuring the strength of matching

Before proceeding with the calculation of match quality, we first need to determine worker and firm types. J. Abowd et al. (1999) propose a method based on a simple Mincer wage equation applied to a panel of linked employer-employee data. The presence of inter-firm worker mobility allows them to identify both firm and worker effects. The correlation between firm and worker effect is taken as a proxy for match quality. A number of studies using J. Abowd et al. (1999)'s estimator failed to uncover any evidence of positive assortative matching,[13] which some have taken as evidence against labour market sorting. However, Eeckhout & Kircher (2011) and Lopes de Melo (2009) argue that because of the non-monotonic effect of firm productivity on wages, identification of worker and firm fixed effects based on J. Abowd et al. (1999)'s strategy will fail to identify sorting. The non-monotonicity is driven by the observation that wages of a given worker will follow an inverted U-shape around his optimal allocation corresponding to the frictionless wage. The intuition goes as follows: if a worker matches with a firm which is of a worse type than himself, his wage will be lower than the frictionless wage. Note however that his wage will also be lower if he matches with a better firm. In this case a larger part of the matching surplus will accrue to the firm, as it will require compensation for its willingness to match with a lower type. So a worker obtains the highest wage if

[13]Andersson et al. (2007) for the US, Lopes de Melo (2009) for France and Brasil.



(a) Log Population of Local Market (slope=1.12, s.e.=0.0087)



(b) Log Population of neighbouring Areas (slope=-0.20, s.e.=0.0072)

Figure 3.7: Number of firms and size of labour market

he meets the 'right' firm and the wage will be lower the further he is distanced from his optimal match. The correlation between worker and firm fixed effects calculated using J. Abowd et al. (1999)'s methodology will then be zero and informative about neither the sign nor the strength of sorting.

Our identification strategy is based on Lopes de Melo (2009). His measure of worker and firm types derives directly from wage data. Wage data implicitly incorporate all relevant skill and productivity characteristics regardless of whether they are observable. Since in search models wages correlate positively with worker type, the average wage of a worker $S_i = \frac{\sum_{t \in T_i} w_{it}}{T_i}$ recovers the true type of the worker, where T_i is the set of years that worker i is observed in the data.[14] We recognize that apart from skill differences, observed wages also reflect variables unrelated to workers' productive characteristics, such as regional variations in labour market conditions, rent sharing or bargaining power. To accommodate this, we construct our measure based on the ranking of workers by their average wages within the same district. Our measure of firm type derives from the quality of the workers it hires. We proceed by calculating the average wage of firms j's workforce, $P_j = \frac{\sum_{t \in T_j} \sum_{i \in N_{jt}} S_i}{\sum_{t \in T_j} N_{jt}}$, or alternatively by taking the wage of the best worker that it employed during the sample period, $P_j = \max_{t \in T_j, i \in N_{jt}}(S_i)$, where N_{jt} is the set of workers employed in firm j at time t, and T_j is the set of years that firm j is recorded in the dataset. The rank correlation between S_i and P_j, $Corr(S_i, P_j)$, then measures the strength of matching. The empirical analysis uses only firms that have at least 3 employees. In addition, firms are required to be part of a 'mobility cluster'. This means that they must employ at least one employee that has switched firms over the sample period.

There are three issues through which the construction of our measure of match quality can pose a threat to our identification strategy. First, if rent-sharing is common, this will lead to an overestimation of the strength of matching. As long as rent-sharing does not systematically vary with labour market scale, this is of no concern. In addition, long sample periods render this concern

[14]For another example of a study that uses wages as a skill proxy, see Eeckhout & Kircher (2011), who measures skill-level by wages adjusted for house prices.

irrelevant, as the measured match quality will converge to its true value if T grows large. Second, the match quality measure will be affected by the degree of inter-firm labour mobility. In the limit, no mobility would result in a perfect correlation between firm and worker quality. Lack of worker mobility therefore upward biases our measure. Since inter-firm mobility of workers has been shown to depend on labour market scale (Freedman, 2008), this could pose a threat to identification. For high-skilled workers, our estimates will provide a lower bound for the true effect of surrounding labour market size on local matching quality, which is predicted to be positive. For low-skilled workers, however, the predicted effect is negative, so the mobility-bias will exaggerate the true effect. To control for the possible artificial impact of inter-firm mobility on our estimates, we supplement our empirical specification with a variable measuring the job switching rate of workers, which measures the percentage of local workers switching jobs in a given year. Third, by construction, the strength of matching is higher for regions with a large mass of small firms. Several studies have documented a positive correlation between city scale and firm size (see for example Campbell & Hopenhayn, 2005; Manning, 2010). This implies that our estimates for the effect of density on matching quality will provide a lower bound for the true effect, which is especially problematic for the specification of the group of low-type workers, where the effect of scale on match quality is predicted to be negative. We resolve this by adding to the empirical specification a control for local average firm size.

3.4.2 Empirical Specification

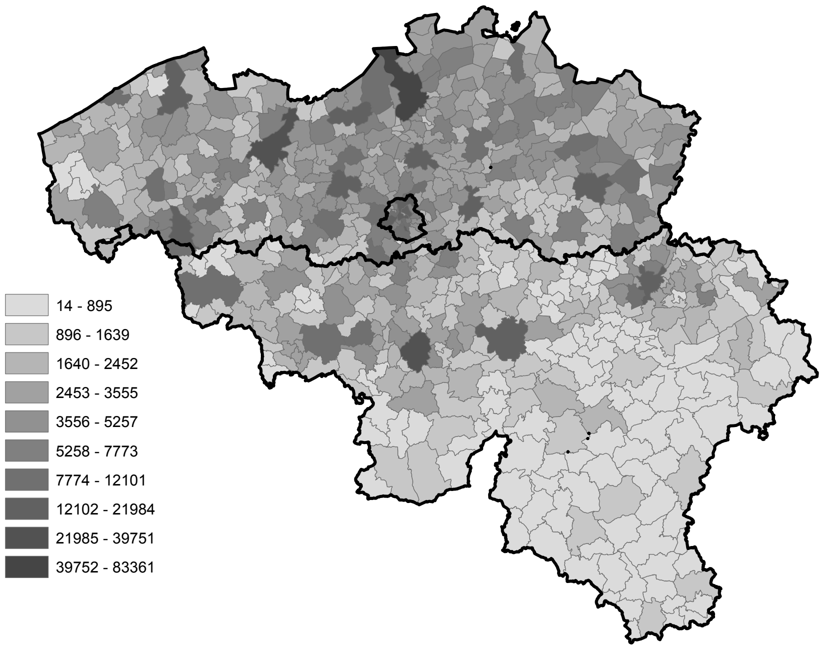
The quality of matching depends both on the size of the local labour market, as well as the size of the labour market in neighbouring areas. Local labour market scale positively affects match quality across skill-levels. This is not the case for neighbouring labour market scale. Although neighbouring scale improves the match quality of high-skilled workers, it diminishes it for low-skilled workers. We will test these theoretical predictions using two specifications, one for each skill-group. The high-skilled group contains all workers in the top 25 percentiles of the skill distribution, which means they have an average daily wage greater than 121.50 Euro. The low-skilled group covers workers in the lowest 25 percentiles of skill distribution, whose daily wage does not exceed 81.74 Euro. The following two equations will be taken to the data:

$$\begin{aligned}\mathrm{Corr}_{i\in r}(S_i,P_j)_H &= \alpha_0+\alpha_1\ln\mathrm{pop}_{local}+\alpha_2\ln\mathrm{pop}_{surr}+\gamma X+\epsilon_{rH}\\ \mathrm{Corr}_{i\in r}(S_i,P_j)_L &= \beta_0+\beta_1\ln\mathrm{pop}_{local}+\beta_2\ln\mathrm{pop}_{surr}+\gamma X+\epsilon_{rL},\end{aligned}\tag{3.18}$$

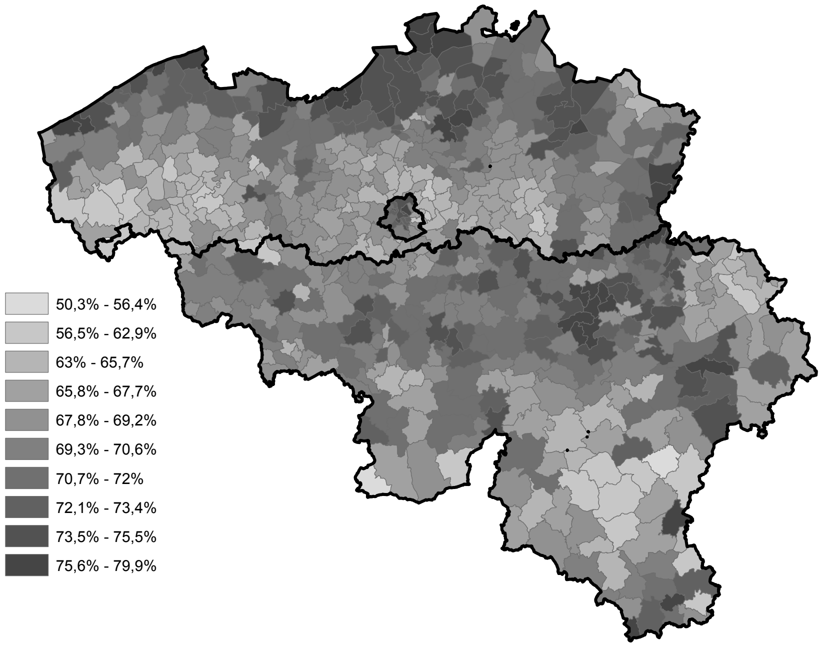
where $\mathrm{Corr}_{i\in r}(S_i,P_j)_H$ denotes the match quality for high type workers and their corresponding firms, and $\mathrm{Corr}_{i\in r}(S_i,P_j)_L$ denotes the match quality of their low type peers. The size of the local labour market L_i is proxied by the log of resident workers in the municipality. Accordingly, the log of resident workers in the neighbouring areas controls for the scale of the surrounding labour market. The geographical extent of the neighbouring labour market is defined both in terms of distance and commuting time.[15] Using the coordinates of the municipalities' geographical centroids, we calculate the great-circle distance between them and for each municipality construct a surrounding circle with a radius of 50km. 73.76 percent of all workers commute within this distance. The measure excludes local resident workers. Estimation first proceeds with the standard OLS estimator. Adding municipality fixed effects to the specification is too demanding on the data as it oversaturates the model. Arguably, the relevant year-to-year variation in the agglomeration measures is limited. In addition, changes in population might not have a contemporary effect on match quality because of the delayed response of vacancy creation to variations in labour market scale. To avoid imposing an a-priori unknown and possibly ad-hoc lag structure on the empirical model, we opt for the Random Effects estimator.

To get a feel for the spatial distribution of two of the model's key variables, we mapped our measure of match quality and municipality population in figure 3.8. Both variables show considerable non-random spatial variation.

[15]The results of the latter can be found in the appendix.



(a) Municipality population anno 2002



(b) Average municipality match quality anno 2002

Figure 3.8: Spatial distribution of population and match quality

3.5 Results

3.5.1 Match Quality and Size of labour Market

The average match quality for high-skilled workers is 0.24, while the average match quality for low-skilled workers is 0.44.[16] The estimation results of equations 3.18 are presented in table 3.1 and A.2. The former table contains the results where firm types are measured by the average workforce wage, whereas the latter table presents the results using the alternative measure of firm quality, proxied by the wage of the highest paid worker. We first estimate a basic version of model and then add a number of additional control variables, which accommodate the identification threats discussed in section 3.4. Results are reported for both the OLS and RE estimator.

From Table 3.1, the size of the neighbouring district positively affects the match quality of high-skilled workers, in line with the predictions of our model. Local labour market scale does not have a significant effect on high-skilled match quality. The estimates based on the Random Effects estimator in column (2) are not much different from the OLS estimates. Columns (3) and (4) supplement the specification with the additional control variables, which leaves the results intact. The last four columns in Table 3.1 confirm the central contribution of this chapter: labour market scale of the surrounding area has a significant negative impact on the match quality of low-skilled workers. Locating in the vicinity of agglomeration areas not only does not come to the benefit of low-skilled workers, it actually deteriorates their labour market prospects. Interestingly, the match quality of high-skilled workers is significantly lower in municipalities along the language border. This is consistent with the findings of Persyn & Torfs (2015b),[17] who analyse the deterrent effect of the Belgian language barrier on commuting behaviour.

[16]This does not contradict the predictions of our model, since the level of the match quality depends on the density of workers in the respective parts of the skill distribution. The lower match quality of high-skilled workers therefore reflects the fact that there are less high type agents in the labour market, who therefore settle with suboptimal partners.

[17]A version of which can be found in chapter 1 of this thesis.

Table 3.1: Match Quality and the Size of labour Market

	High-skilled Workers				Low-skilled Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	RE	OLS	RE	OLS	RE	OLS	RE
Log(pop)	-0.0014	-0.0041	0.000062	-0.00022	0.012***	0.012***	0.013***	0.013***
	(0.0016)	(0.0047)	(0.0019)	(0.0044)	(0.0011)	(0.0025)	(0.0013)	(0.0028)
Log(pop of neighboring areas)	0.0083***	0.0093**	0.011***	0.010**	-0.014***	-0.015***	-0.0091***	-0.013***
	(0.0016)	(0.0046)	(0.0023)	(0.0047)	(0.0012)	(0.0027)	(0.0015)	(0.0032)
Language border dummy			-0.031***	-0.032***			-0.00089	-0.0013
			(0.0029)	(0.0082)			(0.0025)	(0.0060)
Average firm size			-0.00037***	-0.00081***			-0.00092***	-0.00050**
			(0.00013)	(0.00030)			(0.00011)	(0.00022)
Average age of workers			0.0070***	0.0078**			-0.0074***	-0.0031
			(0.0016)	(0.0034)			(0.0011)	(0.0025)
Log(house price)			-0.021**	-0.0063			-0.0020	0.0065
			(0.0088)	(0.0058)			(0.0038)	(0.0056)
Job switch rate			0.22**	0.053			-0.25***	-0.100**
			(0.095)	(0.052)			(0.059)	(0.048)
Year fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Observations	6,468	6,468	5,879	5,879	6,468	6,468	5,879	5,879
R-squared	0.015	0.014	0.04	0.034	0.20	0.20	0.15	0.14

Note: Unit is municipality. The dependent variable is match quality measured by the rank correlation between worker and firm types. Firm types are measured by the average worker type a firm hires. House price is measured by the weighted average price of house, villa, apartment and lot. Herstappe, the least populous municipality in Belgium, is dropped. Robust standard errors are in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

A number of robustness checks test the sensitivity of our findings. The results are reported in section A.3. Table A.2 presents the results using the alternative measure of firm quality, measured by the wage of its highest paid worker. The conclusions remain unaltered. Next, we exclude the 19 municipalities of the Brussels Capital Region from the analysis. Brussels is the largest urban area in Belgium and the results might be driven by a Brussels-effect. Excluding Brussels leaves the results unaltered. As our data are firm-level, we are not able to identify the direct link between workers and firms. In the dataset about 3 percent of firms are multi-plant firms, employing about one third of the total number of employees. For this group of workers we cannot say with certainty that their place of work recorded in the data corresponds to their true location of employment. The dataset contains an indicator that allows us to distinguish between single-plant and multi-plant firms. The last four columns of Table A.3 show the results obtained after omitting the latter group from the sample. The conclusions remain unaltered. Table A.4 experiments with population density as a measure of labour market scale. Also here, the main results still hold. In Table A.5, we redefine the neighbouring area based on commuting time by car. The results remain unaltered.

3.6 Conclusion

This chapter illustrated how urban agglomeration externalities do not come to the benefit of all workers if skills are complementary in production, search activities are subject to scale effects and commuting is costly. Within an urban area, workers choose to concentrate their job-search efforts in those districts that provide them the highest return to search. If job-search is grows more efficient with scale, agglomerated districts will attract search activities from workers living in nearby peripheral districts, who balance the benefits associated with scale effects with commuting costs that need to be paid for inter-district job matches. This further encourages firms to open new vacancies in agglomerated districts, at the expense of the periphery. A driving assumption in our framework is that skills are complements in production. This makes that high-skilled workers benefit more than proportionally from finding a better match. Low-skilled workers living in peripheral districts will find that they cannot afford the mobility cost and get isolated from the labour market pooling effects offered by the surrounding agglomerated urban areas. They therefore not only fail to benefit from nearby concentration of economic activity, they actually suffer and see their labour market outcome deteriorate. We were able to test and confirm this novel finding using a Belgian matched employer-employee dataset.

The added complexity of the assignment framework brings about an important nuance to the policy recommendations commonly formulated in earlier studies. A number of theories (Coulson et al., 2001; Ortega, 2000) predict that policies aimed at decreasing the spatial disconnect between workers in peripheral district and jobs in agglomerated areas will lead to Pareto welfare improvements by alleviating the adverse labour market outcomes of peripheral workers. Empirical studies have repeatedly confirmed that increased access to jobs leads to improved labour market prospects (see Zenou, 2009, for a discussion). However, these studies generally focus on the labour market outcome of those workers that have been *successfully* targeted by such policies. Our results suggest that policies aimed at increasing geographical mobility of workers through commuting subsidies can have unintended consequences, as they will hurt the labour market outcome of left-behind low-skilled workers in peripheral districts.

Chapter 4

Functional Labour Markets in Belgium

4.1 Introduction

This chapter applies the methodology developed in Coombes et al. (1986) and Bond & Coombes (2007) to construct functional labour markets for Belgium. Administratively delimited geographic regions traditionally form the basis for data collection and the economic analysis of labour markets. Their borders are often drawn arbitrarily or rest on a purely historic basis. Consequently, there is no reason to believe that administrative regions correspond to a labour market in any economically relevant sense. In contrast to administratively delimited labour markets, the boundaries of functional labour markets are rooted in the behavior of economic agents. The construction of functional labour markets serves several purposes. First and foremost, they constitute an instrument to monitor regional labour market outcomes and allow to monitor the effectiveness of labour market programs. Several countries have already implemented functional labour markets as an official platform to gather labour market statistics (the 'Travel-to-Work for the U.K.' (Bond & Coombes, 2007), the 'zones d'emploi' for France (Jayet, 1985), the 'Sistemi locali del lavoro' for Italy

(Sforzi & Istituto nazionale di statistica (Italia), 1997), for example). Second, functional labour markets are frequently used as a basis for economic analysis (see for example Di Addario & Patacchini (2008), Hincks (2010), Spencer et al. (2010), Manning (2010) to name but a few).

The Bond & Coombes (2007) algorithm starts from spatially highly disaggregated data on employment and commuting flows. Regions that interact intensively in terms of commuting flows are merged sequentially. When all areas are assigned, a map of the functional labour markets is obtained. We propose a minor modification to the Bond & Coombes (2007) algorithm to resolve discontinuities in the initially constructed TTWAs. The functional labour markets resulting from the Coombes method are commonly referred to as Travel-To-Work-Areas, hereafter simply TTWAs.

The availability of commuting data from three different census waves (1981, 1991, 2001) allows us to study how the Belgian TTWAs have evolved over time. More recently the Belgian Social Security Office has published commuting data for 2007 which is disaggregated along a sector and gender dimension, allowing us to construct sector and gender-specific TTWAs. A section with robustness checks analyses the sensitivity of the results to the chosen parameter values. No recent attempt has been undertaken to construct functional labour markets based on nationwide Belgian commuting data using the Bond & Coombes (2007) methodology. It is our hope that the results in this paper can serve the Belgian statistical agencies in developing labour market statistics for functional labour markets. It will provide policy makers with a meaningful labour market monitoring tool and can serve as the geographical unit of analysis for future studies on the Belgian regional labour markets.

4.2 Related literature

Next to the (Bond & Coombes, 2007) algorithm applied in this paper, a number of other delineation methodologies have been proposed in the literature.

(Van der Laan & Schalke, 2001) develops a multi-level taxonomy to classify different studies that propose delineation methods. He distinguishes between an inductive and deductive approach.[1] Deductive delineation methods start from a priori selected areas and subsequently construct functional regions around them, using a selection of criteria. Deductive methods identify centres independently and uses a different set of rules for the construction of the functional region as a whole (Van Nuffel, 2007). An example of a deductive approach can be found in the Census Agglomerations of Canada, whose construction departs from a focal point (Census Metropolitan Area), which is selected based on a size criterion. Surrounding areas are subsequently merged based on bilateral commuting links with the predefined center. In contrast, inductive methodologies construct functional regions starting from the interaction between areas and thus avoid pre-selecting certain focal points. An example of the latter approach is the INTRAMAX-procedure, as proposed by Masserfil & Brown (1975). The INTRAMAX method minimizes the between-area interaction (and maximizes the within-area interaction) for a given number of regions. Díaz & Coombes (2011) formulate an alternative classification for delineation methods and distinguish between hierarchical and rule-based delineation methods. Hierarchical methods construct functional regions step-wise. Rule-based approaches provide more flexibility as they evaluate the constructed region at each step throughout the algorithm and allow for the possibility break up existing areas and re-evaluating the allocation of its subelements.

The method applied in this chapter provides a middle ground between an inductive and deductive approach. Although focal points play a crucial role in the construction of the TTWAs, they are not identified independently of the subsequent construction of the functional region. This can results in multi-polar local labour markets with multiple centers of economic activity. In addition, its rule-based character implies that at each stage of the algorithm, constructed areas are re-evaluated, leaving open the possibility to break them up and reassign their respective elements to other areas.

[1]For an elaborate explanation of the different classifications, see Díaz & Coombes (2011), Van der Laan & Schalke (2001).

TTWAs have been constructed for a variety of countries: Casado-Díaz (2000) for Spain, Andersen (2002) for Denmark, by Papps & Newell (2002) for New Zealand and by Corvers et al. (2009) for the Netherlands. The popularity of the Bond & Coombes (2007) method is derived from its simplicity and non-stringent data requirements: the algorithm runs using a matrix of spatially disaggregated commuting trips. The wide-spread availability of such data, both over time and across countries, makes it possible to track the historical evolution of TTWAs (see Papps & Newell, 2002; Coombes & Casado-Diaz, 2005), or compare the geographical extent of labour market across different labour market segments (see Green et al. (1986) for a comparison between TTWAs for male and female workers or Casado Díaz et al. (2007) for TTWAs at the occupational level). Furthermore, the resulting regions are constructed based on the principles of non-overlap (Van der Laan & Schalke, 2001), which renders them particular useful to serve as a basis for labour market monitoring or economic analysis.

We are not the first to illustrate the geography of labour markets in Belgium. The first comprehensive study of commuting in Belgium we could find dates back to 1957. (Dickinson, 1957) uses the 1947 census data to document commuting behaviour in Belgium and the Netherlands. The concept of functional labour markets was not yet developed at that time,[2] so the analysis proceeds using basic cartographic methods. The author nevertheless succeeds in providing an interesting geographical representation of the post-war Belgian regional labour markets. More recently, Coombes (1995) applies an early version of the TTWA algorithm on the 1981 Belgian census data. Van Nuffel (2007) provides an example of an inductive functional delineation method for Flanders. Boussauw et al. (2011) does not construct functional labour markets, but rather studies local commuting behaviour by focusing on regional variations in commuting trip length and excess commuting rates. Similarly, Verhetsel et al. (2010) analyse Belgian commuting patterns within pre-defined functional urban areas (Belgian metropolitan areas).

[2]And the computing power needed to run the algorithms (which takes a full day to complete on a 589X589 commuting matrix using modern day advanced processing strength) was lacking.

4.3 Methodology

The methodology is described in Bond & Coombes (2007). It finds its origins in earlier work by Coombes et al. (1986), but the algorithm evolved significantly in response to advances in computational power and improved data-availability (see Coombes et al., 1986; Coombes, 1998). This section will elaborate on the algorithm in detail.

Consider the commuting flows between n areas. Let F_{ij} be the flow of commuting trips from area i to area j. The number of workers that are residents of area i is denoted by R_i and the number of workers who are employed in area i by E_i. Note that $R_i = \sum_{j=1}^{n} F_{ij}$ and $E_i = \sum_{j=1}^{n} F_{ji}$. The methodology starts from the view that areas can only be considered as economically meaningful labour markets (TTWAs) if they are both large enough and their labour market is sufficiently self-contained, both on the demand and the supply side. The size of an area is measured in terms of total number of resident workers R_i. An area's 'supply side self-containment' is the ratio of the number of people that both live and work in the area F_{ii} to the total number of workers living in the area $R_i = \sum_{j=1}^{n} F_{ij}$. 'Demand side self-containment' is the ratio of the number of people that live and work in an area F_{ii} to the number of jobs in the area $E_i = \sum_{j=1}^{n} F_{ji}$. To qualify as a TTWA, Bond & Coombes (2007) list three requirements that need to be fulfilled simultaneously:

Rule 1 - An area with at least 25 000 resident workers requires both supply and demand side self-containment to be higher than 66.67 percent.

Rule 2 - For areas with less then 25 000 resident workers, the minimum supply and demand self-containment ratios linearly increase from 66.67 percent to 75 percent for areas with 3 500 resident workers.

Rule 3 - A TTWA must have at least 3 500 resident workers.

In other words, Rule 1 states that to classify as a TTWA, size is not the only thing that matters. The labour market must also be sufficiently self-contained.

That is, both the share of jobs filled in by locals (demand), as well as the share of resident workers that hold a job locally (supply) should be sufficiently high. Rule 2 imposes stricter self-containment requirements for areas with less than 25 000 residents. Small areas are only considered as independent labour markets if their labour market is sufficiently self-contained and the interaction withsurrounding areas is limited. Rule 3 puts a limit on the minimum size of TTWAs, in terms of resident workers. The threshold values are similar to the ones used in Bond & Coombes (2007), but can be adjusted to fit the needs of the researcher and the problem at hand.[3]

Figure 4.1 illustrates the three rules. All areas that lie to the north-east of the threshold line are considered valid TTWAs. Notice that the vertical axis depicts the lower of the supply of demand side self-containment. Figure 4.1

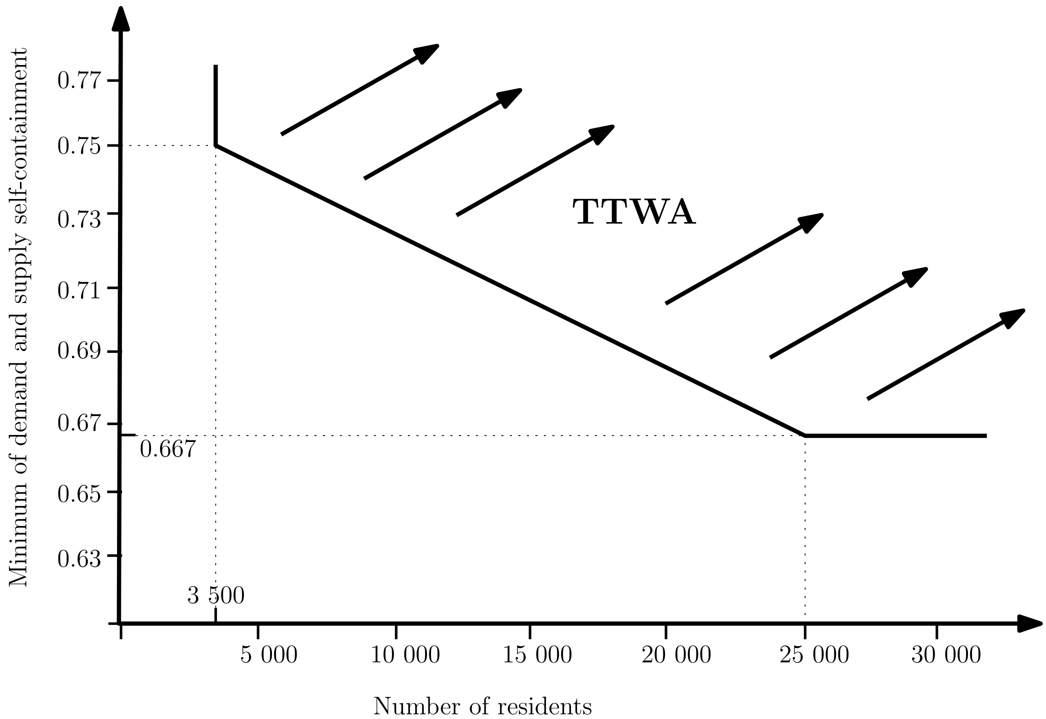


Figure 4.1: The X-equation, (after Bond & Coombes, 2007)

[3]For an illustration of the sensitivity of the algorithm's outcome to the parameter values, see 4.6.4.

corresponds to what Coombes et al. (1986) label ‘the X-equation’. It is the algebraical representation of the threshold line in figure 4.1 evaluated at the threshold levels set out by rules 1 to 3.

$$X_i = \min\left(1; \frac{c_1 R_i}{\alpha}; \frac{c_2 R_i + c_3}{\alpha}\right) \times \min\left(1; \frac{F_{ii}}{\beta E_i}; \frac{F_{ii}}{\beta R_i}\right). \tag{4.1}$$

The X-index consists of two factors. A first factor rewards size in terms of the number of resident workers. The second factor rewards self-containment, having a large share of residents which work in the region relative to the number of jobs and residents of the region. Only the smaller of supply-side and demand-side self-containment matters for the calculation of the X-index. Regions that are both large and self-contained will have a high X_i, but the index allows for a trade off between containment and size, since it rewards regions that are of limited size but have sufficiently high self-containment levels. The required parameter vector for Bond & Coombes (2007)'s rules to hold is $\{c_1 = 6.35;$ $c_2 = 0.129;$ $c_3 = 21783;$ $\alpha = 25000;$ $\beta = 0.75\}$.[4] This means that an area only qualifies as a TTWA if it has an X-index above a threshold value of 0.88933. The algorithm initially considers all areas as potential TTWAs. It starts from the area *least* likely to qualify as a TTWA (lowest X_i) and merges it to the area with which it has the strongest commuting links. To measure the strength of commuting links between two areas, the following formula counts the bilateral travel-to-work journeys relative to the number of resident workers and jobs in both regions.

$$L_{ij} = \frac{F_{ij}}{R_i}.\frac{F_{ij}}{E_j} + \frac{F_{ji}}{R_j}.\frac{F_{ji}}{E_i} \tag{4.2}$$

After merging the first two areas, $n-1$ areas remain. For all remaining areas, the X_i-indices, as well as the L_{ij} values are recalculated. Again, the area with the lowest X_i-index is chosen[5] and merged with the area with which it has the strongest connections. These steps are iterated until the point where the area with the lowest X_i is a group of previously merged areas. Call this area

[4]In section 4.6.4 we show how sensitive the results are to the chosen threshold values implied by the rules.

[5]During the first number of iterations, this will be likely a stand alone area which has not previously been merged.

A. Instead of considering area A as a whole, the group is dissolved and all its elements are again considered as stand alone areas. They are joined one by one with the area with which they have the strongest commuting links, the order by which is determined by ranking them according to the total flow of outgoing commuters $\sum_{j \neq i} F_{ij}$. If all the disentangled areas that formerly belonged to A are merged, a new iteration begins by considering the area that is the furthest away from being a TTWA. This process continues until all areas are TTWAs. As a minor modification to the Bond & Coombes (2007) algorithm, we introduced an additional final step. In this step each individual area gets separated from its TTWA and reassigned to the TTWA which it has the strongest link, as indicated by the L_{ij} measure. This final step avoids a TTWA consists out of discontiguous subelements, as the algorithm does not explicitly contain a rule preventing this.

4.4 Data description. Commuting flows in Belgium

We apply the algorithm on a matrix of commuting flows between the 589 Belgian municipalities. These data stem from two different sources. Commuting data for 1981, 1991 and 2001 were obtained from the Belgian Federal Bureau of Economics and originate from 3 different census waves. The census based commuting data contain only the total flow of workers between municipalities and will be used to study the evolution of the TTWAs over time. For the year 2007, the commuting data stem from the Belgian National Social Security Office (NSSO). Unlike the census data, the 2007 is disaggregated along a sectoral and gender dimension. Both the census and NSSO data cover private and public sector. However, the NSSO data do not include self-employed workers whereas the census data do.[6] As omitting the self-employed might bias the obtained results,[7] we do not explicitly extend the analysis on the evolution of the TTWAs over time to include the 2007 TTWAs. The database takes the form of an origin-destination flow matrix, consisting out of 589^2 cells, where each

[6] See Verhetsel et al. (2007) for a detailed discussion and descriptive analysis of the 2001 census commuting data.

[7] For a discussion on this matter, see section 4.6.1.

cell represents a unique combination of two municipalities.

4.5 Belgian Travel-To-Work-Areas

Applying the algorithm[8] on the 2007 Belgian commuting data gives rise to 11 distinct TTWAs, which are illustrated in Figure 4.2. Each TTWA is named after

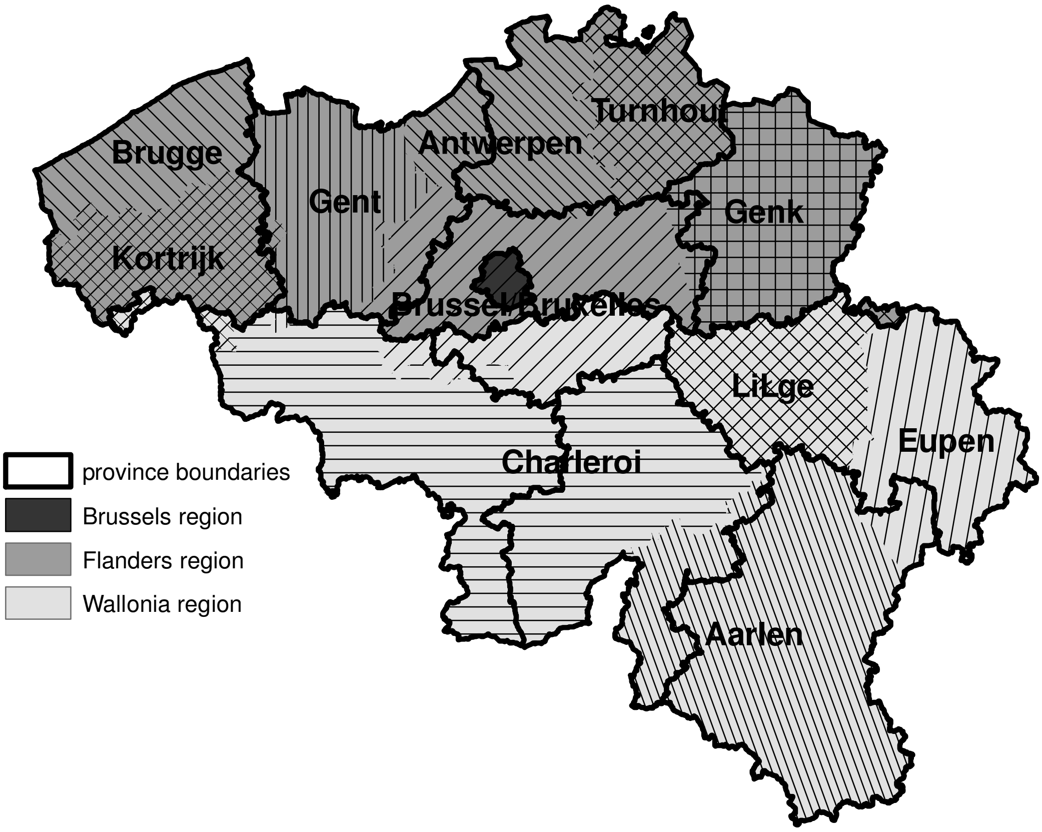


Figure 4.2: The 2007-TTWAs for the aggregate economy

the 'focal point' with which it was merged in the final stage of the algorithm. The black lines in figure 4.2 mark the provinces. It is interesting to see how the administrative borders of provinces often coincide with those of the TTWAs. Take the Genk TTWA for example, which apart from three municipalities,

[8]Calibrated using the parameter values described in section 4.3.

coincides with the province of Limburg. Furthermore, the language barrier separating the Northern region of Flanders from the Southern region of Wallonia seems to act as an impediment for commuters. With the exception of the Brussels TTWA and four French speaking municipalities that belong to the Kortrijk TTWA in the east, the linguistic barrier coincides with the barriers of TTWAs. These findings suggest an important role for linguistic factors in the determination of commuting decisions and hence, the geographical extent of labour markets. This is in line with the findings of Persyn & Torfs (2015b),[9] who formally analyze and quantify the effect of the language barrier on municipality commuting flows. In a different study, Blondel et al. (2010) construct ‘Telephone Areas’, using inter-municipality telephone traffic. They too find that the language border acts as a strong deterrent factor for interaction between the North and the South of Belgium.

4.6 Some applications

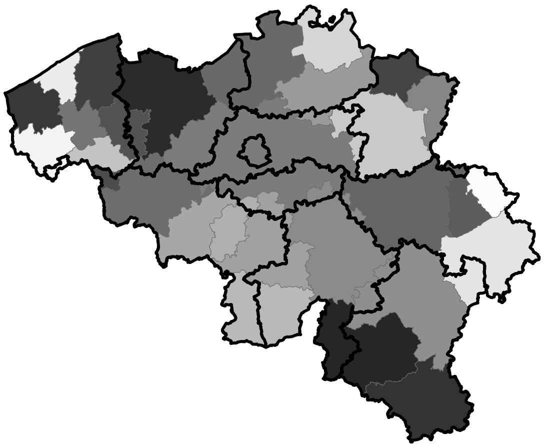
4.6.1 Evolution of time

In this section we consider how the Belgian TTWAs have evolved over time. Figure 4.3 shows the Belgian TTWAs for the years 1981, 1991 and 2001. The size of the functional labour markets in Belgium steadily increased over the past three decades, resulting in a decrease in the total number of TTWAs from 30 in 1981 to only 21 in 2001.

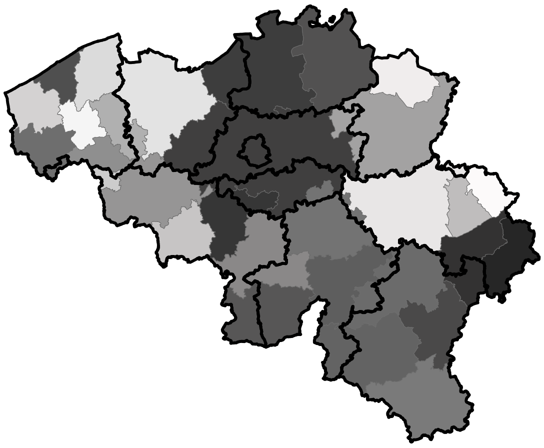
The decline in the number of TTWAs reflects an increase in the geographical mobility of the average worker. This led to the formation of fewer but larger functional labour markets. The average commuting distance increased from 10.73 to 11.84 to 14.61 km over the different years.[10] Van der Laan & Schalke

[9]A version of which can be found in Chapter 1.

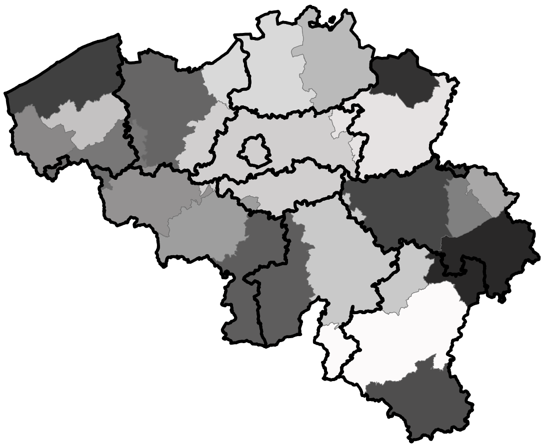
[10]Commuting distances are calculated based on the coordinates of location of the town halls, which is likely to coincide with the economical center of the city, rather than its geographical center. This underestimates the true average commuting distance, as our calculation assumes that the within municipality commuting distance is equal to zero. A comparison between the



(a) 1981



(b) 1991



(c) 2001

Figure 4.3: Evolution of the Belgian TTWAs over time

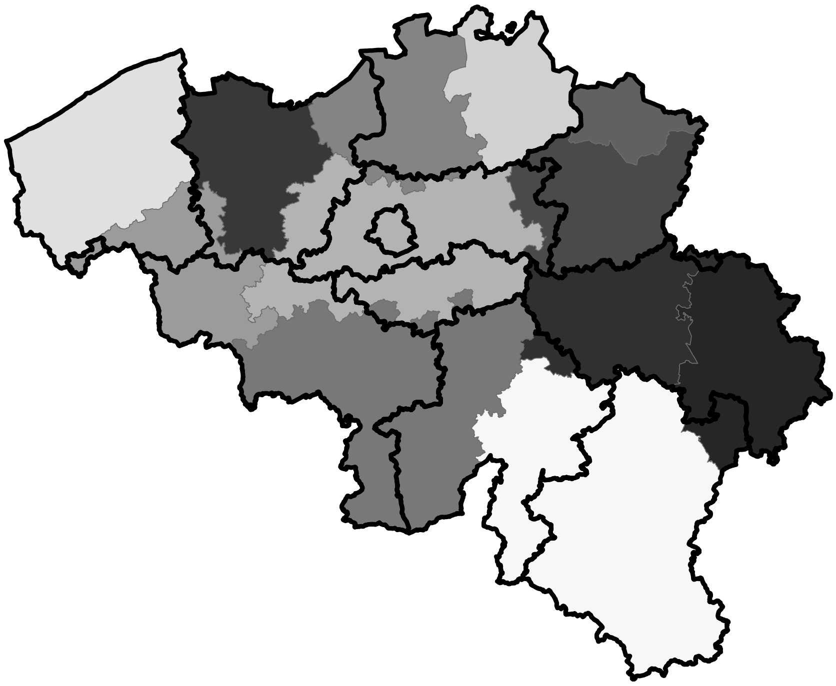
(2001) discusses the implicit centrality of the nature of mobility costs in the TTWA methodology. If relative commuting costs decrease with the wage, because they are fixed or at least contain a fixed component, an increase in the real wage will lead to longer commuting distances. Therefore, real wage increases combined with an increasing degree of spatial concentration of economic activity can explain the emergence of larger and fewer TTWAs, as documented in figure 4.3. Between 2001 and 2007, the number of TTWAs decreased further to 11. However, a direct comparison between the lower panel of figure 4.3 and figure 4.2 is problematic. Both figure are constructed from different source data. The 2001 census data comprise the entire Belgian workforce, whereas the 2007 administrative data only counts payroll employees and does not contain self-employed. Since by definition self-employed work and live in the same location, The 2007 TTWAs will therefore be larger by construction, since they omit the self-employed, which are considered non-commuters and therefore boost the self-containment ratios. Our findings are consistent with other studies that documented the tendency for TTWAs to grow over time (see for example Newell & Perry (2005) between 1991 and 2001 for New-Zealand, and Coombes et al. (1985) for South- and East-England).

4.6.2 Sector-specific TTWAs

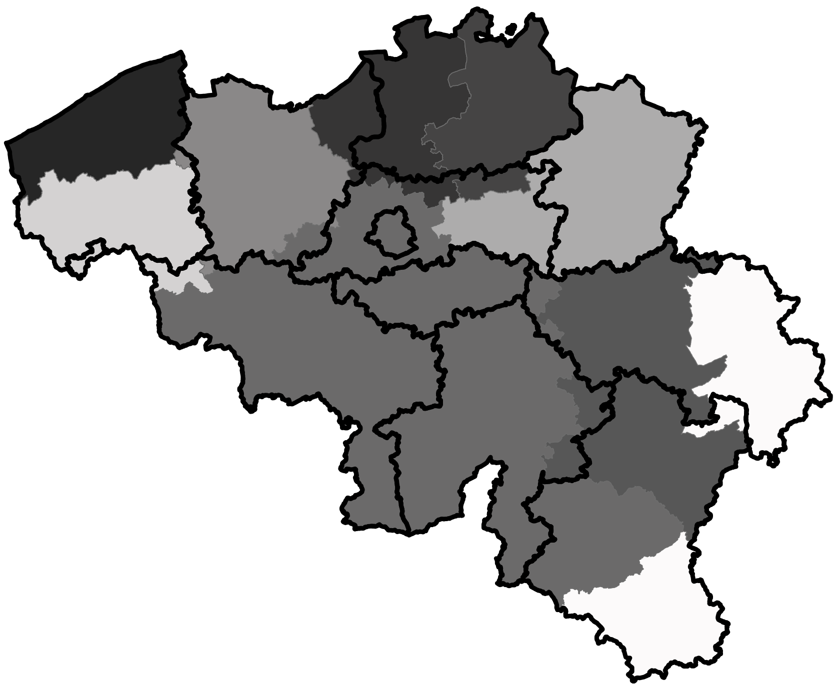
The 2007 administrative payroll employment data are disaggregated according to NACE-sector. We apply the classification proposed by Eurostat to construct TTWAs for four different (private) sectors, subdivided according to technological intensity: low-technology and high-technology manufacturing industries and the less-knowledge intensive and knowledge intensive market services.[11]

2001 average commuting distance in Verhetsel et al. (2007), who had access to the complete census questionnaires confirms this, as they report an average commuting distance of 17.2 km and 19.0 km for 1991 and 2001 respectively.

[11] The class of low-technology manufacturing industries groups low and medium-low tech sectors and includes NACE2 sectors 15 to 22, 36 and 37, 23, 25 to 28 as well as NACE3 sector 35.1. The class of high-technology sectors groups high and medium-high tech sectors and includes NACE2 sectors 29 to 35 as well as NACE3 sectors 24.4 and 35.3. The class of less-knowledge intensive services include NACE2 sectors 50 to 52, 55, 60 and 63. The class

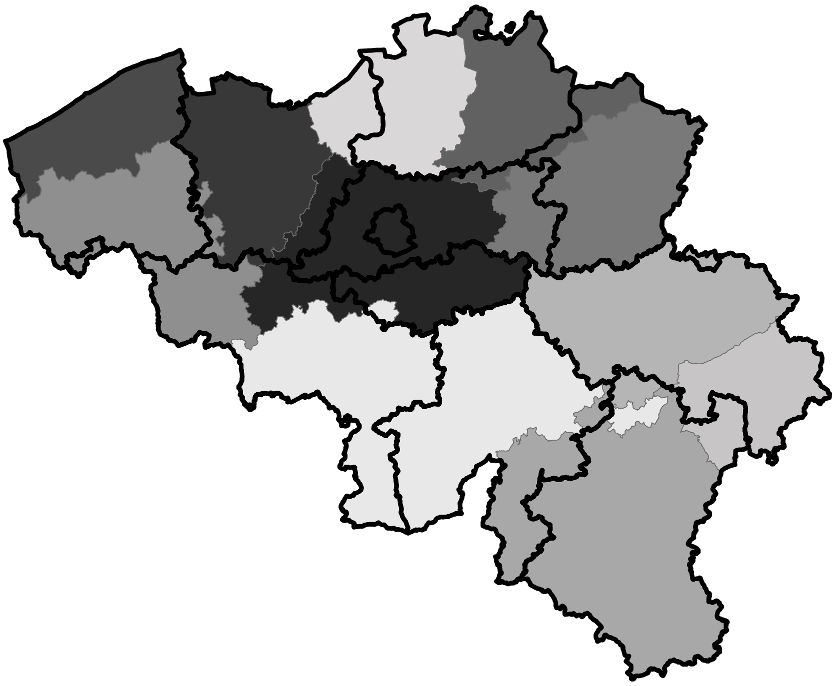


(a) Low Tech Manufacturing

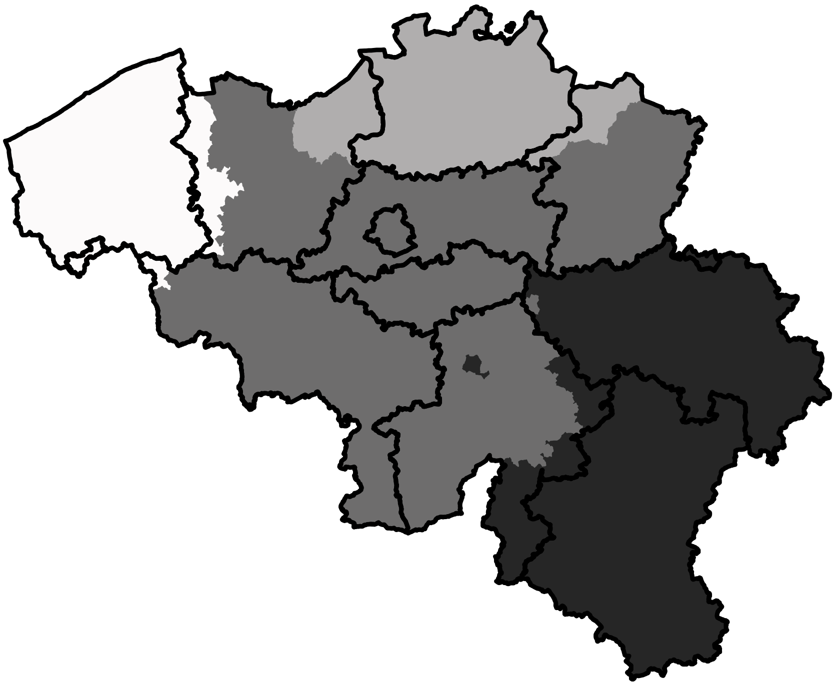


(b) High Tech Manufacturing

Figure 4.4: The TTWAs for the manufacturing sectors



(a) Low Tech Services



(b) High Tech Services

Figure 4.5: The TTWAs the service sectors

For low-tech manufacturing, 10 TTWAs emerge, one less than is the case for their high-tech counterparts. This is driven by the difference in commuting distance between the two sectors: commuters in low-tech industries travel on average 16.29 km , which is marginally less than the 17.04 km average commuting distance in the high-tech manufacturing sector. The relationship between technological intensity and the average commuting distance is substantially stronger in the service sector. There are only 4 distinct high-tech TTWAs and as much as 11 low-tech TTWAs. Workers in high-tech services commute on average 27.1 km and low-tech service workers only 16.29 km. High-tech sectors are subject to strong localisation economies (Henderson, 2003), providing them with a strong incentive to cluster. If high-tech sectors pay higher wages, and part of the commuting cost is fixed, this can explain the tendency of high-tech workers to commute longer distances.

For the sake of comparison, figure 4.6 illustrates the TTWAs for the public sector. Public employees commute on average 21.43 km, leading to the construction of 11 distinctive public sector TTWAs. Note that the boundaries of the public sector coincide remarkably well with the administrative province boundaries.

4.6.3 Gender-specific TTWAs

The matrix of commuting trips based on the 2007 administrative data was disaggregated along a gender dimension, allowing us to construct gender specific TTWAs.

Figure 4.7 reveals that female workers are substantially less mobile than males workers. The algorithm detects up to 14 distinct TTWAs for female workers and only 8 for males. This confirms the results of Green et al. (1986) and Newell & Perry (2005), who construct gender-specific TTWAs for England and New-Zealand, respectively. Woman tend to be employed in less-productive or part-time jobs and therefore earn lower wages (Macpherson & Hirsch, 1995). A recent study by the Belgian institute for gender equality reported a difference

of less-knowledge intensive services include NACE2 sectors 61, 62, 64 to 67 and 70 to 74.

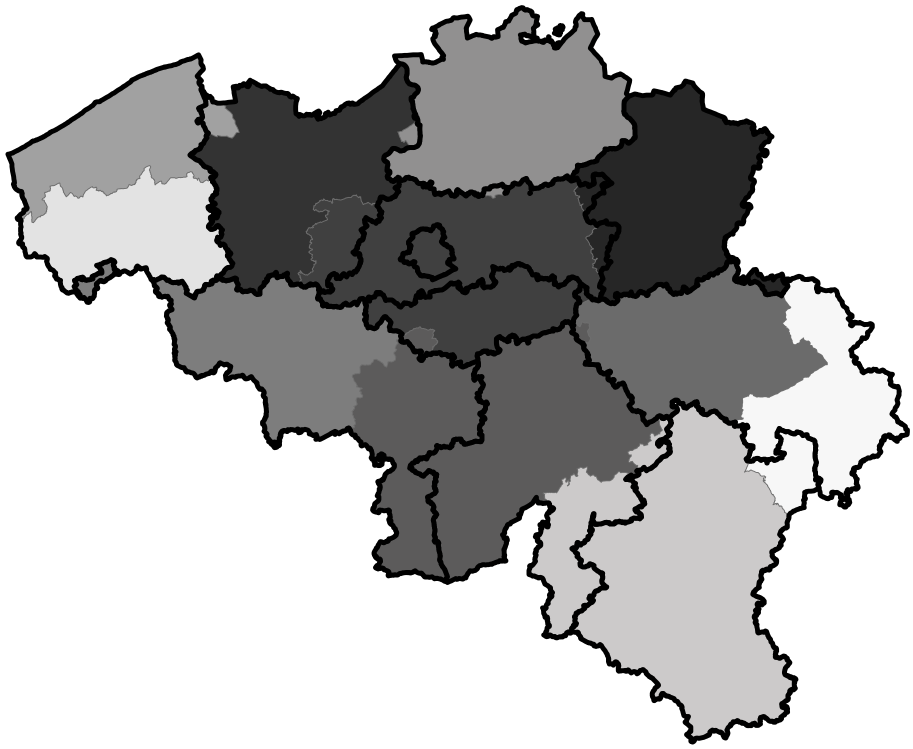
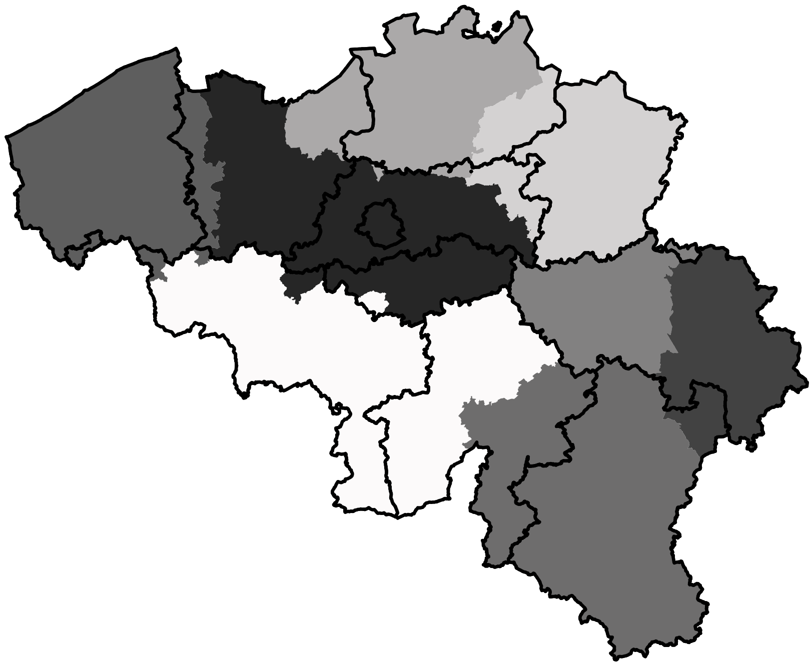


Figure 4.6: The 2007-TTWAs for the public sector

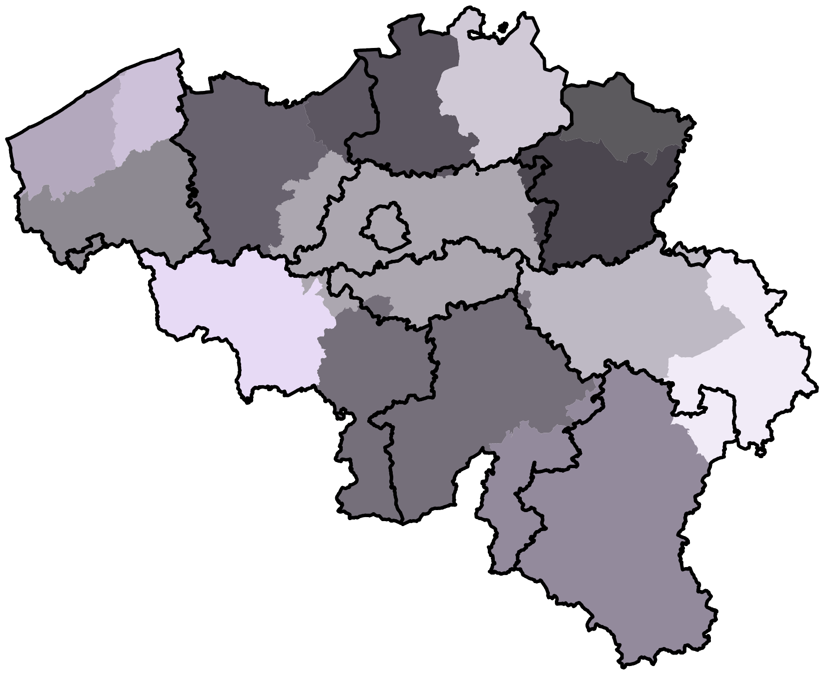
of 23 percent in yearly earnings between men and women. The presence of a fixed component in commuting costs would therefore reduce their average distance commuted, explaining why the TTWAs for female workers outnumber the TTWAs for male workers.

4.6.4 Sensitivity Analysis

So far, the algorithm used a similar parameter vector as the one applied in Bond & Coombes (2007). This section will present a number of sensitivity tests that illustrate the sensitivity of the algorithm to the chosen parameter values. Both from a policy as from an analysis perspective, a crucial aspect of a functional labour market is its degree of self-containment. The higher is the self-containment level, the greater the effectiveness of local labour market policies. An obvious candidate for a sensitivity analysis is therefore the minimum



(a) Male



(b) Female

Figure 4.7: The TTWAs for Males and Females

self-containment requirement an area needs to attain to qualify as a TTWA. Increasing the self-containment ratio can be achieved either directly, by adjusting the minimum containment requirements, or indirectly, by tightening the trade-off between size and containment.

Name	Supply Self-Cont.	Demand Self-Cont.	Resident Workers	Total Jobs	X_i-index
Antwerpen	75.8%	75.8%	501470	512216	100
Brugge	77.6%	85.6%	278858	252867	100
Charleroi	78.5%	82.9%	245086	232109	100
Arlon	73.8%	79.1%	64284	59949	98.3
Eupen	72.8%	80.4%	218374	197749	97.1
Genk	72.0%	77.9%	75743	69946	96
Gent	72.0%	79.2%	161445	146777	96
Kortrijk	70.6%	83.8%	451441	380343	94.1
Brussel/Bruxelles	84.3%	69.0%	842954	1030915	91.9
Liège	67.8%	74.9%	305082	275925	90.4
Turnhout	66.7%	73.3%	156110	142051	89.0

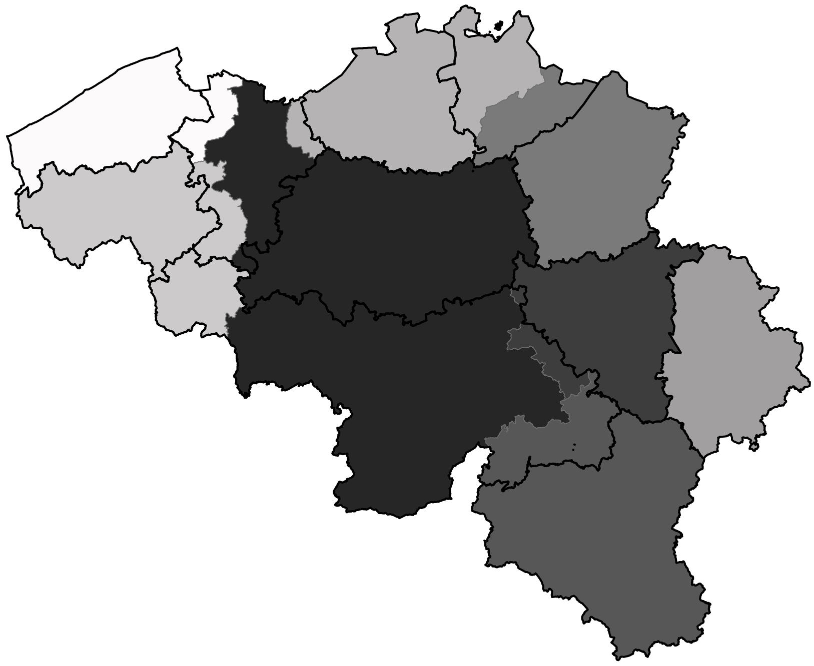
Table 4.1: Statistics for the aggregate 2007 Belgian TTWA algorithm

The starting point of the robustness analysis are the aggregate 2007 TTWA from figure 4.2, using the initial parameter set that is illustrated in figure 4.1. Parameter choice is unavoidably arbitrary, but the technical algorithm results summarized in table 4.1 can provide some guidance on how to adjust the parameter set to achieve certain goals.

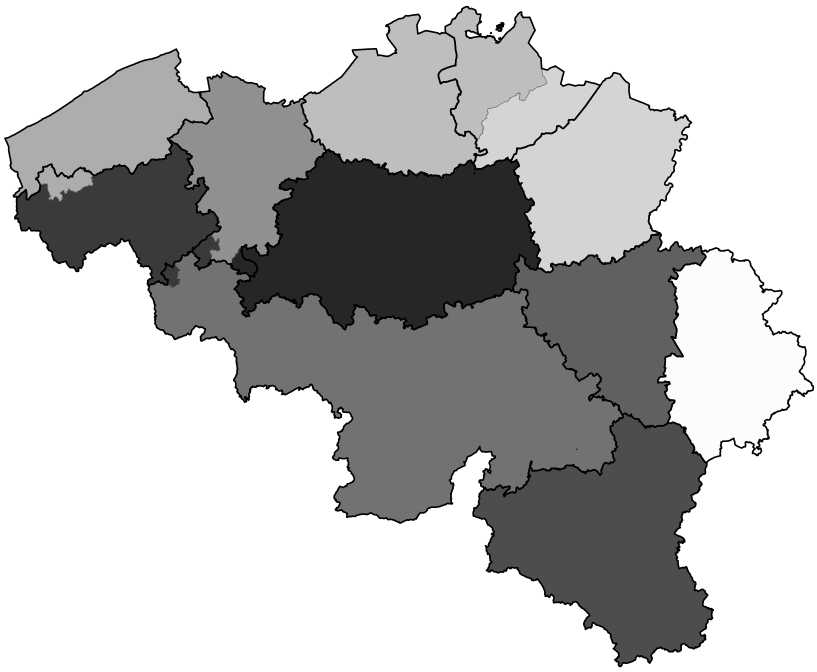
The supply-side self-containment levels of the TTWAs of Liège and Turnhout only marginally pass the minimum requirements (66.67 percent). Also the Brussels TTWA, due to its heavy reliance on labour supply from bordering regions, has a relatively low demand-side self-containment. This gets reflected in low values of the X_i-index. As a first robustness checks, the minimum self-containment requirement is increased from 66.67 percent to 70 percent. This will lead to a reduction in the number of TTWAs, as the algorithm will break up the TTWAs of Liège, Turnhout and Brussels and re-assign their subareas to the other TTWAs. Figure 4.8a compares the 2007 aggregate TTWAs that emerged using the initial parameter values (figure 4.2) to those resulting from increasing the minimum self-containment requirement to 70 percent. The black lines indicate the borders of the TTWAs corresponding to the initial parameter set. A number of observations emerge: as expected, the TTWA of Turnhout was dissolved and assigned to its closest neighbours Antwerp and Genk. The Brussels TTWA dissolved as well and merged with Gent and Charleroi to form a large, seemingly heterogeneous, labour market, ranging all the way from the northern Dutch border to France. Intuitively, this does not seem to make a lot of sense. It is hard to imagine that labour market policy tailored for the needs of the northern regions of East-Flanders would be effective in the French-speaking south, whose labour market issues are of a very different nature.[12]

Given the economic important of the Brussels capital region, which is considered to be the focal point of economic activity in Belgium, it would be desirable if the Brussels area would independently qualify as a TTWA, instead of being broken up and assigned to other TTWAs. From table 4.1, we see that the Brussels capital region is highly self-contained on the supply side. Of all its resident workers, 85 percent also work within the TTWA borders. On the demand side however, the Brussels TTWA relies heavily on the surrounding areas to fill the jobs on its territory. This is not surprising given the central importance of Brussels in the Belgian economy and its geographic centrality. By increasing the size threshold that determines the trade off between size and self-containment, the algorithm's parameters provide a way to avoid breaking up the Brussels region, while at the same time increasing the self-containment requirements for smaller, peripheral TTWAs. As before, self-containment levels become stricter, but since this occurs through strengthening the trade-off between size and self-containment, this is only the case for sparsely populated TTWAs. Table 4.1 again provides some guidance on the required magnitude of the parameter adjustment required to reduce the TTWAs while avoiding the dismantlement of the Brussels TTWA. The Turnhout TTWA has the lowest self-containment levels, just equal to the minimum of 66.67 percent on the supply-side. It however, relatively large in terms of size as it is home to 156 110 resident workers. The size threshold therefore needs exceed this level in order to directly affect the Turnhout TTWA. Setting it to 200 000 brings about 10 distinct functional labour markets, as illustrated in figure 4.8b. They coincide for a large part with the

[12](See Torfs, 2008, for an elaborate discussion on the state of the labour markets in the Belgian regions).



(a) Increasing the self-containment requirement in Rule 1 from 66.67 percent to 70 percent.



(b) Increasing the size threshold in Rule 1 from 25 000 to 200 000

Figure 4.8: Sensitivity analysis

original result. As expected, the Turnhout region failed to qualify as a separate TTWA and it was dissolved and merged with Antwerp in the west and Genk in the east. Apart from a few municipalities that were reassigned to adjacent TTWAs, the parameter adjustment invoked no further significant changes in the initial 2007 TTWAs.

Although it is not possible to escape the arbitrariness associated with parameter selection, one can use a combination of the algorithm statistics, graphical analysis and common sense, to adjust the parameters in order to achieve, or avoid, certain outcomes.

4.7 Summary & discussion

This paper applied the Bond & Coombes (2007) algorithm to construct Travel-to-Work Areas for Belgium. The 2007 aggregate economy result revealed the existence of 11 distinctive labour markets, the boundaries of which often coincided with administrative areas. The size of TTWAs is closely related to workers' average commuting distance. More commuting implies larger TTWAs. Increasing commuting distances have led the total number of Belgian TTWAs to decrease over time, from 31 in 1981 to 21 in 2001. We find that as average commuting distance increased over between the census years 1981 and 2001, the number of distinctive TTWAs decreased, going from 31 to 21. For the year 2007 sectoral level TTWAs were constructed, where sectors were categorized according to technological intensity. TTWAs are on average smaller for low-tech sectors, as well as for female workers. The heavy reliance on the parameter set, whose choice of values is necessarily arbitrary, is an undesirable feature of any delineation methodology designed to construct functional labour markets. Sound judgement combined with careful inspection of the algorithm's statistics could guide a researcher in determining a reasonable set of parameters that suits the needs of the case at hand. The sensitivity analysis attempted to decrease the number of TTWAs produced by the algorithm. To achieve this, we illustrated the difference between directly increasing the self-containment ratio and adjusting the size-containment trade-off. The latter approach delivered results that were more satisfactory, as it avoided breaking up the important central TTWA of Brussels.

It is our hope that the results presented in this chapter will inspire policy makers to use the TTWAs as an economically meaningful monitoring tool for Belgian regional labour market performance. To illustrate why this is important, consider the case of the Brussels Capital Region. When assessing its labour market performance, it is most often compared to the other Belgian NUTS1-regions, Flanders and Wallonia. In 2007, the Brussels unemployment rate was over 21.6 percent, compared to 16.8 in Wallonia and only 6.3 in Flanders.[13] The results of this analysis[14] suggest this might not be fair comparison. It is a well-documented fact that the geographic distribution of unemployment within an urban area is non-random (Anas et al., 1998; Zenou & Patacchini, 2009; Dujardin et al., 2008). The Brussels Capital Region, as delineated by the administrative NUTS1 borders, constitutes only the centre part of the functional urban area of Brussels. The Brussels TTWA (figure 4.2) further contains important parts of the Brabant provinces, along both sides of the language barrier. Brabant Wallon and Vlaams Brabant are both prosperous regions, with low unemployment and a highly educated workforce (Torfs, 2008). Brueckner et al. (1999) argue that the Brussels city structure follows the U.S. pattern, with disconnect between the Central Business District unemployed and the jobs in the surrounding Suburban District. Therefore, comparing the labour market outcome of the Brussels Central Business District to Wallonia and Flanders, which are large regions with a complex network of multiple cities, might not be a very informative exercise. Figure 4.9 illustrates this, by comparing the unemployment rate of the Brussels Capital Region and the Brussels TTWA. The unemployment rates in the functional Flanders and Walloon region are simply the administrative unemployment rates adjusted for the municipalities that belong to the Brussels TTWA. Although the unemployment rate in the latter two regions increases only marginally, the relative position

[13] Based on the administrative unemployment data provided by Steunpunt WSE.

[14] As well as the results of other studies on functional economic regions in Belgium, such as Luyten & Van Hecke (2007).

of the three regions changes significantly. As important parts of the Brabant provinces are assigned to the Brussels TTWA, its unemployment rate decreases drastically from 21.6 to 12 percent. The performance of the Brussels urban labour market is better than it appears from the official NUTS1 statistics.

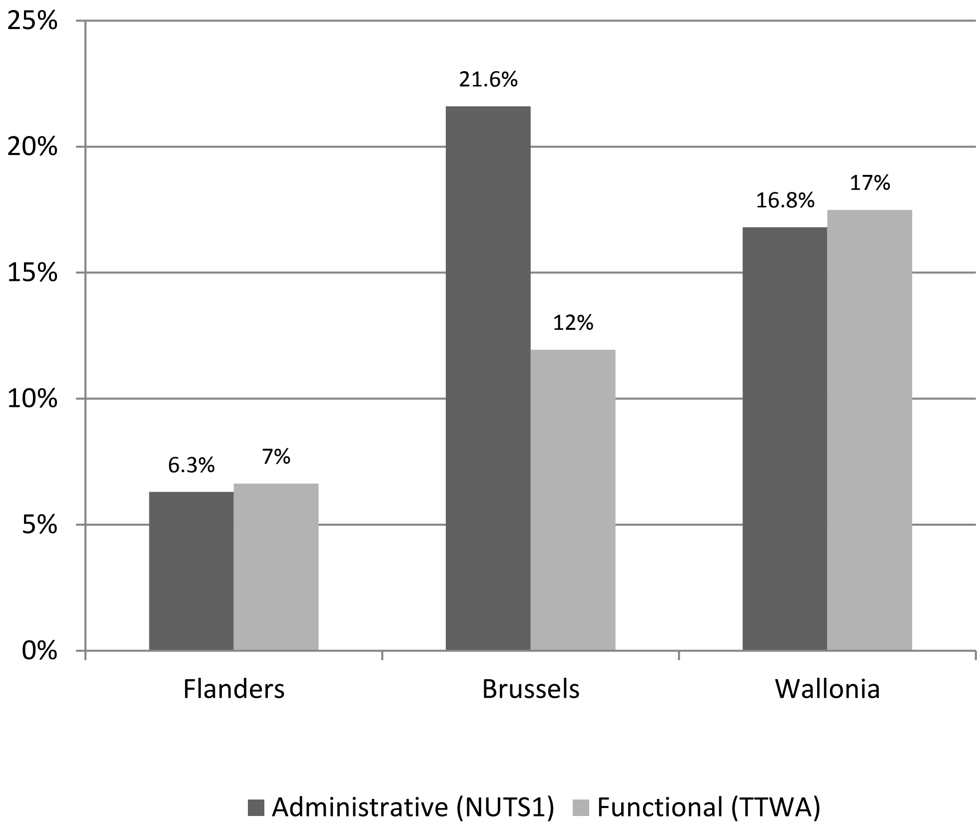


Figure 4.9: Functional versus administrative areas: unemployment rates

The algorithm further revealed a number of interesting geographic features of the Belgian functional labour markets. The regional border between Flanders and Wallonia appears to be a source of significant spatial frictions on the labour market. This was analysed and confirmed by Persyn & Torfs (2015b). This results is not entirely surprising, given the language barrier faced by commuters crossing the Flanders-Wallonia border. Interestingly, the TTWA borders produced by the algorithm at times coincide remarkably well with the borders of the administrative provincial regions (NUTS2). It is likely that the borders of the provinces are historically determined around a focal point. It is remarkable that the relative importance of these focal points is still reflected in today's commuting behaviour. Persyn & Torfs (2015a) apply the Persyn & Torfs (2015b) framework to test whether this can explain the persistence of the historical provincial border on current day commuting decisions. They find that controlling for the geographical distribution of economic activity does not eliminate the border effect. What is driving this peculiarity has to be left as a venue for future research.

General conclusion

The impact of space on labour market outcomes takes many forms. Space is inextricably bound up with time. And time is money. The analysis in Chapter 1 analysed the impact of space on commuting behaviour and quantified the costs space imposes on workers. Using a gravity equation framework, I showed that not only distance imposes spatial frictions on the labour market, but also how regional borders affect workers' commuting decisions. Border-induced frictions are surprisingly strong: regional border crossings reduce commuter flows by 30 percent. This effect varies depending on which border is considered and in which direction it is crossed. The graphical analysis of the wage impact of the border frictions revealed that border municipalities with depressed labour market outcomes that are located nearby cross-border areas with an abundance of employment opportunities could gain most from policies aimed at promoting cross-border commuting.

Interestingly, the analysis of Chapter 3 led to a more nuanced conclusion. Using a more refined urban framework, with heterogeneity on both sides of the labour market, labour market pooling externalities and skill-complementarities in production, revealed that policies aimed at reducing space-related frictions do not necessarily come to the benefit of all workers. We show that peripheral low-skilled workers that reside in the vicinity of agglomerated areas suffer twice. First, mobility costs restrict their job-search radius and excludes them from the agglomerative benefits of dense urban areas. Second, because firms increasingly locate in agglomerated areas to reap the benefits of the concentration of job search activities, at the expense of the periphery. Job opportunities for the low-skilled workers left behind in the peripheral region decline further. Chapter 3 analyses the impact of the *fixed* part of the commuting costs. The combination with skill-complementarities in production and scale effects in search triggers the selection effect that drives our most important result. So policies that aim to promote interregional labour market integrate and target the fixed part of the commuting cost are not Pareto welfare improving, even when considering its effect on the workers of peripheral areas only. The analyses in Chapters 1 and 3 are both of partial equilibrium nature. This implies that policy conclusions should be drawn with caution.

Scale effects in search are an important driver of the results in Chapter 3. This is an example of a labour market pooling externality, discussed at length in Chapter 2. Labour market pooling is one of the three Marshallian sources of agglomeration externalities, which are used to motivate the existence of cities. Although their exists a number of excellent survey papers reviewing different aspect of urban agglomeration externalities, an overview of labour market pooling source was still missing. Chapter 3 filled this void. The survey paid particular attention to linking theory with empirical evidence. It can provide researchers in the field with an overview what already has been done and could inspire them to uncover what is still missing.

Finally, Chapter 4 illustrated the geographical structure of Belgium's local labour markets by constructing Travel-To-Work-Areas. The results confirmed some of the conclusions drawn in the previous chapters, such as the deterrent effect of the Flanders-Walloon border on commuter flows. Using the Brussels Capital Region as an example, I illustrated why labour market monitoring best proceeds using functionally delineated areas, rather than administrative region.

This dissertation illustrated, analysed and quantified the impact of spatial frictions on workers' commuting decisions. Although commuting costs are often compensated for, either by employers or government subsidies, this compensation does not add to a worker's utility, rather it compensates for utility gone lost. The impact of space on the labour market can be interpreted as a wasteful tax on commuting. The analyses in this dissertation show that reducing spatial frictions on the labour market could potentially result in large welfare gains. However, policy makers need to consider the unintended consequences of mobility subsidies, in particular for those workers that are not successfully targeted.

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Appendix A

A.1 Chapter 3 - extensions

A.1.1 Extension: worker migration

Throughout the analysis, the only way workers living in the peripheral district had access to the agglomerated area by commuting. Here, we extend the analysis by allowing workers to migrate. This endogenizes the regional skill distribution. As was the case for commuting, residents in region A have no incentive to move to region B, since the reservation wage A exceeds that of B for all skill levels. Workers face a migration cost of $C_m > 0$, which is assumed to be larger than the cost of commuting.[1] Particularly, C_m is set to 0.55 in the simulation. Workers in district B will migrate if the inter-district gap of the value of unemployment is larger than the migration cost. The incremental value of a mover net of migration cost must be zero in equilibrium. The migration equilibrium condition for residents in district B is:

$$U_A(s) - U_B(s) = C_m \tag{A.1}$$

The upper right panel in Figure A.1 illustrates the cutoffs for migration and commuting. Because the increase in the expected value from moving increases

[1]The cost of migration can be interpreted as the house price gap between the central and the peripheral district. For simplicity, we assume this gap is exogenously given.

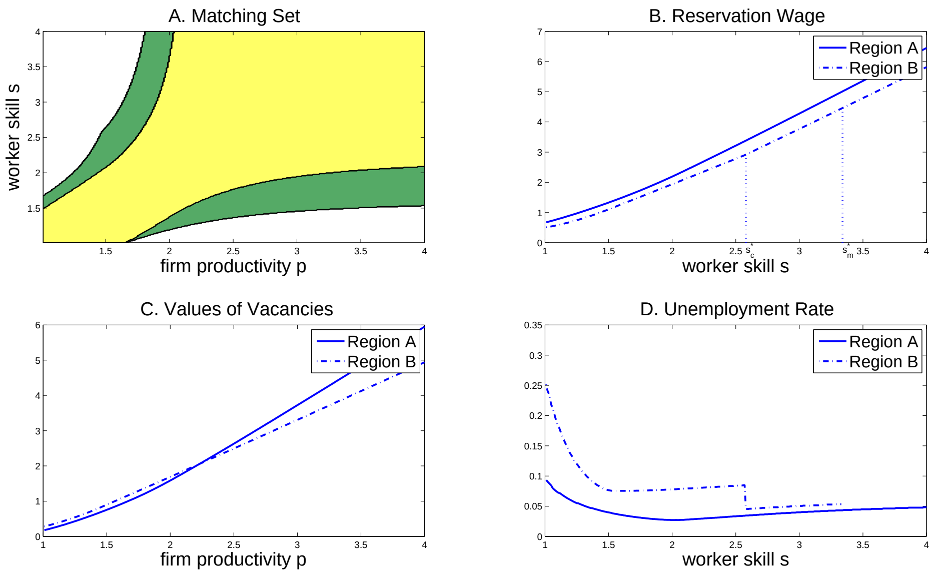

Figure A.1: Equilibrium: Migration

with worker types, only the highest skilled workers (above s_m^*) will migrate. As before, workers in the mid-range of the skill distribution (s_c^*, s_m^*) search for jobs in district A and choose to commute. Low-skilled workers ($< s_c^*$) in district B continue to search jobs locally. Figure A.2 shows the post-migration skill distribution of workers in both districts. Initially identical, the agglomeration A now has disproportionately more high-skilled workers.

A.1.2 Housing market

The focus on this paper is on the labour market, so section A.1.1 makes a reduced form assumption which implies migration costs reflect relative real estate prices. Here we describe how the results are affected if we endogenise the housing market. Each region has a fixed stock of housing H_i. A type s worker in district i has the following preferences:

$$\begin{aligned} &Max\ U(c_i(s), h_i(s)) = c_i(s)^{1-\alpha} h_i(s))^{\alpha} \\ &s.t.\ c_i(s) + h_i(s) P_i \leq w_i(s) \end{aligned} \tag{A.2}$$

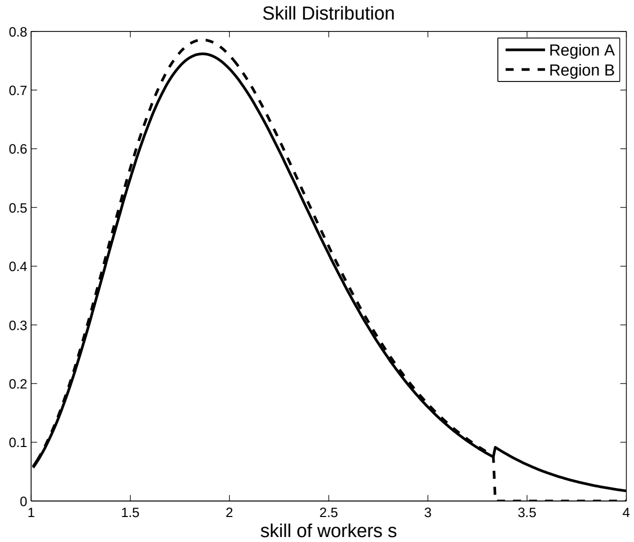

Figure A.2: Skill Distribution in Region A and B

where $c_i(s)$ and $h_i(s)$ refer to the consumption of goods and housing, respectively and P_i refers to the rental price. In equilibrium, we have $c_i(s) = (1-\alpha)w_i(s)$ and $h_i(s) = \alpha\frac{w_i(s)}{P_i}$, where α is the expenditure share on housing. Thus, the utility of a type s worker in district i is $U_i(s) = (1-\alpha)^{1-\alpha}\alpha^{\alpha}\frac{w_i(s)}{P_i^{\alpha}}$. The rental price in i is $P_i = \frac{\alpha\int w_i(s)l_i(s)L_i}{H_i}$, which is a function of the local total wage. Substituting it into the utility function, we have $U_i(s) = (1-\alpha)^{1-\alpha}\frac{w_i(s)}{\left(\frac{\int w_i(s)l_i(s)L_i}{H_i}\right)^{\alpha}}$. When migration costs are exogenously given, the utility of worker s in district i is $U_i(s) = w_i(s)$. The wage premium increases house prices in the agglomerated district. Since residential location is a trade-off between commuting costs and land costs, high-skilled workers will migrate to the agglomerated district.

A.1.3 Relocation of firms

Firm productivity is a random draw from a common distribution. The investment decision of firms is irreversible and once settled, firms are not allowed to relocate. This renders the distribution of productivity identical across districts. If firms are allowed to relocate, high productivity firms will relocate to the large district.

The reward to search in the agglomeration district increases, increasing the number of peripheral high skilled workers who concentrate their search efforts in the agglomerated district. The results of the model are reinforced.

A.2 Data cleaning process

- We start with 35,721,027 observations, each of which corresponds to a worker-firm-year cell.
- All observations with a wage below the 1st percentile or above the 99th percentile of the wage distribution are dropped. This leaves us with 34,655,478 observations.
- Workers who earn less than a minimum wage are dropped.[2] This leaves us with 33,894,307 observations.
- We restrict the sample to the private sector. Using the NACE rev1 classification, firms operating in a 2-digit NACE sector above 74 are dropped. This leaves us with 20,390,188 observations.
- We also discard workers living abroad. The final database contains 20,126,230 observations.

A.3 Robustness checks

This section presents the results of the respective robustness checks that were discussed in section 3.5 of Chapter 3.

[2]The monthly gross statutory minimum wage is 1186.31 Euro in Belgium in 2004, which is equivalent to 54 Euro of gross daily wage.

Table A.1: Summary Statistics

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Observations	1,736,435	1,771,767	1,833,817	1,855,065	1,838,201	1,816,125	1,834,323	1,847,400	1,881,983	1,926,683	1,784,431
Daily wage	94.76	96.47	99.90	103.21	105.08	106.46	108.74	111.95	114.20	115.49	121.80
Age	37.07	37.15	37.14	37.38	37.70	38.03	38.20	38.40	38.54	38.65	38.93
Job switch rate(%)	.	0.101	0.101	0.093	0.123	0.076	0.076	0.074	0.087	0.087	0.084
Male(%)	70.49	69.68	68.76	67.93	67.46	67.14	66.61	66.13	65.60	64.87	66.89
Population	2932.05	3008.09	3113.44	3149.52	3120.89	3083.40	3114.30	3136.50	3195.22	3271.11	3029.59
Average firm size	14.57	14.35	14.31	14.20	13.87	13.58	13.56	13.57	13.72	14.03	13.93
Multi-plant firms(%)	2.84	2.81	2.70	2.70	2.64	2.66	3.15	3.32	3.39	3.39	3.44
No. of firms	120,259	125,080	129,888	132,432	134,257	135,481	137,103	138,000	139,148	139,442	134,679

Note: Daily wage is the full-time equivalent gross daily wage, expressed in Euro. Population is defined as the average number of working population at municipality level. The sample is restricted to workers aged 18-64. *Source:* Author's calculation.

Table A.2: Robustness check: alternative measure of firm type

	High-skilled Workers				Low-skilled Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	RE	OLS	RE	OLS	RE	OLS	RE
Log(pop)	-0.0085***	-0.0098**	-0.015***	-0.012**	0.0064***	0.0094***	0.0081***	0.010***
	(0.0016)	(0.0047)	(0.0020)	(0.0049)	(0.0013)	(0.0030)	(0.0014)	(0.0032)
Log(pop of neighboring areas)	0.014***	0.016***	0.014***	0.019***	-0.014***	-0.016***	-0.014***	-0.016***
	(0.0018)	(0.0058)	(0.0025)	(0.0059)	(0.0014)	(0.0033)	(0.0017)	(0.0037)
Language border dummy			-0.016***	-0.018**			0.0062**	0.0076
			(0.0028)	(0.0082)			(0.0030)	(0.0071)
Average firm size			0.00055***	0.00018			-0.00019*	-0.00027
			(0.00014)	(0.00030)			(0.00011)	(0.00026)
Average age of workers			-0.011***	-0.0024			0.0043***	0.0010
			(0.0017)	(0.0037)			(0.0012)	(0.0029)
Log(house price)			0.010	-0.00025			0.0063**	0.0064
			(0.011)	(0.0046)			(0.0031)	(0.0043)
Job switch rate			0.29***	-0.096			-0.22***	-0.10*
			(0.10)	(0.091)			(0.068)	(0.051)
Year fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Observations	6468	6468	5879	5879	6468	6468	5879	5879
R-squared	0.016	0.016	0.037	0.023	0.071	0.070	0.056	0.052

Note: Unit is municipality. The dependent variable is match quality measured by the rank correlation between worker and firm types. Firm types are measured by the best worker type a firm hires. House price is measured by the weighted average price of house, villa, apartment and lot. Herstappe, the least populous municipality in Belgium, is dropped. Robust standard errors are in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A.3: Robustness checks: excluding Brussels and multi-plant firms

	Exclude Brussels				Single-plant Firms			
	High-skilled Workers		Low-skilled Workers		High-skilled Workers		Low-skilled Workers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	RE	OLS	RE	OLS	RE	OLS	RE
ln(pop)	0.00086	-0.00027	0.012***	0.013***	-0.0020	-0.0038	0.012***	0.014***
	(0.0020)	(0.0045)	(0.0013)	(0.0028)	(0.0028)	(0.0065)	(0.0018)	(0.0038)
ln(pop of neighboring areas)	0.011***	0.0100**	-0.0069***	-0.011***	0.030***	0.033***	-0.0053**	-0.011***
	(0.0023)	(0.0048)	(0.0015)	(0.0032)	(0.0030)	(0.0057)	(0.0022)	(0.0041)
language border dummy	-0.031***	-0.032***	-0.0030	-0.0036	-0.025***	-0.024**	-0.0060*	-0.0066
	(0.0029)	(0.0082)	(0.0025)	(0.0060)	(0.0037)	(0.0094)	(0.0034)	(0.0082)
average firm size	-0.00068***	-0.00096***	-0.00033***	-0.00021	-0.00063***	-0.0010***	-0.0011***	-0.00073**
	(0.00018)	(0.00036)	(0.00012)	(0.00027)	(0.00018)	(0.00040)	(0.00014)	(0.00031)
average age of workers	0.0090***	0.0087**	-0.011***	-0.0066***	0.018***	0.0088*	-0.0054***	-0.00064
	(0.0018)	(0.0037)	(0.0011)	(0.0025)	(0.0022)	(0.0049)	(0.0015)	(0.0033)
ln(house price)	-0.023**	-0.0062	0.0011	0.0077	-0.0075	0.0030	-0.016**	0.0019
	(0.0090)	(0.0059)	(0.0035)	(0.0057)	(0.013)	(0.0073)	(0.0065)	(0.0060)
job switch rate	0.23**	0.059	-0.27***	-0.12**	0.40***	0.038	-0.21**	-0.12
	(0.096)	(0.053)	(0.060)	(0.049)	(0.11)	(0.11)	(0.095)	(0.094)
year fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Observations	5689	5689	5689	5689	5879	5879	5879	5879
R-squared	0.043	0.037	0.16	0.15	0.099	0.093	0.091	0.083

Note: Unit is municipality. The dependent variable is match quality measured by the rank correlation between worker and firm types. Housing price is measured by the weighted average price of house, villa, apartment and lot. Herstappe, the least populous municipality in Belgium, is dropped. Robust standard errors are in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A.4: Robustness check: population density

	Average Worker Type				Best Worker Type			
	High-skilled Workers		Low-skilled Workers		High-skilled Workers		Low-skilled Workers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	RE	OLS	RE	OLS	RE	OLS	RE
ln(emp./sq.km.)	-0.0060***	-0.0047	0.0028**	0.0024	-0.0096***	-0.0096**	0.0030**	0.0056**
	(0.0013)	(0.0037)	(0.0011)	(0.0028)	(0.0014)	(0.0039)	(0.0012)	(0.0028)
ln(emp./sq.km. in neighboring areas)	0.016***	0.015**	-0.0037*	-0.0081*	0.021***	0.027***	-0.017***	-0.019***
	(0.0032)	(0.0074)	(0.0021)	(0.0044)	(0.0034)	(0.0085)	(0.0023)	(0.0049)
language border dummy	-0.032***	-0.032***	-0.0034	-0.0047	-0.015***	-0.018**	0.0050	0.0065
	(0.0029)	(0.0083)	(0.0025)	(0.0061)	(0.0029)	(0.0082)	(0.0030)	(0.0072)
average firm size	0.000018	-0.00068**	-0.00071***	-0.00031	0.00051***	0.00017	-0.000064	-0.00020
	(0.00015)	(0.00031)	(0.00012)	(0.00024)	(0.00015)	(0.00030)	(0.00012)	(0.00028)
average age of workers	0.0082***	0.0080**	-0.0097***	-0.0046*	-0.0076***	-0.0016	0.0020*	-0.00033
	(0.0015)	(0.0034)	(0.0011)	(0.0025)	(0.0017)	(0.0036)	(0.0012)	(0.0028)
ln(house price)	-0.019**	-0.0062	-0.0013	0.0067	0.0053	-0.00045	0.010***	0.0069
	(0.0092)	(0.0058)	(0.0040)	(0.0057)	(0.011)	(0.0046)	(0.0034)	(0.0044)
job switch rate	0.30***	0.058	-0.28***	-0.10**	0.25**	-0.099	-0.19***	-0.095*
	(0.095)	(0.052)	(0.059)	(0.047)	(0.11)	(0.091)	(0.068)	(0.051)
year fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
Observations	5879	5879	5879	5879	5879	5879	5879	5879
R-squared	0.039	0.032	0.13	0.12	0.032	0.024	0.054	0.051

Note: Unit is municipality. The dependent variable is match quality measured by the rank correlation between worker and firm types. House price is measured by the weighted average price of house, villa, apartment and lot. Herstappe, the least populous municipality in Belgium, is dropped. Robust standard errors are in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table A.5: Robustness check: commuting time

	High-skilled Workers		Low-skilled Workers	
	(1)	(2)	(3)	(4)
	OLS	RE	OLS	RE
Log(pop)	0.00036	0.00021	0.012***	0.012***
	(0.0020)	(0.0046)	(0.0013)	(0.0028)
Log(pop of neighboring areas)	0.0088***	0.0090***	-0.0073***	-0.012***
	(0.0023)	(0.0051)	(0.0015)	(0.0031)
Language border dummy	-0.031***	-0.032***	-0.00088	-0.0013
	(0.0029)	(0.0082)	(0.0025)	(0.0061)
Average firm size	-0.00030**	-0.00079***	-0.00098***	-0.00055**
	(0.00013)	(0.00030)	(0.00011)	(0.00022)
Average age of workers	0.0076***	0.0080**	-0.0078***	-0.0035
	(0.0016)	(0.0034)	(0.0011)	(0.0025)
Log(house price)	-0.020**	-0.0062	-0.0033	0.0062
	(0.0088)	(0.0058)	(0.0039)	(0.0056)
Job switch rate	0.26***	0.055	-0.29***	-0.11**
	(0.094)	(0.052)	(0.059)	(0.048)
Year fixed effect	yes	yes	yes	yes
Observations	5879	5879	5879	5879
R-squared	0.038	0.032	0.15	0.14

Note: Neighbouring areas are constructed based on commuting time by car, where we define the surrounding labour market as all municipalities that can be reached within 60 minutes, which cover 84.79 percent of all commuters. The data was obtained through the Google Maps API and reflect the situation in June 2011. Unit is municipality. The dependent variable is match quality measured by the rank correlation between worker and firm types. House price is measured by the weighted average price of house, villa, apartment and lot. Herstappe, the least populous municipality in Belgium, is dropped. The neighboring areas in the first four columns are the regions which can be reached via railway within 120 minutes from the region of residence. The neighboring areas in the last four columns are the regions which can be reached via auto-highway within 60 minutes from the region of residence. Robust standard errors are in parentheses. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

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