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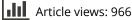


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# Excess commuting and frictions in the labor market

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#### ABSTRACT

We propose a model of excess commuting based on search costs in the labor market and show how the equilibrium rate of excess commuting is determined by the degree of geographical job concentration - without neglecting the importance of the size of the labor market and commuting costs. We test - and largely confirm - the main predictions of our model using Belgian population data on commuting flows between all its 589 municipalities. Our approach is to aggregate the data into 640 sectors and skill-specific groups in order to generate heterogeneity in the excess commuting rate. We find that workers in sectors with a high degree of job concentration have lower rates of excess commuting and that workers that operate in larger labor markets, such as higher educated workers and men compared to women, have higher rates of excess commuting.

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**KEYWORDS** Excess commuting; job

search

# 1. Introduction

Excess commuting refers to the commuting that exceeds the minimum required commuting in an area (Hamilton, 1982; Jun, Chong, Wen, & Kwon, 2018; Kanaroglou, Higgins, & Chowdhury, 2015; Ma & Banister, 2006; Rouwendal, 1998; Small & Song, 1992; van Ommeren & van der Straaten, 2008). This paper investigates how the rate of excess commuting varies across labor markets by proposing a model based on imperfections in the job search process while assuming no residential relocation. Excess commuting is important because commuting time involves opportunity costs in the sense that commuting time cannot be spent working or engaging in leisure activities. Full-time employees in OECD countries on average spend over 30 minutes per day commuting (OECD, 2011), but many workers spend even more time and commuting times are increasing because of congestion problems. For example, the number of hours lost in road traffic jams has almost doubled over the past 10 years in Flanders, the main economic region of Belgium (Vlaams Verkeerscentrum, 2019).

In a seminal study, Hamilton (1982) reports very large levels of excess or `wasteful' commuting and provocatively interprets these as evidence against the monocentric model in which workers choose residential locations by minimizing commuting costs conditional upon housing prices. Hamilton shows that actual commuting is almost what one would expect if commuting were random and concludes that the monocentric model "does an almost unbelievable bad job of predicting commuting

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behavior." Hamilton's findings initiated some debate on the degree of excess commuting and on how to measure it, but the literature appears to agree that excess commuting is substantial (Kanaroglou et al., 2015; Ma & Banister, 2006; Small & Song, 1992).

The question is what explains the presence and the degree of excess commuting. First, some scholars suggest that people may not bother about commuting because commuting costs are relatively limited, for example because of low gasoline prices or transport subsidies. Some even suggest that people value commuting itself or value a clear separation between work and residence (see Ma & Banister, 2006), but this is hard to swallow given the importance of commuting times and congestion in the public debate in many countries and the evidence about the role of congestion in worker's job acceptance decisions (Flemming, 2019). Second, observed excess commuting might reflect the fact that people are minimizing overall travel rather than just individual commuting. Workers may be willing to make longer commutes if that reduces other travel, such as for recreational trips, and in two-worker households, optimizing one partner's commute could increase the commute of the other partner. However, many scholars feel this is not the whole explanation (Hamilton, 1982). Third, the more recent literature sees excess commuting as a result of frictions in the labor and housing markets which prevent a more efficient matching of workplaces to places of residence (Crane, 1996; Larsen, Pilegaard, & van Ommeren, 2008; Rouwendal, 1998; van Ommeren & van der Straaten, 2008). This line of reasoning requires imperfections in both the labor market and the housing market because excess commuting would largely be avoided if there were either perfect residential mobility or perfect job mobility. Frictions in the housing market arise from lack of information about alternative housing and from moving costs, which are thought to be higher for homeowners but which also include psychological costs such as the stress of moving house. Frictions in the labor market arise from reduced job mobility through firm-specific human capital and from incomplete information about vacancies and search costs.

This paper proposes a simple model of excess commuting as a result of search costs – and hence frictions - in the labor market. We include frictions in the housing market as well by assuming no residential relocation. We focus on how the rate of excess commuting is determined by a limited number of labor market parameters: the size of the labor market, the distribution of jobs and workers across places in the market, the reservation wage of job seekers and the level of commuting costs. We use a dynamic model to derive an expression for the equilibrium rate of excess commuting, which is determined by workers' endogenous job acceptance decisions who trade-off commuting costs and search costs, where the latter is the time cost of rejecting a job and waiting for an acceptable offer to arrive - unlike in Wasmer and Zenou (2002). The outcome of the model is a spatial matching of jobs to workers which is suboptimal in the sense that some workers could in principle swap jobs in ways that reduce the excess commuting and increase welfare. In other words, one worker may live in place A and work in B while a similar worker lives in B and does the same job in A, because workers accept job offers while they do not know when to expect a similar offer closer to home. While the outcome of the model itself is suboptimal, firms and workers maximize their individual welfare. If, for example, two commuting workers with the same reservation wages swap jobs so that they become local workers, then the elimination of the commuting costs produces an

additional surplus in the market which could then be shared between the worker and the firm.

Our empirical study tests the main predictions of this model using commuting data for the Belgian working population in 2012. We propose a measure for the rate of excess commuting which is bounded between 0 and 1, defined as the non-required commuters as a proportion of the workers who could potentially work locally. We consider commuting flows as trade-in labor between localities in the labor market and illustrate how concepts and indicators that are commonly used in the analysis of international trade patterns can also be applied to commuting. In the main analysis, our data are aggregated into 640 sectors and skill-specific groups in order to generate heterogeneity in the excess commuting rate and study its determinants.

This paper contributes to the literature by proposing a model that sets out to explain heterogeneity in the rate of excess commuting across groups. More in particular, our paper predicts (and shows empirically) that a higher job concentration results in less excess commuting. The intuition is that in very concentrated sectors (such as mining), the minimum required commuting is very high so there is less need for excess commuting. The effect of job concentration on excess commuting is mechanical, and therefore not surprising: the novelty of this paper is that our model of excess commuting allows for an analytical derivation of the effect of job concentration, and that we present empirical estimates of the size of this effect. A small number of earlier studies have applied job search models to excess commuting, but these are concerned with obtaining estimates of the degree of excess commuting (Crane, 1996; van Ommeren & van der Straaten, 2008). To the best of our knowledge, there is only one paper that also focuses on the role of search costs in the labor market, assumes no residential mobility and proposes a model that shares with ours the prediction that there is less excess commuting when jobs are spatially concentrated, namely van Ommeren and van der Straaten (2008). Our model, however, improves on theirs in several ways: (i) we allow for excess commuting as the direct outcome of the model instead of (indirectly) deriving it through the maximum acceptable commuting distance between two groups (i.e. employed and self-employed); (ii) we theoretically derive the expected impact of the size of the labor market n and the degree of job concentration  $\alpha$  on excess commuting directly – instead of focusing on the (indirect) impact of the arrival rate for job offers ( $\lambda$ ) and the employment density function F(t); (iii) in our empirical application we are able to analyze the impact of the degree of job concentration at industry level on excess commuting and we focus on studying the variation in excess commuting across labor markets.

The remainder of the paper is organized as follows. Section 2 develops a job-search model of equilibrium excess commuting. Section 3 discusses the data and methodology while section 4 presents the empirical results. Section 5 concludes.

#### 2. Model

#### 2.1. A measure of excess commuting

In this section, we derive an expression for the rate of excess commuting ( $\rho$ ) as a function of the percentage of commuters (c) and the rate of required commuting ( $c^{req}$ ). In order to do so, we also introduce the percentage of local workers (l), the percentage of local

workers that could potentially work locally  $(l^p)$  and the rate of non-required commuting  $(c^{non})$ .

Consider a labor market that consists of n places. Assume that the total number of workers in the labor market equals the total number of jobs in the labor market and that the labor market is a closed system, i.e. workers do not commute to places outside the labor market. The commuting flows within the labor market can then be represented by a commuting matrix  $A(c_{ij})$ , which contains as elements  $c_{ij}$  the percentage of workers, relative to the total number of workers in the labor market, from origin place *i* who work in destination place *j*. The sum of all elements of *A* equals 1  $(\sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} = 1)$  because the labor market is assumed a closed system. The shares of workers residing in place k are denoted as  $W_k = \sum_{j=1}^n c_{kj}$  and correspond to the row sums of *A*. The shares of jobs in *k* are denoted as  $J_k = \sum_{i=1}^n c_{ik}$  and correspond to the column sums of A. Workers either hold a job in their place of residence (local workers) or in another place (commuters). We dichotomize the commuting concept, instead of focusing on a more continuous "commuting distance" measure, in order to simplify our model and because it is much more straightforward in this dichotomous case to define excess commuting - which we define intuitively as someone living in place *i* and working in place *j*, while another person lives in place *j* and works in place *i* so that they could potentially swap jobs. The percentage of local workers is denoted as  $l = \sum_{k=1}^{n} c_{kk}$  and the percentage of commuters as c = 1 - l. Since the number of jobs in each place does not necessarily equal the number of workers in that place, a minimal rate of commuting  $c^{req}$  could be required in order to balance workers and jobs in each place. The remaining share of workers could potentially

work locally  $l^p$ , with:

$$l^p + c^{req} = 1 \tag{1}$$

The percentage of workers who could potentially work locally is determined by the distribution of jobs and workers across places. If there are more workers than jobs in k then only  $J_k$  workers could potentially work locally. If there are more jobs than workers then all  $W_k$  workers can potentially work locally. Thus,  $l^p = \sum_{k=1}^n Min(W_k, J_k)$ .

The rate of commuting *c* will generally exceed the required rate of commuting  $c^{req}$  and the difference will be denoted as the rate of non-required commuting  $c^{non}$ , with:

$$c^{req} + c^{non} = c \tag{2}$$

We now define the rate of excess commuting in the labor market as  $\rho = c^{non}/l^p$ , i.e. the non-required commuters as a proportion of the workers who could potentially work locally. Using (1) and (2) allows us to rewrite the rate of excess commuting as:

$$\rho = \frac{c - c^{req}}{1 - c^{req}} \tag{3}$$

For a given distribution of jobs and workers across the labor market,  $c^{req}$  is constant so that the rate of excess commuting  $\rho$  is a linear increasing function of the commuting rate c. The intuition is that, for a given distribution of workers and jobs across space, additional commuting implies a higher rate of excess commuting. A special case arises when in every place the number of workers equals the number of available jobs. In that case, there is no required commuting simplifies to the commuting rate:  $\rho = c$ . From Equation (3) it is also clear that  $\rho$  ranges between 0 and 1: there is no excess commuting  $(\rho = 0)$  when all commuting is required  $(c = c^{req})$  and the rate of excess commuting reaches a maximum ( $\rho = 1$ ) when all workers commute (c = 1).  $\rho$  is not defined in the limiting case where all workers are required to commute  $(c^{req} = 1)$ . For example, this would be the case in a labor market with two places when all workers live in one place while all the jobs are in the other place. Also note that  $\rho$  cannot reach 1 in the exceptional case where a place k has more jobs  $J_k$  than the total number of workers available in the other places  $W_k$  so that some of the workers of k have to work locally (see appendix A1).

Table 1 presents numerical examples of commuting matrices that correspond to minimum and maximum excess commuting in a labor market with three places, where workers are uniformly distributed across space but jobs are not.

Our aim is to study the heterogeneity of the rate of excess commuting across labor markets and the ways in which the rate of excess commuting depends on labor market characteristics such as its size, the degree of job concentration and the presence of commuting costs. With this purpose in mind, we develop a dynamic model of the labor market in which an equilibrium rate of excess commuting arises endogenously as a steady-state outcome.

### 2.2. A dynamic model of excess commuting

In order to clarify the intuition behind our model and its underlying assumptions, we perform a simulation. Suppose there are 1000 workers who are uniformly distributed across 10 places and who initially work in their place of residence, so that there is no excess commuting in 'year 1'. Assume that every year 100 randomly drawn workers retire, that their jobs become vacant and remain in the same place and that 100 new workers enter the labor market as job seekers. Vacancies are matched to job seekers by a process in which a wage is drawn from a wage distribution and offered to a random job seeker. If the offered job is located in the place of residence of the job seeker, then the job is located in a different place, then the wage is compared to a fixed commuting cost (say

No excess commuting	Maximum rate of excess commuting
$A = \begin{pmatrix} .17 & 0 & .17 \\ 0 & .33 & 0 \\ 0 & 0 & .33 \end{pmatrix}$ $\rho = (c - c^{req}) / (1 - c^{req}) = (.1717) / (117) = 0\%$	$A = \begin{pmatrix} 0 & 0 & .33 \\ .17 & 0 & .17 \\ 0 & .33 & 0 \end{pmatrix}$ $\rho = (c - c^{req}) / (1 - c^{req}) = (117) / (117) = 100\%$
Note: The commuting rate c is the sum of the off-diagonal e	lements. The rate of required commuting for both matrices is
$c^{req} = 1 \cdot I^p = 1 - \sum_{k=1}^{3} Min(W_k, J_k) = 1 - [.17 + .33 + .33]$	3] = .17.

Table 1. Numerical examples of minimum and maximum rates of excess commuting.

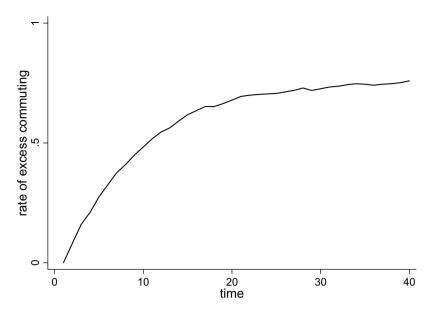


Figure 1. Simulation of the rate of excess commuting.

200) in addition to the reservation wage (so 2000 in total). All workers are assumed to have the same reservation wage, which can be thought of as the value of leisure. If the job seeker rejects the wage offer, then the same offer is made to the second job seeker in a random line, and so on until the vacancy is filled. If no job seeker accepts the offer, then a new wage offer is drawn. Figure 1 shows how the rate of excess commuting in this simulation appears to converge towards a steady-state level.

This simulation illustrates the payoffs, the maximization problem faced by workers and the timing in our model. First, a group of workers retire and an equal number of job seekers enter the labor market. Wage offers are then randomly drawn and made to each job seeker with three possible outcomes: (i) a local job offer is accepted; (ii) a commuting job offer is accepted or (iii) the job offer is not accepted which leads to a new wage draw (replay). For each job offer the worker uses a decision rule in which the wage offer is compared to the implied commuting cost and her reservation wage, which is set to maximize the expected discounted streams of future income. The next section defines the model in a formal way in order to derive how labor market characteristics determine the rate of excess commuting.

## 2.3. Equilibrium excess commuting

We now derive an expression for the equilibrium rate of excess commuting in the labor market ( $\rho^*$ ), as a function of a limited number of labor market parameters: the level of commuting costs ( $\tau$ ), the reservation wage of job seekers ( $\phi$ ), the size of the labor market (n) and – especially – the distribution of jobs and workers across places (by means of a concentration parameter  $\alpha$ ). Modeling these four determinants is a simplification because factors outside this model, such as preferences for commuting, may affect excess commuting patterns as well. The approach we follow to derive an

expression of the equilibrium rate of excess commuting is to look at the steady-state solution in a dynamic model of the labor market in which over a period of time ( $\Delta t$ ) a number of workers retire from the labor market (job destruction) and new job seekers enter the labor market and are matched to job offers (job creation). This rate of replacement is indicated by  $\delta$ . Over this period of time, the stock of excess commuters in the labor market experiences an inflow from non-employment when job seekers accept job offers in places other than their residence and an outflow to non-employment of commuters who retire from the labor market. The steady-state equilibrium in the model is derived by equating these inflows and outflows. The probability that the job seeker receives and accepts a local job offer is  $P(match_l)$  while the probability that the job offer is a commuting/local job is, respectively  $P(o_c)$  and  $P(o_l)$ . The wage offers (w) are assumed to be drawn randomly from a normal distribution with cumulative density function F(w). Finally, the proportion of jobs in a place is given by a probability function h(p), where p is the percentile rank of the places ranked in an increasing order by their proportion of jobs.

Assume that over a period  $\Delta t$  workers leave the labor market at a rate  $\delta$  to be replaced by an equal number of workers who initially enter non-employment. The distribution of jobs and workers is assumed to remain constant over time, so a new job seeker enters the labor market in the same place where a worker retires and a new job is created in the same place where an old job was destroyed. The latter assumption fixes the distribution of jobs and workers over time so that  $c^{req}$  is constant over time and so that  $\rho_t$ , the rate of excess commuting at time t, is a linear function of the rate of commuting at time t:  $\rho_t = (c_t - c^{req})/(1 - c^{req})$ . A steady-state equilibrium in the rate of excess commuting  $(\rho_{t+1} = \rho_t)$  requires the rate of commuting to be in equilibrium  $(c_{t+1} = c_t)$  as well as, which will be more convenient in the derivation, the percentage of local workers  $(l_{t+1} = l_t)$ .

Over a period  $\Delta t$ , a group of  $\delta \Delta t$  workers retire and an equal number of job seekers enter the labor market. The outflow to retirement from the stock of local workers is  $l_t \delta \Delta t$ , i.e. the probability that a retiring worker is a local worker  $(l_t)$  times the number of retiring workers. The inflow of job seekers into the stock of local workers over a period  $\Delta t$  is the number of job seekers  $(\delta \Delta t)$  times the probability that a job seeker is matched to a local job in his place of residence, which we denote  $P(match_l)$ . Equating the inflow to the outflow yields the steady-state equilibrium rate of local workers  $l^* = P(match_l)$ , the equilibrium rate of commuting (given that c = 1 - l):

$$c^* = 1 - P(match_l) \tag{4}$$

and the associated equilibrium rate of excess commuting:

$$\rho^* = (c^* - c^{req}) / (1 - c^{req}) \tag{5}$$

In order to bring commuting costs and the size of the labor market into our model, we develop Equation (4) by expanding  $P(match_l)$ . Call the probability that a job seeker receives and accepts a local job offer  $P(o_l \& acc_l) = P(o_l)P(acc_l|o_l)$ , where the first factor is the probability that a job seeker receives a local job offer and the second factor is the probability of accepting conditional on receiving a local offer. The probability that a job seeker is matched to a local job can now be written as the probability that he receives and

accepts a first local job offer or, if he rejects a first job offer, the probability that he receives and accepts a second local job offer, etcetera. If  $P(\overline{acc})$  is the probability of rejecting a job offer, then  $P(match_l) = P(o_l \& acc_l) + P(\overline{acc})P(o_l \& acc_l) + P(\overline{acc})^2P(o_l \& acc_l) + \dots$  is a geometric sequence that converges to

$$P(match_l) = P(o_l \& acc_l) / [1 - P(\overline{acc})]$$
(6)

if  $P(\overline{acc}) < 1$ .

 $P(\overline{acc})$  can be expanded as:

$$P(\overline{acc}) = P(\overline{acc}|o_l)P(o_l) + P(\overline{acc}|o_c)P(o_c)$$
(7)

where  $P(o_c)$  is the probability that the job offer concerns a commuting job. To keep things tractable, we will assume that workers are uniformly distributed across space. This simplifies the model substantially as the probability that the job offer received by a random job seeker is a local job is then  $P(o_l) = 1/n$  and the probability that the job offer concerns a commuting job is denoted  $P(o_c) = 1 - P(o_l) = (n-1)/n$  (appendix A2). Our assumption of a uniform distribution of workers is not too restrictive because our aim is to study how differences in the spatial distribution of jobs and workers affect the rate of excess commuting. By taking one distribution (workers) to be fixed and allowing the distribution of firms to vary from uniform (in which case both distributions would be the same) to a situation in which all firms are in one place (in which case the distributions differ a lot), we cover a range of differences between the distributions of workers and firms across space.

The probabilities of accepting or not accepting THE wage offer depend on the reservation wage of job seekers ( $\phi$ ), the commuting costs associated with a non-local job ( $\tau$ ) and the wage offers (w) which we assume to be drawn randomly from a normal distribution with cumulative density function F(w). Assume that all job seekers attach the same value to leisure so that they have the same reservation wage and that job seekers accept any wage offer above this reservation wage. The probability of not accepting a local job offer is the probability that a random wage draw is below the reservation wage:  $P(\overline{acc}|o_l) = F(\phi)$ . The probability of not accepting a commuting job offer is the probability that a random wage draw is below the sum of the reservation wage and the commuting cost:  $P(\overline{acc}|o_c) = F(\phi + \tau)$ .

Equation (7) can now be written as  $P(\overline{acc}) = F(\phi)/n + F(\phi + \tau)(n-1)/n$ . The probability that a job seeker receives and accepts a local job offer was  $P(o_l \& acc_l) = P(o_l)P(acc_l|o_l) = [1 - F(\phi)]/n$ . Integrating this in Equation (6) yields an expression for the probability that a job seeker is matched to a local job:

$$P(match_l) = \frac{[1 - F(\phi)]/n}{1 - [F(\phi)/n + F(\phi + \tau)(n-1)/n]} = \frac{1 - F(\phi)}{n - F(\phi) - (n-1)F(\phi + \tau)}$$
(8)

Note the limiting case in Equation (8) when the labor market consists of only one place (n = 1) in which case the probability of a local match is 1. Integrating (8) into (4) yields an expression for the steady-state equilibrium rate of commuting

$$c^* = 1 - \frac{1 - F(\phi)}{n - F(\phi) - (n - 1)F(\phi + \tau)}$$
(9)

which implies the equilibrium rate of excess commuting in the labor market for a given spatial structure of jobs and workers.

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In order to account for the spatial structure of jobs and workers in the labor market, we allow the distribution of jobs to vary across places with a parameter  $\alpha$  reflecting the level of geographical concentration of jobs. We assume the proportion of jobs in a place to be given by a probability density function

$$h(p) = \alpha p^{\alpha - 1} \tag{10}$$

with the parameter  $\alpha \ge 1$  and  $p \in [0, 1]$  the percentile rank of the places ranked in an increasing order by their proportion of jobs. Panel (a) in Figure 2 illustrates how larger values of  $\alpha$  correspond to more top-heavy distributions with a limited number of places holding most of the available jobs in the labor market. Note that the area under h(p) over [0, 1] is always 1 and that h(0) = 0 and  $h(1) = \alpha$ . Remember that we assumed the distribution of workers across places to be uniform, so in Figure 2 the distribution of workers is shown by the horizontal line corresponding to  $\alpha = 1$ .

We now demonstrate that labor markets characterized by a larger degree of job concentration, have lower rates of excess commuting. The spatial distribution of jobs determines the required rate of commuting  $c^{req}$ , i.e. the proportion of workers who cannot potentially work locally. The proportion of workers who can potentially work locally was defined earlier as the sum across all places of the minimum of the shares of jobs and workers in each place. The full line in panel (b) in Figure 2 shows, for each place *p* and given the distributions of workers and jobs we assume in the model, the proportion of all workers that can potentially work locally, i.e  $Min(W_k, J_k)$ . So the area under the full line in panel (b) is  $l^p$ , i.e. the overall proportion of workers who can potentially work locally. Using Equation (1), the required rate of commuting can be written as:

$$c^{req} = 1 - \int_{0}^{s} h(p)dp - \int_{s}^{1} dp$$
(11)

where *s* is the value of *p* where the probability density functions of jobs and workers cross. Solving the equation  $h(p) = \alpha p^{\alpha-1} = 1$  yields the value for  $s = \alpha^{-1/(\alpha-1)}$  which allows us to evaluate the integral  $\int_{0}^{s} h(p)dp = \alpha^{-\alpha/(\alpha-1)}$  and obtain an expression for the rate of required commuting for a given concentration of jobs in the labor market:

$$c^{req} = (\alpha - 1)\alpha^{-\alpha/(\alpha - 1)} \tag{12}$$

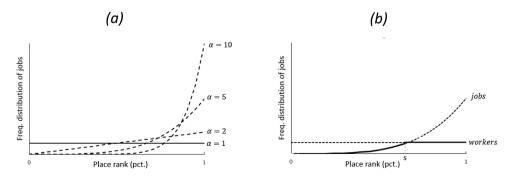


Figure 2. The required rate of commuting for the assumed distributions of jobs and workers.

In order to see how the equilibrium rate of excess commuting  $\rho^*$  is affected by the level of commuting costs, the size of the labor market, reservation wages, and the spatial structure of workers and jobs, we study the partial derivatives of  $\rho^*$  (partially deriving Equation (5) using Equation (9) and Equation (12)). The relation with the reservation wage is not straightforward because the sign of the derivative with respect to  $\phi$  depends on the other variables involved. Larger commuting costs are associated with lower equilibrium rates of excess commuting (appendix A3 shows that  $\partial \rho^* / \partial \tau < 0$ ). The intuition behind this property is that job seekers are less likely to accept commuting jobs when commuting costs are high so that in equilibrium more workers work locally and the rate of excess commuting is low. From Equation (9) it can be seen that  $c^*(\tau = 0) = (n-1)/n$  and that  $c^*$  approaches zero as the commuting costs approach infinity.

Larger labor markets with more places are associated with larger equilibrium rates of excess commuting in our model because  $\partial \rho^* / \partial n > 0$  (appendix A3). The intuition behind this property is that job seekers are more likely to receive commuting job offers in large labor markets, so that in equilibrium more workers commute and the rate of excess commuting is high. From Equation (9) it can be verified that  $c^*(n = 1) = 0$  and that  $c^*$  approaches 1 as the number of places approaches infinity. This property has two implications. The first is methodological: estimates of the rate of excess commuting will be sensitive to the level of spatial aggregation of the data. Such sensitivity is a well-known issue in spatial analysis (for example, in studies of spatial mismatch in the labor market) but it will not affect this study as we will be comparing estimates of the rate of excess commuting of different groups in the same area. The second implication is that groups of workers for which the relevant labor market is larger, for example, high-skilled workers as compared to low-skilled workers, can be expected to have higher equilibrium rates of excess commuting.

The rate of excess commuting is lower in labor markets with a high degree of geographical job concentration because  $\partial \rho^* / \partial \alpha < 0$  (appendix A3). The limiting case in which  $\alpha$  approaches one corresponds to a uniform distribution of jobs, so that the rate of required commuting is zero and any commuting is excess ( $\rho^* = c^*$ ). The other extreme where  $\alpha$  approaches infinity corresponds to a situation where all jobs are located in one place so that the measure for the rate of excess commuting breaks down because there are no workers who can potentially work locally. The intuition behind this result is that when jobs are uniformly distributed across space (say, the labor market for school teachers), job offers will arrive from all directions resulting in more excess commuting. On the other hand, a high geographical concentration of jobs (say, the labor market for airplane technicians) requires workers to commute to these places anyway so that there is less room for choices and tradeoffs and the rate of excess commuting will be low.

## 3. Data and methods

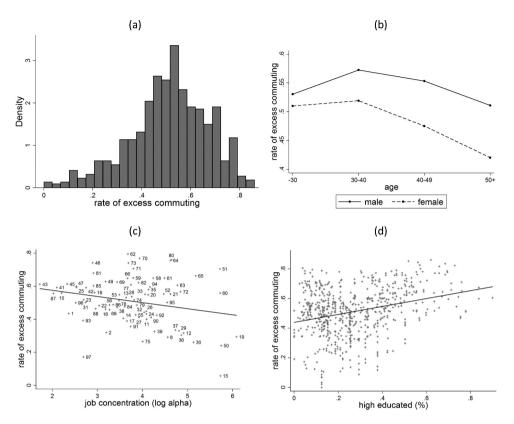
The empirical analysis tests the main predictions of the equilibrium excess commuting model using administrative data on the number of daily commuters between all 589 Belgian municipalities in 2012, where a commuter is defined as a worker who leaves his or her municipality to work. These data on the complete population of all Belgian wage

earners were collected for tax purposes at the Belgian National Social Security Office, using information about individual employees provided by the employers. The data we used are aggregated (we did not have individual-level data) but they are highly disaggregated: each observation in our data set contains the number of commuters in a group (a "cell") defined by the municipality of residence, the municipality of the workplace, the age category of the worker, the gender of the worker and the industry of employment. In total, the data contain over 2.5 million observations about six variables: the number of commuters in each group and the five group characteristics. We use the 2012 data because those are the latest available data. We did not have information on the self-employed, but excluding the self-employed makes sense as they tend to have different commuting patterns (see Roberts, Hodgson, and Dolan (2011) and Dickerson, Hole, and Munford (2014)). We restrict the population to workers aged 18-64 who commute within the Belgian national boundary (this removes 5.3% of all workers) which leaves us with observations on 3,639,204 workers (and the same number of jobs). About 72% of the Belgian payroll workers work in a different municipality than the one they live in. Belgium is a small country with the maximum distance between two municipalities being 282 km as the crow flies. The median municipality has 4100 workers and 2200 jobs. Appendix C contains the programs that reproduce all our results and provides a detailed description on how each variable was constructed.

In order to analyze the determinants of excess commuting, the data are aggregated into groups that are defined by sector, age, and gender. This approach of aggregation into groups, inspired by Borjas (2003), allows us to calculate rates of excess commuting for 640 groups of workers and generates a variation in excess commuting that is required in order to identify its determinants. We use 85 sectors (2-digit NACE Rev. 2), 4 age categories (-30, 30–39, 40–49 and 50+) and 2 genders, so one might expect 680 groups, but we leave out 40 groups that contain 30 workers or less because it is not possible to estimate variable means in a reliable way for these groups (these 40 groups together represent only 290 jobs out of the total of over 3 million jobs, which is less than .01%). For each of the remaining 640 groups (in 81 sectors) the rate of excess commuting was calculated using Equation (3).

To these data, we add estimates for the degree of geographical concentration of jobs ( $\alpha$ ), which are obtained by non-linear regression of Equation (10) for each sector separately. Highly concentrated sectors include mining ( $\alpha = 604$ ) and air transport ( $\alpha = 304$ ), while the least concentrated sector is construction ( $\alpha = 6$ ) and to a lesser extent retail ( $\alpha = 13$ ) and education ( $\alpha = 18$ ).

A weakness of our administrative data is that it contains no information on educational levels. Education is important because it is well known that highly educated workers operate in larger labor markets and because an exploratory analysis of our data (the relation with the sector that will be discussed in Figure 3, panel c) shows the importance of education for explaining differences in the rate of excess commuting. For each of the 640 groups, we added the percentage of highly educated workers (defined as having a degree in tertiary education) which we estimated using data from the European Social Survey. The variable should be considered a proxy for the percentage of highly educated workers in each group in Belgium in 2012 because we had to pool the survey data for 2010, 2012, and 2014 for 10 countries in order to have the sample size required to



**Figure 3.** The rate of excess commuting – univariate and bivariate descriptives. Notes: (a) has 640 observations that correspond to gender, age, and industry-specific groups. (b) and (c) show unweighted averages across these groups by age and gender, and for 81 industries in 2-digit NACE (Rev. 2) categories. (d) has 640 observations but it relies on 415 unique values for the educational variable because for some groups these were calculated at aggregated levels to avoid limited sample sizes as explained in the text.

obtain reliable estimates for each of the 640 subgroups (a detailed discussion on the creation of the educational variable is in appendix B).

## 4. Results

### 4.1. Descriptive analysis: commuting as trade in labor

The fact that our raw data contain numbers of commuters between each pair of municipalities inspired us to adopt indicators for the descriptive analysis that is common in the analysis of bilateral data on international trade. The analogy with international trade is not only useful in terms of methods. It also emphasizes the point that commuting can be regarded as a geographical exchange in labor that can be described in the ways trade economists describe patterns in international trade. Some places may have more outgoing commuting (labor exports) or incoming commuting (imports), resulting in imbalanced trade. Some places may be exchanging one type of labor in exchange for another type (say service for manufacturing labor), resulting in a pattern of "inter-industry" trade in labor. Other places could be part of an "intra-industry" commuting

Tab	le 2.	Commuting	as	bilateral	trad	e in	labor.
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	Mean	Std. dev.	Min	Max	Ν
<sup>a</sup> ONEWAY <sub>i</sub>	.37	.22	.00	0.85	589
<sup>b</sup> ONEWAY <sub>s</sub>	.83	.12	.49	1.00	85
<sup>c</sup> INTER_INDUSTRY <sub>i</sub>	.76	.07	.59	1.00	589

<sup>a</sup>ONEWAY<sub>i</sub> is the ratio of overall net commuting to total commuting in a municipality (1 implies that in municipality *i* all commuting is either incoming or outgoing). <sup>b</sup>ONEWAY<sub>s</sub> is the ratio of overall net commuting to total commuting in each industry (1 implies that in industry *s* all commuting between each pair of municipalities is either incoming or outgoing). <sup>c</sup>INTER\_INDUSTRY<sub>i</sub> represents the degree of inter-industry trade in labor via commuting (0 implies an equal number of incoming and outgoing commuters within each industry in a municipality).

pattern in which they both import and export the same type of labor. We thus consider commuting flows as trade-in labor between localities in the labor market and illustrate how concepts and indicators that are commonly used in the analysis of international trade patterns can also be applied to commuting.

Table 2 presents descriptive statistics for a number of trade indicators for our Belgian commuting data. The first indicator measures the extent to which overall commuting to and from municipality *i* is one-way rather than two-way. If  $X_{ij}$  and  $M_{ij}$  are the numbers of outgoing and incoming commuters in municipality *i* to/from another municipality *j* 

 $(j \neq i)$ , then we define the indicator ONEWAY<sub>i</sub> =  $\frac{\left|\sum_{j} X_{ij} - \sum_{j} M_{ij}\right|}{\sum_{j} X_{ij} + \sum_{j} M_{ij}}$ . The indicator can be

interpreted as a measure of trade imbalance ranging between 0 (no trade deficit or surplus) and 1 (one-way trade). The unweighted average across all 589 municipalities (.37) is high compared to imbalances typically observed in international trade because in the latter the fact that exports allow a country to pay for its imports tends to eliminate large imbalances. There is no similar mechanism in commuting where, for example, residential municipalities continually export labor to a few large cities that account for most of the labor imports. Among the 50 municipalities with the highest degrees of one-way commuting in Belgium, only one is a net importer: the municipality of Brussels – i.e. the central business district within the larger Brussels capital metropolitan area – imports almost 10 times more workers than it exports (ONEWAY<sub>i</sub> = .77).

The second indicator measures the extent to which commuting is one-way rather than two-way within each industry or sector s. The indicator ranges between 0 (equal outgoing and incoming commuting in sector s between each pair of municipalities) and 1 (all commuting between each pair is either incoming or outgoing) and is comparable to (one minus) the within-industry Grubel-Lloyd index in international trade.<sup>1</sup> If X<sub>iis</sub> and M<sub>iis</sub> are the numbers of outgoing and incoming commuters between municipalities *i* and *j* ( $j \neq i$ ) in sector s, then ONEWAY<sub>s</sub> =  $\sum_{i} \sum_{j} \frac{|X_{ijs} - M_{ijs}|}{X_{ijs} + M_{ijs}} w_{ijs}^{s}$  is a weighted average of the shares of one-way trade between pairs of municipalities with weights that represent the share of overall each bilateral trade flow in the trade within that sector:

 $w_{ijs}^s = (X_{ijs} + M_{ijs}) / \sum_s (X_{ijs} + M_{ijs})$ . The average for the indicator across all 85 sectors

<sup>&</sup>lt;sup>1</sup>The Grubel–Lloyd index measures intra-industry trade of a particular product. It was introduced by Grubel and Lloyd in 1971. Intra-industry trade refers to the exchange of similar products belonging to the same industry.

is .83, which implies that in most sectors the bilateral commuting flows are largely oneway. The degree of one-way trade in labor is particularly high in sectors that are geographically concentrated, such as mining (ONEWAY<sub>s</sub> = 1) and air transport (.98). The sectors with the largest degrees of two-way commuting are construction (ONEWAY<sub>s</sub> = .49), retail (.54), residential care (.56), and education (.57).

The third indicator measures the extent to which a municipality is engaged in a pattern of intra-industry trade in labor (exporting labor in one sector in exchange for labor in another sector) or inter-industry trade (two-way commuting in each sector). We define INTER\_INDUSTRY<sub>i</sub> =  $\sum_{i} \sum_{j} \frac{|X_{ijs}-M_{ijs}|}{X_{ijs}+M_{ijs}} \cdot w_{ijs}^{i}$  as a weighted average of Grubel-Lloyd type indices for each sector and pair of municipalities with weights that represent the share of each bilateral trade flow in the overall trade to and from that municipality:  $w_{ijs}^{i} = (X_{ijs} + M_{ijs}) / \sum_{i} (X_{ijs} + M_{ijs})$ . The average of the indicator across all

municipalities is .76 which suggests that most municipalities are characterized by an inter-industry pattern of trade in labor. The municipality with the maximum value is Beauvechain (INTER\_INDUSTRY<sub>i</sub> = .89), where 76% of all jobs are in the military (it hosts an air base) and which imports mainly military personnel while its outgoing commuters are in different sectors. The value is lowest in municipalities that are more diversified in terms of sectoral composition, such as Izegem (INTER\_INDUSTRY<sub>i</sub> = .59). The inter-industry indicator should be interpreted with some caution because the measure is affected by overall imbalances (as measured by ONEWAY<sub>i</sub>). This is a known issue in international trade but it is more serious here because overall imbalances tend to be limited in international trade. When the sample is restricted to municipalities that have similar levels of overall outgoing and incoming commuting (ONEWAY<sub>i</sub><.1), then the mean inter-industry indicator falls – but only to a limited extent (mean = .71, N = 76).

Given that a substantial part of the observed commuting is two-way and part of that is of the intra-industry type, the question naturally arises what is the extent of excess commuting.

#### 4.2. Excess commuting

We now present the main results of our empirical analysis regarding the determinants of the rate of excess commuting, where we focus on the impact of both the size of the labor market and the degree of geographical job concentration. How do we define the size of the labor market when we take our model to the data? The literature on geographical labor markets is well aware of the fact that the frequently used regional administrative boundaries are a poor approximation for actual labor markets, especially since this does not capture trends over time in the geographical mobility of workers (Nimczik, 2018). In our model, the actual (or effective) size of the labor market is the number of places with accepted job offers – where the largest possible labor market is the total number of places n in the area under study. The actual size of a labor market differs across groups of

workers because some groups are more likely to search, receive, or accept job offers at larger distances. For example, low-skilled workers may have less information about vacancies at larger distances and women may be less likely to accept offers for such jobs because of family obligations. This understanding of the actual size of a labor market can also be found in the work of Manning and Petrongolo (2017), who find that labor markets are quite local since the matching rate sharply decays with distance.

As explained before, the commuting data are aggregated into 640 groups defined by sector, age categories, and gender-to-generate heterogeneity in the excess commuting rate. The regression analyses estimate linear equations of the type  $\rho_{ijk} = \theta \alpha_{ijk} + \beta x_{ijk} + s_i + a_j + g_k + \varepsilon_{ijk}$ , where  $\rho_{ijk}$  is the rate of excess commuting in a particular labor market for workers in sector *i*, age *j* and gender *k*,  $\alpha_{ijk}$  is the degree of geographical job concentration in the labor market defined by *i*, *j* and *k*,  $x_{ijk}$  the educational level in the labor market and  $s_i$ ,  $a_j$  and  $g_k$  are vectors of fixed effects indicating the group's sector, age and gender, and  $\varepsilon_{ijk}$  is a random error term.

Figure 3 describes the distribution of the rate of excess commuting and its relation with the core explanatory variables. Panel (a) demonstrates that there is a substantial degree of heterogeneity in the rate of excess commuting across groups, with values ranging from close to zero to .86. Panel (b) shows that there is less excess commuting in female labor markets and that excess commuting is lower in age groups above 40 years old (for both men and women), which is suggestive of on-the-job search<sup>2</sup> or residential relocation. Panel (c) shows a negative bivariate correlation between excess commuting and the degree of geographical job concentration across sectors (r = -.24, p < .05, N = 81). The residuals in panel (c), i.e. the vertical distances between the data points and the estimated regression line, are indicative for the role of education: for example, domestic workers (sector 97), who are mostly low educated, have a relatively low rate of excess commuting, whereas software developers (62) have a relatively high rate. Panel (d) further demonstrates the positive correlation between excess commuting and the proportion of highly educated workers across all 640 groups (r = .29, p < .001).

5		5		
	(1)	(2)	(3)	(4)
	Base	Clustered	Unweighted	Industry FE
Gender: female (ref = male)	062***	062***	059***	066***
Age: 30–40 (ref = .<30)	.008	.008	.006	.029***
Age: 40–50	010	010	008	004
Age: 50+	047**	047***	044**	051***
Highly educated (%)	.286***	.286***	.330***	.017
Concentration: In(a)	048***	048**	055***	No
Industry (81 categories)	No	No	No	Yes
R-squared	.22	.22	.23	.89
Number of groups (N)	640	640	640	640

Table 3. Regression of the rate of excess commutine	Table 3.	Rearession	of the	rate of	excess	commuting
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\* p < .05; \*\*\* p < .01; \*\*\*\* p < .001. All models are linear and include a constant. All models, except (3), use weights that are proportional to the log of the number of workers in each group. All tests use robust SE, except in (2) where SE are clustered at the industry level.

<sup>&</sup>lt;sup>2</sup>The finding about the above-40-year-olds is indeed suggestive of on-the-job search if one looks at panel (d) in Figure 2. Combining it with the estimation results in Table 3, we might however obtain a more nuanced result. It appears to be mainly the above 50-year olds that have a lower rate of excess commuting. Although this might indeed be due to on-the job-search, in this age category it could also be caused by the fact that workers are less "prepared" to commute as they grow older.

Table 3 presents the results of the regression analysis of the rate of excess commuting. Our main specification (the base model in column 1) indicates that the predicted rate of excess commuting among women is 6.2 percentage points below that of men and that workers over 50 years old have a predicted rate that is 4.7 points below that of workers vounger than 30 years old. The estimated coefficient for education implies that the predicted rate of excess commuting in a sector with only highly educated workers (100%) is 28.6 percentage points above that of a sector with no (0%) highly educated workers. In order to appreciate the size of this effect, it is worth noting that the interquartile range for the educational variable is around 25 percentage points, which implies that a sector at the third quartile in the education distribution has a predicted rate of excess commuting that is about 7 percentage points (.25 times .286) above that of a sector at the first quartile in the education distribution. Thus, the effect of education appears to be of the same order of magnitude as the effects of gender and age. The estimated effect of the degree of geographical job concentration implies that doubling the concentration parameter  $\alpha$  reduces the predicted rate of excess commuting by 4.8 percentage points. The interquartile range on  $\alpha$  is about 1.4 log points, so a sector at the first quartile of the concentration distribution has a predicted rate of excess commuting of 6.7 percentage points above that of a more concentrated sector at the third quartile.

Models (2) and (3) demonstrate that the results are robust to the use of industry-level clustering of standard errors and the application of weights in the base specification. Model (4) adds industry-fixed effects which leave no variability in the job concentration variable and little variation in the educational variable. The gender and age effects largely remain, except for the 30–40 year olds who have higher predicted rates of excess commuting than younger workers in the same sector.

# 5. Discussion and conclusion

We develop a simple model of excess commuting as a result of search costs in the labor market and focus on how the resulting excess commuting in equilibrium is determined by a limited number of labor market parameters. We show that a larger labor market implies more excess commuting, while higher commuting costs and a higher degree of geographical job concentration decrease the rate of excess commuting. We test the main predictions of our model using data on commuting flows between all 589 Belgian municipalities and find confirmation of our theoretical predictions. We aggregate the data into 640 sectors and skill-specific groups in order to generate heterogeneity in the excess commuting rate. We find that women, workers aged above 50 and workers in sectors with a higher job concentration have a lower rate of excess commuting. Higher educated workers on the other hand have a higher rate of excess commuting. We can only speculate about the reasons for these group differences in excess commuting rates, so further research is needed to investigate to what extent these differences are due to preferences versus more structural constraints and determinants.

An important implication of our findings is that there are benefits to what is generally considered to be "excess" commuting. It is useful to consider excess commuting as excess trade in labor, which relates it to the literature on excess trade in goods and opens avenues for both methodological and theoretical renewal. In the international trade literature, intra-industry goods trade was initially considered wasteful. The development of New Trade Theory altered the common conception of intra-industry trade by showing how, in the presence of internal economies of scale, it may produce gains from trade and increase the variety of products available to consumers. The debate on excess trade in labor is very similar. If excess commuting arises from search costs in the labor market, then there are benefits to ("excess") commuting. Just like reducing intra-industry trade in goods by producing locally would increase fixed costs per input, reducing excess commuting (for example, by a tax on commuting costs to discourage excess commuting) might result in longer job search.

As far as our model is concerned, we see some possibilities for future extensions. First, we model and measure excess commuting using essentially a binary distance measure since commuting is defined as not working locally. Future work could include other distance measures, for example, by constructing a distance-weighted measure of excess commuting. Second, the model could be extended to allow for residential relocation. In a world of perfect residential mobility in which every worker moves to her job location, there would be no excess commuting (in fact, there would be no commuting whatsoever). In a more realistic world of imperfect residential relocation towards jobs, the equilibrium rate of excess commuting can be expected to be smaller than in the case of no residential mobility which our model assumes, because the residential relocation partly offsets the continuous inflow of excess commuters resulting from the job search process. Finally, our empirical analysis could be strengthened by using more detailed data on the skills offered by workers and required by jobs. Within each labor market, workers are assumed to be interchangeable so that errors in defining and delineating labor markets are likely to affect the resulting estimates of excess commuting. Richer data could allow future research to distinguish more clearly between and identify the effects of the determinants of excess commuting.

Our model of excess commuting has implications for the development of excess commuting over time. The tendency towards market concentration in many industries, with an increasing average firm size and decreasing number of firms (De Loecker & Eeckhout, 2017; The Economist, 2016) can be expected to mechanically reduce the rate of excess commuting. However, this decrease in the rate of excess commuting can be attenuated if concentration in the presence of economies of scale leads to an increase in productivity. In that case, the overall effect of increased spatial concentration on excess commuting is ambiguous, which is clear from Equation (3). On the other hand, and more importantly, increasing levels of education and improvements in work/life balance through policies such as childcare provision or teleworking, allow workers to find and accept commuting job offers, so that excess commuting is not likely to end being a feature of labor markets any time soon.

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