TI 2006-077/3

Tinbergen Institute Discussion Paper

The Effect of Search Frictions on Wages

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September 20, 2005

Abstract

Labor market theories allowing for search frictions make marked predictions on the effect of the degree of frictions on wages. Often, the effect is predicted to be negative. Despite the popularity of these theories, this has never been tested. We perform tests with matched worker-firm data. The worker data are informative on individual wages and labor market transitions, and this allows for estimation of the degree of search frictions. The firm data are informative on labor productivity. The matched data provide the skill composition in different markets. Together this allows us to investigate how the mean difference between labor productivity and wages in a market depends on the degree of frictions and other determinants. We correct for worker self-selection into high-wage jobs. Using within-market variation, we also investigate the extent of (and explanations for) positive assortative matching.

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Keywords: labor market imperfections, job durations, productivity, heterogeneity, sorting, assortative matching. *JEL-codes:* E24, J41, J42.

Acknowledgements: We thank two anonymous Referees, the Editor, Ken Burdett, Dale Mortensen, John Kennan, Paul Gregg, Chris Pissarides, Carol Propper, Chris Ferrall, Hilmar Schneider, and other participants at conferences in Iowa City, Mannheim, Venice, Washington DC, Amsterdam, and Berlin, and seminars at Bristol, Stockholm, and UCL London, for their comments. We thank the Netherlands Ministry of Economic Affairs, and Eric Bartelsman in particular, the University of Aarhus, and Niels Westergaard-Nielsen in particular, and the Netherlands Organization for Scientific Research, for financial support. The empirical analyses were carried out at Statistics Denmark / University of Aarhus.

1 Introduction

Nowadays, a substantial amount of labor economics research takes account of informational frictions or search frictions to understand economic behavior in the labor market (see e.g. various chapters in Ashenfelter and Card, 1999). In standard neo-classical labor market models, the equilibrium wage is determined by equality of demand and supply. In equilibrium models with search frictions, the situation is different. The presence of frictions implies that there may be a rent (or surplus) at the moment at which the employer and the worker meet. If a contact does not result in a match then the worker's instantaneous utility flow remains at its previous level, and the firm is left with the vacancy. Both parties then have to search further for a partner. If a contact does result in a match then a wage has to be determined. A wage effectively divides the rent of a match into a portion for the employer and a portion for the worker. In general, the wage level is affected by the market power of both parties, which in turn may depend on the amount of frictions in the market. So, wage determination is affected by the presence of search frictions.

The models that have been developed in the literature make marked predictions on the effect of the degree of frictions on the mean equilibrium wage. Often, the effect is predicted to be negative. Underlying reasons for this are that the labor force is more or less fixed whereas firms and vacancies can be created relatively quickly, and each single worker can match with only one firm whereas firms can match with many workers at the same time. If frictions decrease then firms benefit less per match than workers do, because new firms may enter the market, and because existing firms may have been constrained in their labor demand because of the frictions. For examples of theoretical models, see the surveys in Mortensen and Pissarides (1999), Van den Berg (1999), Weiss (1991), and Rogerson and Wright (2001). The predictions on the effect of frictions on the mean wage are fundamental in the sense that they relate an indicator of the amount of labor market imperfection to the equilibrium price in the market, and as such this concerns the relevance of frictions. However, they have never been tested.

This paper empirically investigates the effect of frictions on the mean wage, using matched worker-firm data. The results are informative on the relevance of frictions in general, and the specification of different popular equilibrium search models of the labor market (making different predictions on the sign of the effect) in particular. In addition, the results have policy relevance. A popular way to reduce the monopsony power that firms derive from frictions is to impose a minimum wage. This has as a negative side-effect that it may create structural unemployment. A subsidy on search effort may be considered as an alternative policy to achieve an increase in the workers' share of the rent of the match. A reduction of high marginal income tax rates may also achieve this. Finally, if frictions are important for wages, then they may also have effects on other important variables, like firms' capital investment (see e.g. Acemoglu and Shimer, 2000).

To estimate the equilibrium effect, we compare different market equilibria with each other. In particular, we compare the mean wage across markets that have different search technologies. For such a comparison, it is necessary to control for (the distribution of) characteristics of the firms and the workers in a market.[1] As our measure of search frictions, we use the mean number of job offers in a spell of employment (i.e., in between two spells of non-employment; a spell of employment may consist of multiple consecutive job spells). We argue that this measure is less sensitive to considerations of reverse causality than a measure based on unemployment durations or job offers during unemployment. The worker data are informative on individual wages and tenures, and on worker characteristics, and these data allow for estimation of the amount of search frictions in a market without functional form assumptions. The firm data are informative on the distribution of labor productivities and wage costs in a market, and on firm characteristics. The matched data allow for an assessment of the productivity effects of the skill composition in different markets. Together this allows us to investigate how the mean difference between labor productivity and wages in a market depends on the degree of frictions and other determinants. We use certain observable characteristics to define different labor markets.

The wage variable of interest is the mean wage across firms in a market rather than across workers in that market. This is because workers self-select themselves into high-wage firms if frictions are low. Even if firms do not take the frictions into account when they set wages, the mean wage across workers may be negatively correlated to the amount of frictions due to this selection effect. To assess the equilibrium effect of frictions on the mean wage across workers one has to correct for the selection effect. As we shall see, in the context of a wide range of economic models, using the mean (skill-specific) wage across firms in a market avoids this identification problem.

In the empirical analysis we use register data from Denmark. The geographical structure of Denmark (with many islands) allows for the use of the region as a natural labor market identifier. The data enable us to follow single individuals and firms over time. In addition, they contain information on all workers employed at a firm.

[1] Alternatively, one may follow one labor market over time. We address this below.

Our estimation procedure exploits variation in outcomes across markets. We claim that the adoption of panel data methods is not useful in our situation, so we do not allow for unobserved market-fixed effects. First, the theoretical literature on the dynamics of going from one steady-state equilibrium to another is not well developed, panel data methods require a data time span covering different steady-state equilibria. This requires many more years of observation than we have available in our database. Also, the impact of search frictions is only identifiable in a fixed effects model if there is variation over time in the amount of search frictions, and this variation is unlikely to occur without additional major changes in the labor market. [2]

It should be emphasized that we do not impose the structure of equilibrium search models to the data, as has been done in previous studies (see e.g. the survey in Van den Berg, 1999), although for each market we need to estimate the measure of frictions in a market, which is a structural parameter. But the inference on the impact of search frictions on the mean wage is made without an *a priori* committal to any outcome. Note that we are forced to be specific on what constitutes a labor market. We start by defining a market as a specific combination of a region and a sector of the economy. A major problem with this is that workers may move between regions and sectors, and indeed the data display positive flows between regions and sectors. If all sectors and regions together are viewed as one single large labor market then it is not possible to identify the effect of frictions on wages. However, transitions between regions and sectors are less common than job-to-job transitions within regions and sectors, and they may be driven to a larger extent by factors that are unrelated to wages. For example, workers may move to another region because their partners have found a job there, and they may move between sectors because they have been re-educated. We develop empirical analyses that focus on the relation between frictions and wages within a sector and region but that do take into account that workers may move to other sectors and regions, assuming that the latter moves are less strongly driven by wages. In order to obtain an understanding of the role of moves to other regions and sectors we advance on the theoretical literature by developing an equilibrium search model that allows for cross-market transitions (where market is now just a shorthand definition of region $\times$ sector). As a second

[2] In principle, major geographical changes in labor market imperfections may be adopted to identify these effects. Notably, the construction of the Great Belt bridge in Denmark can be interpreted as such a major change. However, this does not solve the problems concerning out-of-equilibrium outcomes. Besides this, our database does not contain any information after the construction of this bridge.

approach to deal with cross-market flows, we carry out sensitivity analyses with the definitions of region and sector. Specifically, we merge sectors and regions with adjacent sectors and regions.

Recently, a number of equilibrium models have been developed that allow for heterogeneity of agent-specific productivity at both sides of a given market, while at the same time allowing for search frictions (like assignment models; see Shimer and Smith, 2000, Burdett and Coles, 1999, and Shi, 2001). In such models, the equilibrium effect of frictions on the mean wage is often not determined. Intuitively, this is because the mean wage within a market strongly depends on the exact shape of the production function. Our data enable us to address to what extent the equilibrium displays positive assortative matching: for each firm we can quantify the firm-specific productivity component, and this can be correlated with the fraction of high-skilled workers within the firm. Obviously, a high correlation can be due to positive assortative matching or to the fact that the labor markets for high-skilled workers have less search frictions. We distinguish between these explanations by examining whether markets where this correlation is high also have a low amount of search frictions for high-skilled workers relative to low-skilled workers. If it turns out that inter-skill differences in frictions are empirically important for positive assortative matching then the latter is partly due to supply behavior (self-selection), whereas otherwise it is due to demand behavior (production technology). Note that whereas we use between-market variation to examine the relation between frictions and wages, we use within-market variation to examine assortative matching, and we use both to examine the reason for assortative matching.

The estimation results allow for a quantification of the effect of frictions on the firms' wages in equilibrium. They also allow for a decomposition of the wage variation across markets into a part due to cross-market differences in frictions and a part due to productivity variation across markets. The latter can be due to cross-market differences in the average skill composition of the workforce and cross-market differences in the mean firm productivity. Our results can be related to those in the literature on inter-industry wage differentials (see e.g. Krueger and Summers, 1988, Gibbons and Katz, 1992, and Goux and Maurin, 1999). These studies do not examine differences between labor market frictions as an explanation of these wage differentials.

It is also useful to relate our approach to the pivotal work by Abowd, Kramarz and Margolis (1999) on the decomposition of the individual wage into covariates, individual and firm fixed effects, and a residual component (see also Abowd, Finer and Kramarz, 1999, and Abowd, Creecy and Kramarz, 2002). Typically, the residual component of the (individual-firm-time specific) wage is taken to be orthogonal to the firm fixed effect. In our framework, workers who search for better jobs in their labor market are only concerned about the wage level of the current job and the wage they may earn elsewhere, and they are not concerned about other job characteristics, so mobility is driven by wage dispersion. Workers who get a job offer leave their current firm if and only if the wage of the new firm exceeds the wage of the current firm. The ensuing joint distribution of consecutive wages of job movers can then not be captured by the Abowd, Kramarz and Margolis (1999) framework. Thus, the relation between wages and job mobility differs between these two approaches. For example, our analysis may break down in case of compensating wage differentials. More recently, Buchinsky et al. (2005) estimate a dynamic structural model including equations for optimal participation and mobility decisions and including random-effects unobserved heterogeneity. Optimal firm behavior concerning wage levels is not incorporated, so the analyses can not straightforwardly be used to study the importance of search frictions for wages.

The paper is organized as follows. The next section discusses the theoretical considerations. Section 3 deals with the actual measure of frictions that we use in the empirical analysis. The data are discussed in Section 4. Section 5 concerns the estimation and testing strategy. The results are in Section 6. Section 7 deals with the empirical analysis of assortative matching. Section 8 concludes.

2 Theoretical considerations

This section considers the relationships between wages and search frictions. It is not intended to develop a single structural specification for our empirical model. Instead we show that a negative relationship can often be expected, and it suggests possible measures of frictions, which will be discussed further in Section 3.

2.1 The general framework

Intuitively, at a very general level, a decrease in frictions stimulates participation at both sides of the market, so both the supply curve and the demand curve shift outward. The effect on the equilibrium wage depends on the relative magnitudes of the demand and supply elasticities. If demand is more elastic than supply then the wage increases. Of course, models with search frictions are inherently dynamic, and this complicates the analysis. In addition, they allow for heterogeneous agents, incomplete information, and equilibrium wage dispersion. Consider a stylized model. It takes time and effort for an employer and a worker to find each other. Opportunities to form a match arrive at random time intervals. If an opportunity arrives it has to be decided whether to take it or leave it. It is not known in advance when a potential partner will be found or what are his properties and the properties of a match. If a contact does not result in a match then the worker's instantaneous utility flow remains at its previous level, and the employer is left with the vacancy. Both parties then have to search further for a partner. This implies that a *rent* (or surplus) may be created at the moment at which the employer and the worker meet. If the rent is negative then a contact does not result in a match. A wage contract effectively divides the rent of a match into a portion for the employer and a portion for the worker. The division reflects the relative power of both parties.

One way to classify equilibrium search and matching models of the labor market is to distinguish between wage posting models (where the employer posts or sets the wage before he meets applicants), and wage bargaining models (where the employer and the worker bargain over the wage; see Mortensen and Pissarides, 1999). This distinction is not relevant for our purposes. In bargaining models, the equilibrium wage is a weighted average of the worker's and the employer's minimum and maximum acceptable wage values, where the weight captures the relative bargaining power of the parties, and the minimum and maximum acceptable wage values may depend on the market opportunities, i.e. on the amount of frictions. In wage posting models, employers act as monopsonists, and they take account of the behavior of all other parties on the market when they determine their optimal ex ante wage offer. In addition, the wage should allow for profitable production. Typically, the level of the wage offer captures the relative market power of the firm, which depends on the amount of search frictions (see Van den Berg and Ridder, 1998, for a more detailed exposition; see also below). In both cases, the resulting wage is bounded by threshold values reflecting outside options of both parties, and the precise location of the wage in between these bounds reflects their relative power. Thus, in both cases the wage level may depend on the amount of frictions in the market.

What happens when the amount of frictions changes? The values of the outside options of the employer and the worker may change, and the power balance between the parties may change. For example, with lower frictions unemployed workers find it easier to find a good alternative job offer, so their outside option has a higher value, which implies a higher threshold value (reservation wage). However, it is intuitively clear that in a model where workers and employers are fully symmetric, both parties benefit with the same amount from a decrease in frictions, and the equilibrium wage may remain the same (this is demonstrated formally later in this section). Still, as noted in the introduction, many models in the literature predict that the mean equilibrium wage decreases in the amount of frictions (see for example the models in Burdett and Mortensen, 1998, Pissarides, 1990, Albrecht and Axell, 1984, Bontemps, Robin and Van den Berg, 2000, Postel-Vinay and Robin, 2002a, and Acemoglu and Shimer, 2000). All of these models are asymmetric in workers and employers. Fundamentally, a worker corresponds to a relatively long-lived physical unit whereas a firm can expand and contract and can be created and destroyed relatively quickly. When frictions decrease, the value of creating a vacancy increases, and this may prompt an instantaneous inflow of new firms. The latter mitigates the effect of the decrease in frictions on the firms whereas it increases the effect on the workers, and as a result the wage increases. So, entry and exit of firms creates an asymmetry in the effect of frictions on employers and workers. Alternatively, suppose that firms are quantity-constrained in their labor demand because of search frictions. It would be profitable for them to expand, but the inflow of workers is not sufficiently high for that. When frictions decrease, the firms expand. However, at the same time it is easier for the workers to leave a firm and move to another firm, and this pushes up the wage. In all these cases, the wage in the limiting case where frictions vanish exceeds the wage in the presence of frictions. The opposite result can be obtained if firms do not wish to expand and workers' search efforts are strongly dependent on labor market outcomes. In the next subsection we examine some specific models to illustrate the above mechanisms and to shape thoughts for the empirical analysis. It is beyond the scope of this paper to analyze the effect of frictions on wages in a meta-model that incorporates all models previously derived in the literature.

2.2 A benchmark equilibrium search model

We describe the equilibrium model developed by Bontemps, Robin and Van den Berg (2000) in some detail, because some of the model parameters and expressions are used later in this paper when we define the measure of frictions. Also, some of the empirical specifications can be motivated by this model. Finally, as a by-product to the paper, we test some specific predictions of this model.

The model generalizes the Burdett and Mortensen (1998) model. Consider a labor market consisting of fixed continuums μ and n of workers and firms, respectively. The measure of unemployed workers is denoted by u. The supply side of the model is equivalent to a standard partial job search model with on-the-job search (see Mortensen, 1986). Workers obtain wage offers, which are random drawings from the (endogenous) wage offer distribution $F(w)$, at exogenous rates λ_0 when unemployed and λ when employed. Firms post wage offers and they do not bargain over the wage. Layoffs accrue at the constant exogenous rate δ.[3] The opportunity cost of employment is denoted by b and is assumed to be constant across individuals and to be inclusive of unemployment benefits and search costs. The optimal acceptance strategy for the unemployed is then characterized by a reservation wage ϕ. Employed workers simply accept any wage offer that exceeds their current wage. In sum, workers climb the job ladder to obtain higher wages, but this effort may be frustrated by a temporary spell of frictional unemployment.

Now consider the flows of workers. First, note that active firms do not offer a wage below ϕ, so that all wage offers will be acceptable for the unemployed. Let the distribution of wages paid to a cross-section of employees have distribution function G. These wages are on average higher than the wages offered, because of the flow of employees to better paying jobs. The stock of employees with a wage less than or equal to w has measure $G(w)(\mu - u)$. The flow into this stock consists of unemployed who accept a wage less than or equal to w, and this flow is equal to $\lambda_0 F(w)u$ The flow out of this stock consists of those who become unemployed, $\delta G(w)(\mu - u)$ and those who receive a job offer that exceeds w, $\lambda(1 - F(w))G(w)(\mu - u)$. In the steady state, the flows into and out of the stock are equal, so

$$G(w) = \frac{\delta F(w)}{\delta + \lambda(1 - F(w))} \tag{1}$$

where we have substituted for u using the equilibrium condition that the flows between unemployment and employment are equal.

Now consider the employers' behavior. We examine a labor market with workers who are fully homogeneous, and we assume that an employer pays the same wage to all of its employees. The steady-state labor force of an employer who sets a wage w is denoted by $l(w)$. Somewhat loosely, this must equal the number of workers earning w divided by the number of firms paying w. One may therefore express $l(w)$ in terms of $\mu, n, \delta, \lambda_0, \lambda$ and F. Now consider a firm with a flow p of marginal revenue product generated by employing one worker. We assume that p does not depend on the number of employees, *i.e.* we assume that the production function is linear in employment. Occasionally we refer to p as *the* (labor) pro-

[3]The separation rate δ can be interpreted to capture an idiosyncratic instantaneous large decrease in the productivity of the worker in his current job.

ductivity of this firm. Each firm sets a wage w so as to maximize its steady-state profit flow

$$(p - w)l(w)$$

given F and given the behavior of workers.

We assume that p is continuously distributed across firms within the market. It should be emphasized that p is a firm characteristic and not a worker characteristic. Dispersion of p can be rationalized as an equilibrium outcome by letting ex ante homogeneous firms choose their capital before production starts (Acemoglu and Shimer, 2000, Robin and Roux, 2002). Alternatively, it may be the result of differences in product market power or match-specific capital (Mortensen, 2000). If the firms' profit function is additive in worker types then without loss of generality a single firm may employ different worker types, and all results below are for a given worker type. The results at the firm level can then be obtained by simple aggregation.

We denote the distribution function of p across all firms by $\Gamma(p)$. The lower bound of the support of Γ is denoted by $\underline{p}$ and the mandatory minimum wage in the market is denoted by $\underline{w}$. We assume that the model parameters are such that $\phi < \underline{w} \leq \underline{p}$.[4,5] In equilibrium, the profit maximizing wage for a firm of type p defines a mapping $w = K(p)$,

$$w = K(p) = p - \left(1 + k\overline{\Gamma}(p)\right)^2 \left[\frac{\underline{p} - \underline{w}}{(1+k)^2} + \int_{\underline{p}}^{p} \left(1 + k\overline{\Gamma}(x)\right)^{-2} dx \right] \tag{2}$$

with $\overline{\Gamma} := 1 - \Gamma$ and $k := \lambda/\delta$. The distribution of wage offers is $F(w) = \Gamma(K^{-1}(w))$. Note that a firm always offers $w < p$.[6]

[4]The first inequality is in line with the empirical observation that within each labor market some wages are at or close to the mandatory minimum wage. The inequality facilitates the comparative statics analysis, because marginal changes in ϕ do not affect equilibrium wages. Sufficient for the first inequality is that $b < \underline{w}$ and that $\lambda_0 \leq \lambda$.

[5]We do not address existence and multiplicity of equilibria; see Van den Berg (2003).

[6]In equilibrium, firms with a higher labor productivity offer higher wages, have a larger labor force and have higher profit flows. The model thus explains the firm-size wage effect and persistent inter-firm wage differentials. The model displays similarities to "turnover costs" efficiency wage models (see e.g. Stiglitz, 1985, and Weiss, 1991). See Ridder and Van den Berg (1997), Acemoglu and Shimer (2000) and Montgomery (1991) for overviews of the empirical evidence supporting these types of models. Barth and Dale-Olsen (1999) find a negative relation between the relative (compared to other firms) level of an establishment's wage and the amount of excess turnover at the establishment. The presence of such an upward sloping labor supply curve can be regarded as a necessary condition for a meaningful relation between wages and the amount of frictions.

The mean wage across firms equals the mean wage offer, because all firms always want to expand, i.e. all firms have a (costless) vacancy. It can be shown that the mean wage satisfies[7]

$$\begin{aligned} \mathrm{E}_F(w) = & \frac{2}{3}\mathrm{E}(p) + \frac{1}{3}\underline{w} - \frac{1}{3}\left(\mathrm{E}(p) - \underline{w}\right)\frac{k+2}{(k+1)^2} \\ & - \frac{1}{3}\frac{k}{(k+1)^2}\int_{\underline{p}}^{\infty}\Gamma(x)\overline{\Gamma}(x)\frac{k(k+2)\overline{\Gamma}(x)+2k+3}{(1+k\overline{\Gamma}(x))^2}dx \end{aligned} \tag{3}$$

This provides a useful decomposition into three additive factors. The *first term* $\frac{2}{3}\mathrm{E}(p) + \frac{1}{3}\underline{w}$ is equal to the mean wage across firms that prevails if $\lambda = \infty$, *i.e.* if there are no search frictions for the employed (see Van den Berg and Ridder, 1998). In this limiting case, every unemployed individual who finds a job moves immediately to the job with the highest wage. This highest wage then in turn converges to the highest productivity level. However, F converges to a nondegenerate distribution. In the limit, profits are zero for the firm offering this highest wage as well as for the firms offering a lower wage.

Without firm heterogeneity, the mean wage offer is equal to the sum of the first and the second term. Thus, the *second term* in the decomposition of the mean wage represents the change in the mean wage due to search frictions. It should be emphasized that in this case wages are dispersed (Burdett and Mortensen, 1998) so that workers do move between jobs. Taken together, the first and second term are a weighted average of $\mathrm{E}(p)$ and $\underline{w}$. The latter reflect the threshold values or outside options of both parties. The precise location of the wage in between these bounds only depends on the frictional indicator k. The second term is actually always negative and it increases in k. This is the effect that we discussed in the previous subsection. If k is large then the amount of frictions is low, so it is easy for employed workers to find other job opportunities. Firms with high productivity then have an incentive to offer a relatively high wage, since that will generate a larger inflow of workers. Stated differently, it increases the workers' market power and this pushes up the mean wage and reduces the profit rate.[8]

The *third term* captures the component in the mean wage that is due to heterogeneity of p. More precisely, it is non-zero if and only if both $0 < \lambda < \infty$ (so that $0 < k < \infty$) and $\mathrm{var}(p) > 0$. So the third term is an interaction effect between the indicator λ of frictions and an indicator of productivity dispersion

[7] See also Koning, Van den Berg, Ridder and Albæk (2000).

[8] More precisely, what happens to the profit rate depends on whether λ_0 changes as well.

among firms.[9] If on-the-job search is impossible (i.e., $\lambda = 0$ so $k = 0$) then the equilibrium wage satisfies the "Diamond (1971) solution": $w \equiv \underline{w}$ regardless of whether firms are heterogeneous or not.

In fact, with $0 < \lambda < \infty$ and $\mathrm{var}(p) > 0$, this third term is always negative. So, if firm heterogeneity is introduced such that the mean productivity level remains equal to the productivity level in the homogeneous model, then the mean wage offer is lower than in the homogeneous model. This can be understood as follows: because of the wage floor, the firms with a low productivity all have to pay a wage close to their productivity level, and this pushes down all wages. As a by-product of this paper, we test this empirically.

In the limiting competitive equilibrium solution, all workers are employed at the firm with the highest productivity in the market. The wage equals this productivity level, and profits are zero. Bontemps, Robin and Van den Berg (2000) show that $dK(p)/d\lambda > 0$ for all p in the support of Γ. By implication, $d\mathrm{E}_F(w)/d\lambda > 0$. Moreover, the monopsony power index $(p - w)/w$ decreases in λ. It is important to note that even though all firms pay higher wages, profits do not decrease for all firms. For small, low-productivity firms they do, as their labor force diminishes. The wage increase paid by high-p firms is more than offset by the increase of their labor force.

Let us return to the wages earned in a cross-section of workers at a particular moment. From equation (1) it follows that $\mathrm{E}_G(w) > \mathrm{E}_F(w)$, and that the difference between these means increases in λ given a certain F, so that $d\mathrm{E}_G(w)/d\lambda > d\mathrm{E}_F(w)/d\lambda$. This is of course the selection issue that was mentioned in Section 1. For $\mathrm{E}_G(w)$ we obtain the following expression, with a similar structure as (3),

$$\mathrm{E}_G(w) = \mathrm{E}(p) - \frac{1}{k+1}(\mathrm{E}(p) - \underline{w}) - \frac{k}{k+1}\int_{\underline{p}}^{\infty} \Gamma(x)\overline{\Gamma}(x)\frac{1 - k^2\overline{\Gamma}(x)}{\left(1 + k\overline{\Gamma}(x)\right)^2}dx \tag{4}$$

It follows that mean-preserving productivity dispersion among firms can have a positive or a negative effect on $\mathrm{E}_G(w)$, depending on λ and on the particular shape of the distribution $\Gamma(p)$. If λ is very large then workers can move to high-productivity firms very fast, so it is advantageous for the workers to have high mean-preserving productivity dispersion.

Postel-Vinay and Robin (2002a, 2002b) generalize the model by allowing firms to post worker-dependent wages and to renegotiate on a wage when a worker

[9] The integral in the third term is similar to the Gini coefficient of p, which can be shown to equal $\int_{\underline{p}}^{\infty} \Gamma(p)\overline{\Gamma}(p)dp/\mathrm{E}(p)$. The Gini coefficient increases in a scale parameter of the distribution.

obtains a better outside option. It can be shown that the mean wage has the same qualitative properties as above.

The production function of Bontemps, Robin and Van den Berg (2000) is linear. It has been proven to be very difficult to generalize this linearity in wage posting models. One reason is that the expected profit flow no longer equals the profit margin times the expected number of workers. In addition to this, it can sometimes be optimal for the firm to reject workers when they arrive at the firm. Since the focus of this paper is not to develop new models, but to test existing models, we do not want to elaborate on this. This also implies that we do not focus on models with worker heterogeneity in which the production function is non-perfectly substitutable (such as in the Cobb-Douglas case).

2.3 Wage posting and transitions to other markets

Based on the theoretical analyses of Van den Berg and Ridder (1993) and Ridder and Van den Berg (1997), we introduce an extension of equilibrium search models that includes transitions from and to other markets. The ultimate purpose of this is to inquire the impact of these transitions on the relation between frictions and wages.

We assume that cross-market transitions are governed by a Markov process and we denote the individual transition rate from market i to market j by ξ_{ij}. For the remainder of this section we define μ_m as the size of the market m (the measure of workers). The equilibrium unemployment rate and the relationship between offered and earned wages change in comparison to models without transitions between markets. The equilibrium unemployment rate is now equal to

$$\frac{u_m}{\mu_m} = \frac{\delta_m}{\delta_m + \lambda_{0,m} + \sum_{j \neq m} \xi_{mj}}.$$

We assume that, in a given market, the ξ_{ij}, as seen from the point of view of a single firm, do not depend on the wage offer w of the firm. Below we use index m for a particular market and running indices i and j for source markets and destination markets, respectively. For clarity we omit the indices m of the rates λ_0, λ and δ. In obvious notation,

$$G_m(w) = \frac{\delta}{\lambda_0} \frac{\lambda_0 + \frac{\delta + \lambda_0 + \sum_{j \neq m} \xi_{mj}}{\delta \mu_m} \sum_{i \neq m} \xi_{im} \mu_i}{\delta + \lambda \overline{F}_m(w) + \sum_{j \neq m} \xi_{mj}} F_m(w)$$

The distribution of workers across markets can be characterized by the following set of equations

$$\mu_m = \frac{\sum_{i \neq m} \xi_{im} \mu_i}{\sum_{j \neq m} \xi_{mj}}$$

and

$$\mu_K = \mu - \sum_{m=1}^{K-1} \mu_m$$

with K the total number of markets. This system can be solved to obtain the equilibrium distribution between markets.

In order to obtain more insights, we examine the implications of cross-market transitions in the Bontemps, Robin and Van den Berg model. By using the same techniques as presented earlier it is possible to derive the mean of the steady-state distribution of the workforce of the firm in market i,

$$l_m(w) = \delta \frac{\delta + \lambda + \sum_{j \neq m} \xi_{mj}}{\delta + \lambda_0 + \sum_{j \neq m} \xi_{mj}} \frac{\lambda_0 + \frac{\delta + \lambda_0 + \sum_{j \neq m} \xi_{mj}}{\delta \mu_m} \sum_{i \neq m} \xi_{im} \mu_i}{\left(\delta + \lambda \overline{F}_m(w) + \sum_{j \neq m} \xi_{mj}\right)^2}$$

By analogy to Bontemps, Robin and Van den Berg (2000) it follows that

$$w = K(p) = p - (1 + \widetilde{k}\overline{\Gamma}(p))^2 \left[\frac{p - \underline{w}}{(1 + \widetilde{k})^2} + \int_{\underline{p}}^{p} (1 + \widetilde{k}\overline{\Gamma}(x))^{-2} dx \right]$$

with

$$\widetilde{k} := \frac{\lambda}{\delta + \sum_{j \neq m} \xi_{mj}}$$

where again the dependence on index m is suppressed.

Note that the function $K(p)$ is exactly the same as (2), with k replaced by $\widetilde{k}$. In both k and $\widetilde{k}$, the denominator is the rate at which an employee leaves employment in the market.

2.4 The Pissarides model

We start by listing the differences between the "prototype" Pissarides (1990) model (see also Pissarides, 1984, 1986) and the model of Subsection 2.2. In the Pissarides model, a firm is equivalent to a single job task for a single worker. Let v denote the measure of vacancies in the market. Then $n - v = m - u$ denotes the measure of filled jobs. In addition, there is no search on the job, so $\lambda \equiv 0$. Workers and firms are homogeneous. Note that from the point of view of an employer the arrival rate of workers equals $\lambda_0 u/v$. A firm with an unfilled vacancy pays a vacancy cost flow equal to c_v.

A worker and an employer bargain over the wage whenever a match is consummated. The bargaining solution is the axiomatic Nash solution. This means that the wage is determined such that the worker gets a fraction β of the surplus of the match. It is not difficult to see that this implies that w is determined by[10]

$$\beta \left[\frac{p - w + c_v}{\delta + \lambda_0 u/v} \right] = (1-\beta) \frac{w-b}{\delta + \lambda_0} \tag{5}$$

for a given fixed measure of vacancies v. The threshold values or outside options of both parties depend on the frictional indicators $\lambda_0, u/v$ and δ and on monetary flows. The precise location of the wage in between these bounds depends on the bargaining power indicator β.

In the prototype Pissarides model, the equilibrium value of v is determined by a free entry condition for firms. This states that the present value of having a vacancy is equal to zero. It is not difficult to see that this gives

$$(p-w)\lambda_0 u/v = \delta c_v \tag{6}$$

for a given wage level w. Substitution into (5) gives

$$w = p - \frac{\delta}{\delta + \beta\lambda_0}(1-\beta)(p-b) \tag{7}$$

which is a weighted average of p and b. Obviously, this also equals $\mathrm{E}_F(w)$ and $\mathrm{E}_G(w)$. Note the similarity between the right-hand side of equation (7) and the first two terms at the right-hand side of equation (4). If $\lambda_0 < \infty$ then the wage is smaller than if $\lambda_0 = \infty$. However, some care should be taken here, since λ_0 is not a structural parameter anymore. It depends on the market size by way of a constant returns to scale matching function $M(u,v)$. We write $M(u,v) := \alpha M_0(u,v)$, where α is a structural parameter denoting the efficiency of the matching technology.[11] As such this is a better indicator of the amount of frictions than λ_0. There holds that $\lambda_0 := M(u,v)/u = \alpha M_0(1, v/u)$. By substituting this into equations (5) and (6), and by elaborating, we obtain the following results:

$$\frac{d(v/u)}{d\alpha} > 0, \quad \frac{d\lambda_0}{d\alpha} > 0, \quad \frac{dw}{d\alpha} > 0.$$

[10]For expositional reasons we restrict attention to the limiting case in which the discount rate is infinitesimally small (just as in the previous subsection). The results do not depend on this.

[11]In the model of the previous subsection this would be irrelevant, as all agents search there.

The derivative $dw/d\alpha$ captures the effect that we discussed in Subsection 2.1. If α is large then the amount of frictions is low, so it is easy for workers to find a job opportunity. This provides an incentive for firms to create vacancies and for new firms to enter the market. This increases the workers' market power and this pushes up the mean wage. The firms' contact arrival rate also increases, but the positive effect of this on the value of a vacancy is offset by the wage increase.

In a recent paper, Shimer (2004) extends the Pissarides model with on-the-job search. He finds that the model predictions look similar to those of the wage posting models. Among other things, it can be shown that search frictions decrease the mean wages among firms.

2.5 Some other models

Let us return to the Pissarides model, but let us now assume that the number of firms (and, therefore, vacancies) is fixed. This case is examined by Pissarides (1984). We assume that $n = m$ so that $v = u$: the number of filled and unfilled jobs equals the labor force size. Equation (5), which describes w for a given amount of vacancies, now reduces to

$$w = \beta(p + c_v) + (1 - \beta)b$$

This does not depend on the amount of frictions in the market. By making the model completely symmetric between workers and employers, each party benefits with equal amount from a reduction in frictions, and the wage is not affected. This highlights the importance in the previous subsections of the assumption that labor supply is less elastic than labor demand.

We now briefly examine a model in which frictions actually increase the mean wage. The results for the Bontemps, Robin and Van den Berg (2000) model depend on the production technology being such that it is always profitable for firms to expand if possible. Burdett and Vishwanath (1988) examine an equilibrium search model with decreasing returns to scale in labor such that firms do not want to expand indefinitely. In addition, the measure of firms is fixed. The search effort of workers is endogenous. If frictions decrease then, at the going wage, the inflow of potential workers at a firm exceeds the outflow. When employers reduce the wage, the unemployed workers' search effort decreases. Each employer is therefore able to reduce the wage until the inflow is just enough to maintain its optimal labor force. In sum, search frictions and wages are positively related.

We end this subsection by noting that in models with two-sided productivity heterogeneity and search frictions, the equilibrium effect of frictions on the mean wage is sometimes hard to derive or is not determined. In general, the mean total productivity across firms within a market depends on the skill distribution across firms and on the labor market tightness. At one extreme, in a market without frictions, the matching between workers and firms is positive assortative in the sense that there is a positive deterministic equilibrium relationship between skill level and firm-specific productivity (provided that the production function has certain properties)[12]. At the other extreme, in a market with a very large amount of frictions, the equilibrium is often pooled: all agents are willing to match with all agents at the other side of the market. In both cases, the mean wage strongly depends on the productivity of the matches that can be formed. We return to assortative matching in Section 7.

3 Measures of frictions

This section discusses the measure of search frictions that we use in our empirical analysis. We introduce the main measures and explain their usefulness.

3.1 Definitions

It has become common to quantify the amount of search frictions in a labor market by way of the expected number of job offers in a spell of employment (see Mortensen, 2003, and Ridder and Van den Berg, 2003). We denote this measure by k. It captures the ease with which workers can make job-to-job transitions before becoming non-employed, so it is informative on the speed at which they can climb the job ladder. More specifically, it equals the rate at which job opportunities arise as a fraction of the rate at which they are needed.

In on-the-job search models and their equilibrium extensions, like the Bontemps, Robin and Van den Berg (2000) model, k is a function of structural parameters by way of $k := \lambda/\delta$. In many equilibrium models, k is an indicator of the relative power of workers vis-à-vis employers. This is obvious in the Burdett and Mortensen (1998) model and its spin-offs. In these equilibrium models, the wage distributions F and G and their means depend on λ only by way of k. In

[12]Basically, positive assortative matching can only occur when workers and firms are complements. When there are no search frictions this is also a sufficient condition. Shimer and Smith (2000) derive sufficient conditions in case there are search frictions. Basically, high skilled workers are more productive at high productive firms than they are at low productive firms, whereas low skilled workers may be more productive at high productive firms but the difference must be lower than the difference for high skilled workers.

the model of Subsection 2.3, the cross-market transitions result in a small change of the friction parameter, namely $\widetilde{k} := \lambda/(\delta + \sum_{j\neq m} \xi_{mj})$ instead of k.

The dependence of k on the transition rate from employment to unemployment implies that k is sensitive to the stringency of job protection laws. If the latter is high then, ceteris paribus, k is high, but this does not mean that labor market imperfections are small. In fact, strong job protection may actually be an important source of labor market frictions. For this reason, we do not focus exclusively on k as the index of search frictions, but we also examine the value of the job offer arrival rate of employed workers. In line with the above model, this is denoted by λ.

More in general, since we exploit cross-market variation to study the effect of frictions on wages, it is natural to ask what drives cross-market variation in λ and k. One may think of at least three factors. First, by relating λ to an aggregate matching function (as in Subsection 2.4) it is clear that λ depends on the number of agents on both sides of the market. Secondly, it may depend on the availability of institutions that facilitate meeting agents from the other side of the market. Related to this, it may depend on the agents' private search costs. Thirdly, it may depend on product market turbulence[13], although the amount of this turbulence may also have a direct effect on wages. To the extent that these determinants differ across markets, λ also differs across markets.

3.2 Reverse causality

For a parameter to be a sensible measure of frictions, it has to be a fundamental market characteristic that does not depend on wages or their distribution. In reality, it is conceivable that wages affect the individual job offer arrival rate by way of the effort that the individual decides to spend on search. As in the Burdett and Vishwanath (1998) model, if wages are high then the unemployed worker's optimal search effort is high. This creates a positive causal effect from the mean wage to the job offer arrival rate of the unemployed. As a result, if frictions are captured by the latter arrival rate then it is difficult to identify the causal effect of frictions on wages.

We now argue that this issue is less problematic if k or λ are used to capture frictions, by referring to on-the-job search models with endogenous search effort (see e.g. Albrecht, Holmlund and Lang, 1991). Whether the optimal search effort for an employed worker depends on the wage is determined by the way in which direct (utility equivalents of) search costs depend on the current wage. If they

[13] See Amable and Gatti, 2004, for a recent overview of empirical evidence on this.

increase in the current wage then the optimal search effort may be constant. In general, the mean search effort and the resulting average arrival rate are very sensitive to the wage variance given the mean wage, but not to the mean wage itself. Intuitively, this is because a change in the location of the wage offer distribution involves an equivalent change in the current wage of the average employed searcher such that his ranking in the wage offer distribution does not change. If all monetary values change by the same amount then the optimal behavior does not change. For unemployed searchers, the situation is different: if the mean wage offer increases then the gap between the value of leisure and the expected income flow in employment increases, and this increases the search effort. It should also be noted that in the limiting case where wages are not dispersed, the optimal search effort for employed workers is zero, so that it does not depend on the wage at all (whereas for unemployed workers search effort is positive and dependent on the wage).[14] In the empirical analysis we also examine the relation between the coefficient of variation of wages across firms and the measure of frictions.

4 The data

We use the Pay and Performance dataset from Denmark. This dataset merges variables from the Danish "Integrated Database for Labour Market Research" (IDA) to firm variables. The dataset is constructed by the Danish Bureau of Statistics from a variety of data registers used for the production of official statistics. The IDA data allow for matching of workers at establishments but does not contain business statistics of firms. The IDA data have been used in many studies, including Bingley and Westergaard-Nielsen (1996), Albæk and Sörensen (1998), Koning et al. (2000), Bunzel et al. (2001), Christensen et al. (2005) and Mortensen (2003). The Pay and Productivity dataset allows for matching of firms, establishments, and employees, and enables one to follow all of these entities over time. It is all-encompassing in the sense that all Danish residents are included. The information is collected on a yearly basis. Attrition is for all practical purposes absent. These data have been used before by Bingley and Westergaard-Nielsen (2000) and Bingley and Eriksson (2001). Note that our empirical analysis primarily focuses on relations between variables at the market level, i.e. averages across individuals and firms.

The first set of variables is from IDA and has the individual as basic unit. It

[14] In empirical studies, the estimates of λ and k are often positively correlated across markets with the estimate of the job offer arrival rate of the unemployed (see e.g. Ridder and Van den Berg, 1997).

is collected as of 1980 and includes information on the level of occupation, level of education, sector of the firm, residence, labor market state, and earnings. Our variables cover 1980–1994.

The labor market status of each person is recorded at November each year. This gives one labor market state per individual per year. We exclude individuals who were self-employed, out of the labor force or working in the public sector during at least one year between 1980 and 1994. It is possible that the behavior of such individuals, at least in a certain period, deviates substantially from the behavior that search models intend to describe. Note that the requirement that individuals are in the labor force all the time leads to exclusion of individuals who are young in the nineties or old in the eighties. This requirement, as well as the exclusion of public sector workers, also lead to a heavy underrepresentation of women (on average, about 40% of all workers is employed in the public sector). The dataset does not contain individuals who were unemployed in all years.

We define an individual's sector, occupation level, and education level as the levels observed in the latest year at which the individual was employed. The firm sector classification of employed workers is based on the 1993 Standard Industry Classification (SIC). We delete individuals who work in agriculture, fishery, mining, financial services, education, and medical services, because for these sectors the data do not provide business statistics of firms.

There are six different occupation levels: CEO, high-level management, low-level management, office worker, skilled blue collar worker and unskilled blue collar worker. We merge the first three. The place of residence gives one of the 276 cities (*kommune*). These can be aggregated into 13 regions (*amt*). We use the values in 1994. Based on the type and years of education, we define 6 education levels: (1) primary schooling, (2) high school, (3) apprenticeship, (4) short education, (5) bachelors degree and (6) masters degree and higher.

Table 1 lists some descriptives. The first column concerns the raw dataset. The second column concerns our sample (621,628 individuals). The sector and occupation fractions in the first column do not add up to one because the corresponding sample includes individuals in sectors who are excluded or for whom sector or occupation level are unobserved.

The yearly earnings concern the job held at November 1. This variable is taken from income tax registers and includes extra payments for overtime hours, wage taxes and social security payments for the employee, but not the wage and labor taxes and social security payments that are borne by the employer. The data are not well suited for calculation of the number of hours worked in a year (see Koning et al., 2000). The earnings variable is deflated by the average yearly

Variable	Original	Sample
Education level		
Primary education	–	0.331
Apprenticeship	–	0.550
Short education	–	0.035
Bachelors degree	–	0.045
Masters degree	–	0.016
Region ("Amt")		
Copenhagen	0.303	0.316
Roskilde	0.046	0.033
Vestjælland	0.054	0.046
Storstrøm	0.046	0.039
Bornholms	0.008	0.007
Funen	0.087	0.086
Sonderjylland	0.047	0.048
Ribe	0.042	0.045
Vejle	0.065	0.077
Ringkøping	0.053	0.059
Århus	0.119	0.117
Viborg	0.042	0.042
Nordjylland	0.089	0.086

Table 1: Descriptive statistics of the individuals dataset

Variable	Original	Sample
Sector		
Food & Tobacco	0.030	0.068
Textiles, wearing, leather	0.009	0.019
Wood & paper	0.008	0.025
Publishing	0.014	0.033
Chemicals, petroleum	0.022	0.062
Metals	0.018	0.046
Machines	0.034	0.103
Cars, trucks etc.	0.012	0.023
Furniture	0.011	0.027
Construction	0.004	0.124
Trade in cars, etc.	0.017	0.036
Groceries	0.047	0.116
Stores	0.050	0.059
Hotels and restaurants	0.020	0.014
Transportation	0.026	0.077
Services in transportation	0.008	0.026
Real estate	0.009	0.020
Business services	0.038	0.067
Other services (non medical)	0.004	0.057
Total number of observations	2870756	621628

Table 1: Descriptive statistics of individuals dataset (continued)

earnings increase in the sample. Bingley and Westergaard-Nielsen (1996) and Koning et al. (2000) show that within-job earnings increases are small compared to earnings increases in case of a movement from one establishment to another without an intervening unemployment spell. This is in agreement to the models discussed in Section 2. As we shall see in Section 5, the earnings variable is not used for the estimation of the measure of frictions.

The first set of variables (IDA) also includes firm and establishment identifiers. A firm (or company or enterprise) is a legal entity. The firm identifier changes when the ownership of the firm changes or when it changes location. An establishment (or plant) is basically a production unit at a specific location. A firm may consist of multiple establishments. The database contains considerable information on movements and other major changes of establishments. If most workers at an establishment move to another physical location while the sector code for those workers is unchanged, then the establishment is considered a continuing establishment. Note that the year-by-year labor market history of a worker can be represented by a sequence of establishments occupied in consecutive months of November (possibly interrupted by unemployment) with corresponding earnings. Unfortunately, regional data at the establishment level is unavailable in our database.

A distinguishing feature of the dataset is that for each worker we can identify the records of all other workers at the same establishment or firm in November of that year. Koning et al. (2000) give descriptive statistics concerning employment and job spells, the relation between labor market transitions and earnings changes, and establishment size.

The second set of variables concerns business statistics of individual firms. These include the firm identifier, total wage costs, the total value added, firm size, and the value of the fixed assets, with observations for the years 1992–1997. Firm size is the number of individuals who were working at the firm in November at the year of observation. We have this both in number of employees and in number of full time equivalents (fte). Every year, only firms with over 20 employees are included. Corrections are made for fluctuations in the stock of primary goods. The firm's productivity level is defined as the total value added divided by firm size. Depreciation costs are the figures as they appear on the firms' balance sheets. Throughout the paper we take the within-firm average over 1992–1997 to quantify the value of a variable for a firm. The main reason for averaging is that tax laws may induce firms to concentrate gains and losses in single years.

The total wage costs of the firm concern the total wage bill of the firm. This

	Average	Standard deviation
Education level		
Primary school	136.43	42,43
Highschool	184.16	40.19
Apprenticeship	210.29	30.46
Short education	175.34	32.83
Bachelors degree	276.73	81.96
Masters degree	236.74	131.81

Table 2: Skill-specific wage across firms.

includes wage and labor taxes and social security payments for both employers and employees. Using the data from the individual workers, it is possible to quantify wage costs net of employer taxes and payments, by taking the sum of the yearly earnings in the November job over all workers at the firm in November. A regression of the total wage costs of the firm on this sum gives $R^2 = 0.995$, indicating that both wage measures capture the same variation across firms. Using the data from the individual workers, it is also possible to quantify wage costs by worker type, by taking the sum of yearly earnings in the November job over all individuals of this type who are working at the firm in November (see Table 2 for summary statistics by level of education).

Both the productivity level per worker and the wage costs per worker can be measured by either physical units or the number of full time equivalents. Note that both are averages for the whole firm. The wage costs by worker type are only available by physical units. Table 3 summarizes the business statistics of the firms. In Section 5 we argue that the estimation results are robust with respect to a range of mismeasurements of variables.

5 Estimation strategy

This section discusses the empirical implementation. We define the markets, which are the main units in the analysis. Next, we estimate the measure of search frictions as defined in Section 3 for all markets. Finally, we show how these measures are used to estimate the effect of search frictions on wages.

Variable	Mean
Over-all firm characteristics	
Average firm size	115.3
	(413.6)
Average firm size (fte)	97.7
	(341.0)
Wage sum per worker	248.72
	(93.33)
Wage sum per worker (fte)	290.47
	(360.48)
Value added per worker	487.84
	(575.26)
Value added per worker (fte)	564.83
	(734.54)
Fixed assets	271.02
	(553)
Fixed assets (fte)	367.40
	(2674)
Distribution over regions	
Copenhagen	0.339
Roskilde	0.033
Vestjælland	0.041
Storstrøm	0.030
Fyn	0.007
Bornholms	0.076
Sonderjylland	0.044
Ribe	0.044
Vejle	0.076
Ringkøping	0.070
Århus	0.112
Viborg	0.044
Nordjylland	0.084

Table 3: Descriptive statistics of the firms' economic variables

Variable	Mean
Distribution over sectors	
Food & Tobacco	0.041
Textiles, wearing, leather	0.031
Wood & paper	0.030
Publishing	0.033
Chemicals, petroleum	0.050
Metals	0.059
Machines	0.105
Cars, trucks etc.	0.015
Furniture	0.040
Construction	0.130
Trade in cars, etc.	0.058
Groceries	0.171
Stores	0.060
Hotels and restaurants	0.027
Transportation	0.041
Services in transportation	0.016
Real estate	0.006
Business services	0.080
Other services (non medical)	0.008

Table 3: Descriptive statistics of the firms' economic variables (continued)

5.1 Identification of labor markets

We have to decide on a segmentation of the total labor market into (sub)markets. As discussed in the introduction, we start off by assuming that a worker is in one single labor market throughout the observation window. Initially, we also make this assumption for firms. Note that we only observe the total value added by a firm, and not the separate contributions to this by employees who may belong to different labor markets. We assume that markets are defined by sector and region. We distinguish between 19 sectors and 13 regions. We omit markets with less than 6 firms. This gives 206 markets.

There are several reasons for why this characterization of what constitutes a separate labor market may lead to incorrect results. First, each of these markets contains workers with different skill levels, and the sector and region specific labor market for high-skilled workers may have different determinants than the sector and region specific market for low-skilled workers. In Subsection 5.5 we develop and apply methods that allow for this. These exploit information on the composition of the labor force within markets.

Secondly, workers may not be attached to just one specific market. As mentioned above, the use of region as a market characteristic is reasonable for Denmark, with its many islands and with prohibitively large commuting times between these islands. In Section 6 we correct for commuting, by estimating models in which the mean wage in a market is also allowed to depend on the amount of frictions in the same sector in the adjacent region. In Subsection 5.4 we allow for cross-market mobility. Concerning residential moves, Table 4 lists the frequencies of retentions and transitions between regions, using 1980 as the baseline year and 1994 as the outcome year. For most regions around 90 percent of the individuals stayed in their region over the 15 years covering the observation period. This confirms that the assumption that individuals in Denmark are attached to a single region is reasonable. In a recent study, Deding and Filges (2003) analyze the geographical mobility of workers across regions in Denmark using survey data. They find that actual interregional mobility is mainly driven by family formation and dissolution, whereas job-related reasons only play a minor role. This suggests that any actual mobility is exogenous for labor market differences between regions.

It may be less realistic to assume that individuals are attached to just one specific sector than that they are attached to just one specific region. Table 5 presents results analogous to Table 4, for sectors instead of regions.[15] Indeed,

[15]Since we do not consider all sectors in our sample, it is possible that an individual in 1994 works in a sector that is not considered. These individuals are counted together with the unemployed in 1994 in the last column of Table 5.

	Copenhagen	Roskilde	Vestjæland	Storstrøm	Fyn	Bornholms	Sonderjylland	Ribe	Vejle	Ringkøbing	Aarhus	Viborg	Northern Jutland
Copenhagen	89.7	3.9	1.8	1.4	0.2	0.7	0.2	0.2	0.4	0.2	0.6	0.2	0.4
Roskilde	10.5	81.6	3.0	2.5	0.1	0.6	0.1	0.2	0.4	0.2	0.5	0.2	0.3
Vestjæland	4.3	2.0	89.1	2.0	0.1	0.5	0.2	0.2	0.4	0.2	0.5	0.2	0.3
Storstrøm	4.6	1.9	2.1	88.9	0.1	0.6	0.2	0.1	0.3	0.1	0.4	0.1	0.3
Fyn	6.2	0.9	0.6	0.5	89.3	0.5	0.2	0.2	0.3	0.2	0.6	0.3	0.3
Bornholms	1.7	0.3	0.3	0.2	0.0	93.2	0.6	0.4	1.4	0.4	1.0	0.2	0.3
Sonderjylland	1.4	0.2	0.2	0.1	0.0	1.1	90.6	1.6	2.0	0.5	1.2	0.4	0.4
Ribe	1.4	0.2	0.2	0.1	0.0	1.0	1.7	88.9	2.7	1.5	1.3	0.4	0.5
Vejle	1.2	0.2	0.2	0.1	0.0	1.6	1.3	1.6	89.9	0.8	2.1	0.4	0.5
Ringkøbing	1.2	0.2	0.2	0.1	0.0	0.7	0.5	1.2	1.5	89.7	2.4	1.5	0.8
Århus	1.7	0.2	0.2	0.1	0.0	0.7	0.4	0.4	1.6	0.8	91.1	1.4	1.3
Viborg	1.2	0.2	0.2	0.1	0.0	0.5	0.3	0.4	8.3	1.8	3.4	81.7	2.0
Northern Jutland	1.6	0.2	0.2	0.1	0.0	0.5	0.2	0.3	0.6	0.5	1.6	0.8	93.4

Table 4: Cross tabulation of moves between regions in 1980 (y-axis) and 1994 (x-axis), by region in 1980.

there is a lot more mobility between sectors than between regions. For example, 16% of the individuals in metals in 1980 move to machines, and 10% of the individuals in the car and truck sector in 1980 move to machines. Again, in Subsection 5.4 we present results that allow for cross-market mobility.

5.2 Estimating the measures of frictions

At this stage it is useful to summarize the minimal theoretical structure that we impose to interpret the data and quantify the measures of frictions. As stated above, we do not impose a specific full equilibrium search model on the data, and we do not make any assumption on the effect of search frictions on wages. We assume however that the behavior of employed workers is governed by the basic partial on-the-job search model with determinants λ, δ and F. We start our analysis in a model in which transitions between sectors are not allowed. Recall that this describes the behavior of employed workers in the model of Subsection 2.2. This implies that the exit rate out of a job with a given time-invariant wage w equals

$$\theta = \delta + \lambda(1 - F(w)) \tag{8}$$

This is the hazard rate of the distribution of the duration an individual spends in a job given the wage w. Secondly, we assume that flows in the labor market are in equilibrium (implying that equation (1) applies). Thirdly, we assume that the reservation wage of the unemployed is at or below the wage floor in the market. The exit rate out of unemployment then equals the job offer arrival rate λ_0 in unemployment. Note that we regard λ, λ_0 and δ to be fundamental determinants that do not have an individual-specific component.

These assumptions on the individual supply-side behavior facilitate the estimation of λ, λ_0 and δ, and, consequently, of k. In addition, we occasionally interpret results using the assumption that the production function is linear in the number of employees with a certain skill and is additive across skills.

The empirical analysis consists of two steps. In the first step, the measures are estimated for each market. In the second step, the mean wage across firms in a market is related to the measures of frictions and other determinants.

In the first step we use the observations of the individual labor market states in the years 1992, 1993, and 1994. We assume that individuals change job whenever their establishment changes. Data on labor market states and wages identify $\lambda, \delta, \lambda_0$, and F (see e.g. Eckstein and Van den Berg, 2006, for an overview). However, at this stage we are not interested in F, and the individual data on earnings

	Food & tobacco	Textiles, wearing	Wood & paper	Publishing	Chemicals, petroleum	Metals	Machines	Cars, trucks etc.	Furniture	Construction	Trade in cars, etc.	Groceries	Stores	Hotels and restaurants	Transportation	Services in transportation	Real estate	Business services	Other services	Other sectors
Food & tobacco	54	1	1	0	4	2	3	1	1	2	0	5	2	1	3	1	1	3	0	15
Textiles, wearing	4	45	2	1	4	2	4	1	4	1	1	4	3	1	2	1	1	2	1	18
Wood & paper	3	1	47	2	5	4	4	1	5	5	1	6	1	0	2	0	1	2	0	10
Publishing	1	0	4	61	2	1	2	1	0	1	1	4	1	0	1	0	1	4	0	14
Chemicals, petroleum	3	0	1	1	52	3	4	2	1	5	1	5	1	1	3	1	1	3	0	13
Metals	3	0	1	1	5	36	16	4	2	6	1	6	1	0	3	1	1	3	0	11
Machines	2	0	1	0	3	6	51	4	1	3	1	7	1	0	2	0	1	3	0	11
Cars, trucks etc.	2	0	1	0	4	7	10	43	1	4	1	5	1	0	3	1	2	3	0	12
Furniture	3	1	4	1	3	4	5	2	47	4	1	5	2	0	2	0	1	2	0	12
Construction	2	0	2	0	3	3	4	1	2	53	0	4	1	0	3	1	2	3	0	15
Trade in cars, etc.	2	0	1	1	3	3	5	2	1	3	43	7	2	0	6	1	1	2	0	15
Groceries	4	1	1	1	4	2	4	1	1	3	2	46	4	1	3	1	1	6	0	14
Stores	4	1	1	1	3	1	3	1	1	2	1	9	42	1	2	1	1	3	0	22
Hotels and restaurants	4	1	1	1	3	1	3	1	1	2	1	4	5	27	5	1	1	5	1	33
Transportation	2	0	1	0	2	1	2	1	1	3	1	4	1	1	59	5	1	2	0	12
Services in transportation	2	0	1	1	2	1	2	1	0	2	1	6	1	1	12	51	1	3	0	13
Real estate	2	1	1	1	2	1	2	1	1	4	1	5	3	2	3	1	42	4	1	24
Business services	1	0	0	1	2	1	3	1	0	3	1	5	1	1	2	1	2	50	0	25
Other services	2	1	0	1	2	1	3	1	1	2	1	3	2	1	2	1	1	12	41	25

Table 5: Cross tabulation of moves between sectors in 1980 (y-axis) and 1994 (x-axis), by sector in 1980.

may be insufficiently reliable to use them for the purpose of estimating the measures of frictions. For example, we do not observe the exact accepted hourly wage, and we may occasionally observe individuals moving from a job with high earnings to a job with low earnings. We would have to modify the model to take account of this, and this in turn would lead to formidable computational costs. Instead, we adopt the unconditional inference procedure developed by Ridder and Van den Berg (2003) for the estimation of measures of frictions in repeated search models. This basically involves the estimation of λ, δ and k from marginal distributions of job durations. The likelihood function is obtained by integrating the job duration distributions over the relevant wage (offer) distributions. The likelihood function does not depend on F. Wages become unobserved heterogeneity terms, and the measures of frictions are identified from the shape of the job exit rate as a function of tenure. In particular, the job offer arrival rate for employed workers is identified from the speed at which the workers in the worst jobs leave their job for a better job. The empirical analysis is more complicated than in Ridder and Van den Berg (2003) due to the fact that we observe consecutive job spells. Moreover, the analysis becomes more complicated below when we allow for multiple destination states after a spell (that is, when we simultaneously estimate cross-market transition rates).[16]

The estimation results are not affected by measurement errors in earnings data or by misspecification of the wage (offer) distribution. Because of the latter, the results are valid irrespective of what drives wage dispersion, and, more generally, irrespective of the determinants of the wage (offer) distribution, including the level of an institutional wage floor like a minimum wage.[17] The estimation procedure is computationally convenient despite the sample sizes of over 0.5 million. Moreover, the fact that the earnings data are not used here facilitates the computation of standard errors in the second stage of the estimation.

As stated in the data section, we do not observe the regional location of the establishment. Instead we use the regional location of the worker in order to identify the market, in the first estimation stage. Most workers are more attached to their region of residence than to the region of their establishment or firm, if these are different. Hence, if the worker is employed at a firm in a different region than his own residence, the average offered wage of the firms in his own region

[16]Details and programs are available upon request.

[17]Indeed, the results are valid irrespective of which job characteristics induce workers to change jobs. To see this, note that w is treated as unobserved and so may be interpreted as an index of job characteristics. However, if non-wage job characteristics are relevant then it is not clear what to expect theoretically from the effect of frictions on the mean wage across firms in a market.

will be mainly affected by the frictions that he or she faces. Of course, this creates a measurement error for the wage data in our second step estimators since larger firms with multiple establishment in different regions face a mixture of different markets and are likely to base their strategy on this. For example, a firm situated in an area with very low levels of search frictions may employ many workers at establishments situated in areas with much higher frictions. Hence, the average offered wage of such a firm is expected to be lower than of a firm in the same low frictions area that does not have many establishments in other areas as well. Since this also has an impact on the measurement and definition of the productivity variable, we do not take this problem into account in our empirical analysis. Since our analysis is based on firms rather than the number of employees in these firms and since most firms consist of only a single establishment, our results are not likely to be affected by this restriction.

If we allow for skill heterogeneity, then we require measures of frictions for each combination of sector, region, and skill level. In the data, the number of sampled individuals in a given market can then be too small to estimate the frictional parameters separately for each market. Therefore, we take the log frictional parameters to be additive in sectoral, regional, and skill effects (e.g., $\lambda \equiv x'\beta_\lambda$), and we estimate them simultaneously for all markets.

We do not take account of possible unobserved components in the ability of the workers. Although including unobserved heterogeneity may change our results in the first step of the estimation procedure, the second step is only marginally affected by including this complex part in the estimation process. We do not know the distribution of the unobserved components between markets and hence the best choice would be to assume that the unobserved components are equal among the different markets. Such a method is unlikely to produce different results than a model without unobserved heterogeneity. However, ability differences may bias our results when they are unequally distributed among the different markets.

What changes in a model in which individuals are able to change markets? In that case we should take into account that some observed transitions are to a job outside of the market, because otherwise our estimate of the measure of frictions within the market is biased. This means we should apply the equations in Section 2.3 and use $\widetilde{k}$ as our measure of frictions. Separate estimation of all the transition rates involves 247 times 247 parameters. Even with the available number of observations, this is not feasible. Instead, we make the following restriction on the parameters ξ_{ij},

$$\xi_{ij} = \exp(x_i'\beta_{\xi_i} + x_j'\beta_{\xi_j})$$

where x_i is a vector of dummy variables that indicates the market of origin by region and sector. Similarly, the vector x_j indicates the market of destination. We normalize the constants of β_{ξ_i} and β_{ξ_j} in order to identify these parameters. However, even with these restrictions, it is not feasible to estimate the model using the three periods as set out above. Instead we estimated a two-period model where we use the years 1993 and 1994 and we use a 10 percent random sample of our dataset.[18] Since this estimation procedure limits the power of our final results, we start with the analysis using the restriction that cross-market transitions are excluded. Next, we allow for these transitions in order to investigate their impact on the final results. This implies that even though in our opinion a more flexible model is preferred, the restrictive model acts as a benchmark for our empirical analysis. As we shall see, the qualitative results are robust to this.

The IDA (labor supply and flow) data have been used for structural estimation of equilibrium search models, by e.g. Bunzel et al. (2001), Christensen et al. (2005) and Mortensen (2003). These studies also report estimates of λ_0, λ and δ, but their definitions of what constitutes a separate market differ from ours (e.g. because of stratification on gender).

5.3 Estimation of the mean-wage regression without skill heterogeneity

The endogenous variable of interest is the mean wage (in levels) across firms in a market $\mathrm{E}_F(w)$. Let indices m and i denote the market m and the firm i. The endogenous variable is then denoted by $\mathrm{E}_i(w_{mi})$ and the explanatory variables are $\mathrm{E}_i(p_{mi})$, $\log(k_m+1)$ and the institutional wage floor $\underline{w}_m$ in market m. In fact, Denmark has no clearly defined or observable minimum wage. We follow studies in which equilibrium search models are estimated with Danish data (see e.g. Bunzel et al., 2001) by ignoring institutional wage floors. Both $\mathrm{E}_i(w_{mi})$ and $\mathrm{E}_i(p_{mi})$ are obtained from the firm data (average firm-specific wage costs and average firm-specific revenue product, averaged over the observation window for the firm data, and subsequently averaged over firms within a market).

The basic specification of the regression equation is:

$$\mathrm{E}_i(w_{mi}) = \alpha_0 + \alpha_1 \mathrm{E}_i(p_{mi}) + \alpha_2 \log(k_m+1) + \varepsilon_m \tag{9}$$

The parameter of interest is α_2, and we test whether it is positive. We also estimate versions in which λ and δ are included separately (instead of only by way

[18] The descriptive statistics of the subsample are available on request.

of $\log(k+1)$), since λ is an interesting measure of frictions by itself. Specifications like (9) are ad hoc (or "reduced-form"). To some extent they can be motivated by mean wage equations in the theoretical frameworks of Section 2. It should be emphasized that we also estimate other specifications. For example, we allow for interactions of $\mathrm{E}_i(p_{mi})$ and the measure of frictions.

In the regression, the unit of observation is a market rather than an individual firm. This means that the number of observations equals the number of markets instead of the much larger number of firms. However, note that we are only interested in the determinants of the *mean* wage. Moreover, our specification is less sensitive to the impact of measurement and specification errors. In particular, our method is insensitive to heteroskedasticity due to intra-sector heterogeneity of firms.

The regression is non-standard in the sense that its variables $\mathrm{E}_i(w_{mi})$, $\mathrm{E}_i(p_{mi})$, and k_m are estimated rather than observed (albeit they are estimated from very large samples). We take this into account when we estimate the standard deviations of the regression parameters, by way of the usual two-step procedures for fully parameterized models as described in for example Newey and McFadden (1994) and Wooldridge (2002).[19]

A number of comments are in order. First, recall that only firms with more than 20 employees are included. As firm size is correlated to wages and productivity, this may pose a problem for the mean-wage regression analysis. However, if the relation between firm size and mean wages across firms is captured by the effects of productivity and frictions on wages (as it is in the theoretical model of Subsection 2.2), the selection is on explanatory variables, and the estimates are consistent. For essentially the same reason we do not include variables like firm size and profits as explanatory variables: at best they are deterministic functions of productivity and frictions, and at worst they are endogenous.

Secondly, the empirical analyses in the second stage are based on firm data whereas the estimation of the measures of frictions assumes that a transition between establishments is equivalent to a job change. This is mutually consistent if a firm constitutes of one or more competing and equivalent establishments. Alternatively, one may assume that a transition between firms is equivalent to a job change. However, as mentioned in Section 4, firm identifiers may change from year to year even when the firm remains essentially the same. This makes it difficult to establish on the basis of these identifiers whether an individual makes a transition. To the extent that workers make transitions between establishments within a firm, the relevant λ from the firm's point of view will be over-estimated.

[19]Details are available upon request.

If such a bias has similar magnitude across markets then the empirical analyses in the second stage are not affected.

From an econometric point of view, what drives identification of the parameters in the regression equation is that the determinants of the market-specific measure of frictions do not have a direct causal effect on the mean market-specific wage across firms. If region and sector dummies are added to the right-hand side of equation (9) then α_2 is only identified from the interaction between region and sector in k. This may convey the suggestion that identification is fragile, but one should remember that we also use the mean productivity as an explanatory variable. This variable is usually absent in cross-market analyses. In addition, as shown below, we correct for the worker skill composition in sectors and regions. It is plausible that these variables represent the direct regional and sectoral effects on the mean wage to a sufficient degree.

5.4 Estimation of the mean-wage regression with transitions between markets

We estimate the following relationship between the expected offered wages and the search frictions allowing for transitions between markets,

$$\mathrm{E}(w_{mi}) = \alpha_0 + \alpha_1 \mathrm{E}_i(p_{mi}) + \alpha_2 \log(\widetilde{k}_m + 1) + \varepsilon_m \tag{10}$$

where $\widetilde{k}$ has the same definition as before. This reflects that cross-market transitions are less driven by wages than transitions within markets. Specifically, the former type of transitions should not be driven by the actual wage found in the new market, so that any firm considers them to be unaffected by its wage policy.

What happens if cross-market transitions may be driven by differences in *average* wage offers across markets, meaning that one may move to a market because its mean wage is high? Consider a market with a high mean wage across firms. Then an effect of mean wages on transition rates into and out of the market implies a higher inflow rate into the market and a lower outflow rate. This leads to a relation between the total inflow and outflow rates and the mean wage across firms. As a robustness check, we therefore estimate versions in which we include k and the total inflow rate into and outflow rate out of the market as separate regressors (including all ξ_{ij} parameters is not feasible).

Apart from the difference in the measure of search frictions, equation (10) is essentially the same as equation (9). Hence, in order to save space, the next subsection only focuses on the regression analysis using k as the measure of search frictions.

5.5 Estimation of the mean-wage regression with skill heterogeneity

Within each market as defined in the previous section, firms employ workers with different skills j. If high skilled workers face a different amount of frictions, a different wage determination process, or a different wage floor than low skilled workers, then the procedure as described above gives biased estimates. To proceed, we may subdivide each labor market as defined above into different markets, one for every skill level. To facilitate the analysis, we assume that firm production is additive in the production by skill group within the firm. Also, the subdivision into markets should not have an effect on the choice of agents to participate in a certain market, so that the skill distribution across markets is exogenous to wage determination. As a result, the markets by skill level do not affect each other at all.

To see the bias involved when ignoring skill heterogeneity, consider the mean wage regression equation for market[20] i, j, specified analogously to equation (9), and with wage floor $\underline{w}$,

$$\mathrm{E}_i(w_{mji}) = \alpha_{0j} + \alpha_{1j}\mathrm{E}_i(p_{mji}) + \alpha_{2j}\log(k_{mj}+1) + \alpha_{3j}\underline{w}_{mj} + \varepsilon_{mj} \qquad (11)$$

Let us take the average over j. If $\alpha_{sj} \equiv \alpha_s (s = 0, 1, 2, 3)$ then this gives,

$$\mathrm{E}_i(w_{mi}) = \alpha_0 + \alpha_1\mathrm{E}_i(p_{mi}) + \alpha_2\mathrm{E}_j(\log(k_{mj}+1)) + \alpha_3\mathrm{E}_j(\underline{w}_{mj}) + \varepsilon_m$$

For the aggregated version of (11) to reduce to equation (9) we need the following three assumptions to hold true. First, $\alpha_{sj} \equiv \alpha_s (s = 0, 1, 2, 3)$, which basically means that the wage policies are the same for all skills. Secondly, $\underline{w}_m \equiv \mathrm{E}_j(\underline{w}_{mj})$. This is unlikely to be true since $\underline{w}_m = \min_j\{\underline{w}_{mj}\}$. Thirdly, the amount of frictions k_{mj} is the same for all skill groups (otherwise the k_m estimates are biased). As we shall see, the data refute these assumptions.

However, we cannot directly estimate equations (11) either, because the firm data do not provide skill-specific wages or productivities. For the wages this can be dealt with by using the worker data. We observe all workers in the firm, so we can directly quantify $\mathrm{E}_i(w_{mji})$.[21]

[20] We use "market" to denote a specific combination of sector, region, and skill, as well as to denote a specific combination of sector and region.

[21] Note that this effectively replaces the mean wage costs by the mean gross wage, as the endogenous variable. The wage costs are the price of labor from the perspective of the employer, whereas the gross wage is the price of labor from the perspective of the worker.

Concerning the productivity levels, we assume that the productivity p_{mji} of skill j in firm i in market m can be decomposed as follows,

$$p_{mji} = p^0_{mi} + \psi_j \tag{12}$$

where p^0_{mi} is the firm-specific productivity and ψ_j is the skill-specific productivity. Note that the latter is assumed to be the same in all sectors and regions.[22] In fact, we only need an aggregated version of (12),

$$\mathrm{E}_i(p_{mji}) = \mathrm{E}_i(p^0_{mi}) + \psi_j \tag{13}$$

By aggregating this over j we obtain,

$$\mathrm{E}_i(p_{mi}) = \mathrm{E}_i(p^0_{mi}) + \sum_j \pi_{mj}\psi_j \tag{14}$$

where π_{mj} is the fraction of workers with skill j in market m, so $\sum_j \pi_{mj} = 1$. Note that the left-hand side and the π_{mj}'s are observable, while the ψ_j's are parameters, and the $\mathrm{E}_i(p^0_{mi})$ terms are unobserved and potentially different across markets.

By substituting (13) and (14) into equation (11) (and removing $\underline{w}$ for convenience) we obtain

$$\mathrm{E}_i(w_{mji}) = \alpha_{0j} + \alpha_{1j}\mathrm{E}_i(p_{mi}) + \sum_{x\neq j} \alpha_{1j}(\psi_j - \psi_x)\pi_{mx} \ + \alpha_{2j}\log(k_{mj}+1) + \varepsilon_{mj} \tag{15}$$

for all j.

Note that we may normalize $\psi_1 := 0$. For two skill levels, equations (15) simplify to

$$\mathrm{E}_i(w_{mui}) = \alpha_{0u} + \alpha_{1u}\mathrm{E}_i(p_{mi}) + \alpha_{1u}(\psi_u - \psi_s)(1-\pi_m) + \alpha_{2u}\log(k_{mu}+1) + \varepsilon_{mu} \tag{16}$$

$$\mathrm{E}_i(w_{msi}) = \alpha_{0s} + \alpha_{1s}\mathrm{E}_i(p_{mi}) + \alpha_{1s}(\psi_s - \psi_u)\pi_m + \alpha_{2s}\log(k_{ms}+1) + \varepsilon_{ms} \tag{17}$$

where subscripts u and s denote low skill and high skill, respectively, and $\pi_m \equiv \pi_{mu}$ denotes the fraction of low skilled workers in market m.

[22] Equations like this are estimated by Haltiwanger, Lane and Spletzer (1999). They use log firm sales divided by the size of the firm's workforce as the measure of productivity, and regress this on skill indicators of the workforce.

Equations (15) are very similar to (9), the only substantial difference being that the π_{mj}'s are added as explanatory variables. The parameters of interest are the α_{2j}'s for the different skill levels. The equations can be estimated in the same way.[23]

The derivation of equations (15) determines the signs of the effects of π_{mx} on $\mathrm{E}_i(w_{mji})$. For example, in equation (17) the effect of $\pi_m(\equiv \pi_{mu})$ on $\mathrm{E}_i(w_{msi})$ is positive. This is because for a given average market productivity $\mathrm{E}_i(p_{mi})$, a large fraction of low skilled workers implies that the market average $\mathrm{E}_i(p^0_{mi})$ of the firm-specific productivity component is high, and this implies that the average skill-specific market productivity $\mathrm{E}_i(p_{mji})$ is high, and the skilled workers in this market benefit from this by way of a high average wage. In reality there may be reasons for a negative effect. For example, for a given average market productivity $\mathrm{E}_i(p_{mi})$, a large fraction of low skilled workers may indicate that these workers are relatively skilled and that higher skilled workers are not in demand in this market, leading to a negative effect on $\mathrm{E}_i(w_{msi})$. We therefore adopt an alternative motivation for equations (15): start with equation (9), take $\mathrm{E}_i(w_{mji})$ as the endogenous variable, and add the π_{mx} as explanatory variables in the hope that these correct for the effects of skill heterogeneity within market m:

$$\mathrm{E}_i(w_{mji}) = \alpha_{0j} + \alpha_{1j}\mathrm{E}_i(p_{mi}) + \sum_{x \neq j} \gamma_{xj}\pi_{mx} + \alpha_{2j}\log(k_{mj}+1) + \varepsilon_{mj} \tag{18}$$

for all j. An equation-by-equation analysis of identification suggests that one needs to have more values of m (i.e., more combinations of sectors and regions) than skill levels.[24]

Note that annual earnings in the November job may be low if frictions are low, simply because with low frictions relatively many workers work only part of the year in this job. This creates a positive effect of frictions on the average

[23]By analogy to Haltiwanger, Lane and Spletzer (1999), one may also estimate the ψ_j directly from a fixed effects analysis at the firm level of equation (12) aggregated over j, using the series of yearly firm data and assuming that only the firm-specific skill fractions π_{mji} change over time. However, this does not work well here, due to the facts that there is little variation over time in π_{mji} and there is much measurement error in the yearly observations of p_{mi}.

[24]In equations (15), the $\psi_j - \psi_x$ parameters appear in equations for different j, so then the joint set of equations may have some overidentifying restrictions. This can potentially be used to relax the assumption that the skill-specific productivity components ψ_j are the same across sectors and regions. For example, one may adopt a more flexible factor loading structure. Of course, one may test whether the cross-equation parameter restrictions hold.

skill-specific wage across firms in a market. So, if a negative effect is found then this bias only affects the estimated magnitude but not the sign of the relation.

6 Estimation results

This section contains the main results of the paper. First, we estimate the amounts of search frictions. This act as inputs for the second step of the empirical analysis. In the subsequent subsections we find that there is a negative relationship between search frictions and wages. We find that this relationship is robust against many different specifications of the model. At the end of the section, we show that even though the effect of search frictions on wages exists, it is quantitatively not important for explaining differences in wages.

6.1 Estimates of the measures of frictions

Throughout the remainder of the paper, the monetary unit is 1000 Danish Kroner, and the unit of time is a month, except for wage and productivity related variables, which are measured per year. In all subsections of this section, we start by giving the main (baseline) results and we subsequently present results of sensitivity analyses.

In our analysis we start with a model that uses k as a measure for frictions. Whenever we allow for cross-market transitions, we use $\widetilde{k}$ instead. Table 6 presents the estimates for λ, λ_0 and δ, taking these to be proportional in sectoral, regional, and skill (i.e., education level) effects. These are estimated simultaneously for all markets (see Subsection 5.2). We find that the job offer arrival rate of employed workers increases with education level whereas the job separation rate decreases with education level. As a result, k increases with education level. The job offer arrival rate for the unemployed increases even more across education levels. Compared to the rest of Denmark, Copenhagen has a low job offer arrival rate for the unemployed and a high arrival rate for the employed. The sectors hotels and restaurants, transportation and real estate have relatively high job offer arrival rates. High job separation rates are found for construction, transportation and the real estate sector.

Table 7 gives statistics of the implied estimates of $\lambda_0, \lambda, \delta, k$ and $1/(k+1)$. The average values are in line with those found in the empirical literature mentioned earlier. Most of the estimates of λ and k are in the ranges $(0.05, 0.14)$ per month and $(11, 28)$, respectively. The variance of the measures of frictions over sectors is smaller than the variance over regions, which in turn is smaller than the variance

	β_{λ_0}	β_λ	β_δ
Constant	-3.423	-2.542	-5.591
	(0.013)	(0.022)	(0.006)
Education level			
Highschool	0.189	0.078	0.136
	(0.017)	(0.031)	(0.010)
Apprenticeship	0.255	0.092	0.130
	(0.015)	(0.023)	(0.008)
Short education	0.330	0.107	0.042
	(0.014)	(0.022)	(0.007)
Bachelors degree	0.428	0.115	-0.050
	(0.017)	(0.047)	(0.011)
Masters degree	0.319	0.117	0.008
	(0.007)	(0.010)	(0.003)

Table 6: Results of the estimation of the friction parameters

over education levels.

It is interesting to investigate the correlation between our measure of search frictions and other directly observable measures of frictions that one might consider. Examples of these are population density, road density, etc. We use the first one in our analysis. Based on the population density of the regions considered, we find a correlation equal to 0.22 between population density and our measure of search frictions.[25]

We also estimated λ, λ_0 and δ with less than 6 skill categories, and without skill effects, and we also estimated λ, λ_0 and δ separately for each combination of sector and region, but for sake of brevity these estimates are not reported.[26]

6.2 Results without skill heterogeneity

Table 8 presents the estimation results for the mean wage regression equation. The measure of frictions is based on estimates of λ and δ that take these to be proportional in sectoral and regional effects, estimated simultaneously across markets. The left-hand side variable is based on firms' wage costs divided by

[25]The most densely populated area in our analysis is Copenhagen with 767 inhabitants per square kilometer. The least densely populated area is Ringkøping with only 55 inhabitants per square kilometer.

[26]These and all other results not reported for sake of brevity are available upon request.

	β_{λ_0}	β_λ	β_δ
Region			
Roskilde	0.058	-0.053	-0.015
	(0.015)	(0.039)	(0.012)
Vestjælland	0.119	-0.075	0.055
	(0.013)	(0.020)	(0.006)
Storstrom	0.050	-0.110	0.059
	(0.015)	(0.026)	(0.007)
Fyn	-0.133	-0.297	-0.176
	(0.022)	(0.078)	(0.019)
Bornholms	0.109	-0.077	-0.046
	(0.014)	(0.015)	(0.006)
Sonderjylland	0.393	0.003	-0.026
	(0.016)	(0.021)	(0.006)
Ribe	0.348	-0.027	-0.042
	(0.017)	(0.022)	(0.006)
Vejle	0.285	0.002	-0.039
	(0.012)	(0.016)	(0.006)
Ringkøping	0.473	0.048	0.024
	(0.014)	(0.027)	(0.006)
Århus	0.131	-0.029	0.004
	(0.011)	(0.016)	(0.005)
Viborg	0.328	-0.002	-0.049
	(0.020)	(0.030)	(0.009)
Nordjylland	0.083	0.011	0.133
	(0.010)	(0.016)	(0.005)

Table 6: Results of the estimation of the friction parameters

	β_{λ_0}	β_{λ}	β_{δ}
Sector			
Textiles, wearing, leather	-0.187	-0.129	0.121
	(0.020)	(0.035)	(0.014)
Wood & paper	0.075	-0.093	-0.075
	(0.023)	(0.043)	(0.009)
Publising	-0.271	-0.045	-0.042
	(0.025)	(0.032)	(0.013)
Chemicals, petroleum & rubber	0.179	-0.008	0.083
	(0.017)	(0.025)	(0.007)
Metals	0.090	-0.014	0.151
	(0.014)	(0.034)	(0.007)
Machines	0.050	-0.104	-0.072
	(0.015)	(0.022)	(0.007)
Cars, trucks etc.	-0.014	-0.206	0.078
	(0.022)	(0.035)	(0.008)
Furniture	0.166	-0.001	0.035
	(0.027)	(0.044)	(0.009)
Construction	0.280	0.157	0.576
	(0.014)	(0.021)	(0.007)
Trade in cars, etc.	0.126	-0.075	-0.179
	(0.019)	(0.051)	(0.011)
Groceries	0.066	0.049	0.019
	(0.015)	(0.027)	(0.009)
Stores	-0.047	0.034	0.067
	(0.017)	(0.031)	(0.007)
Hotels and restaurants	-0.086	0.261	0.627
	(0.022)	(0.049)	(0.019)
Transportation	0.548	0.328	0.500
	(0.014)	(0.020)	(0.006)
Services in transportation	0.216	0.190	0.283
	(0.018)	(0.035)	(0.011)
Real estate	0.276	0.219	0.299
	(0.021)	(0.035)	(0.013)
Business services	0.032	0.098	0.076
	(0.018)	(0.026)	(0.008)
Other services (non medical)	0.145	0.091	0.144
	(0.014)	(0.036)	(0.012)

Table 6: Results of the estimation of the friction parameters

		λ_0	λ	δ	k	$1/(k+1)$
Simple statistics of the estimates						
Over all markets:	mean	0.057	0.087	0.005	19.49	0.050
	standard deviation	0.016	0.014	0.001	3.17	0.008
	minimum	0.022	0.050	0.003	11.43	0.033983
	maximum	0.138	0.135	0.009	28.43	0.080473
Over regions:	standard deviation	0.017	0.015	0.001	3.20	0.00868
Over sectors:	standard deviation	0.017	0.014	0.001	3.14	0.00839
Over education levels:	standard deviation	0.0167	0.015	0.001	3.20	0.00843
Statistics weighted by number of workers in the market						
Over all markets:	mean	0.052	0.089	0.005	18.92	0.051
	standard deviation	0.130	0.242	0.014	49.61	0.135
Over regions:	mean	0.062	0.105	0.006	22.3	0.061
	standard deviation	0.141	0.262	0.015	53.6	0.146
Over sectors:	mean	0.0615	0.104	0.006	22.4	0.059
	standard deviation	0.143	0.268	0.015	55.2	0.147
Over education levels:	mean	0.037	0.064	0.003	15.5	0.038
	standard deviation	0.081	0.146	0.007	34.3	0.084

Table 7: Statistics of the estimated friction parameters (standard deviations concern the distribution of the estimated parameters)

their size in number of employees in November. We find a negative and significant impact of the amount of frictions on the mean wage in the market, controlling for productivity. The mean productivity level in the market has a positive and significant effect on the mean wage in the market.

In the first sensitivity analysis (second column of Table 8) we use the number of fte's in November as a measure of firm size in the construction of the left-hand side variable. This also results in a negative and significant effect of frictions. The third column presents the results when we calculate the firm-specific wage as the average of the wages of the employees at the firm in November, using again the number of individuals in November as a measure of firm size. Note that this is the way in which skill-specific mean wages are calculated in the next Subsection. Like in the baseline analysis, the effect of frictions is negative and significant.

The other sensitivity analyses that we present use the same left-hand side variable as the baseline regression. The above-mentioned alternatives for the left-hand side variable give the same results. The fourth column concerns a regression on $\log k$ instead of $\log(k+1)$, and the fifth a regression in which λ and δ enter separately instead of by way of their ratio. The latter is important in that it describes the results when λ is used as measure of frictions instead of k. Clearly, the significantly positive effect of k on the mean wage in the market is due to a marginally significant positive effect of λ and an significantly negative effect of δ. The sixth column concerns a regression in which k is estimated for each market separately in the first stage. The seventh column includes as a regressor the measure of frictions in the bordering regions (informally chosen). These results should be less sensitive to interregional mobility of workers. The results in these two columns are qualitatively the same as in the others. The effect of the amount of frictions in the nearest region is insignificantly different from zero.

The eighth column concerns a regression where the coefficient of variation of p across firms in a market is included as an additional regressor. The theoretical model of Subsection 2.2 suggests that this regressor has a negative effect, for a given mean productivity.

The results above could be due to differences in the capital stock of firms. Firms with a large capital stock may need to use a larger fraction of their productivity to keep their stock at the same level. An analysis that ignores this might conclude that workers at such firms have an unreasonably high labor productivity. The estimated residuals from a regression of value added p_i on the amount of fixed assets d_i of firm i provide an estimate $\widehat{p}_i$ of the productivity level that corrects for this,

	(1)	(2)	(3)	(4)	(5)	(6)
constant	131.2	124.5	116.8	137.1	67.81	121.9
	(14.8)	(21.9)	(9.37)	(14.3)	(58.7)	(30.0)
Productivity	0.157	0.242	0.079	0.150	0.148	0.171
	(0.049)	(0.066)	(0.014)	(0.017)	(0.017)	(0.016)
$\log(k+1)$	10.1	8.52	15.50			11.2
	(3.80)	(4.05)	(3.14)			(8.90)
$\log k$				9.69		
				(3.58)		
$\log \lambda$					6.84	
					(4.13)	
$\log \delta$					-21.22	
					(10.24)	
R^2	0.40	0.50	0.31	0.38	0.39	0.38
# markets	206	206	206	206	206	

Table 8: Mean wage regression results without skill heterogeneity. Columns: (1) baseline, (2) fte's in November, (3) November earnings, (4) with k, (5) with λ, δ, (6) k separately estimated by market.

	(7)	(8)	(9)	(10)	(11)	(12)
constant	131.2	119.42	120.5	111.4	139.9	121.9
	(5.56)	(15.10)	(11.95)	(11.2)	(12.8)	(49.95)
Productivity	0.210	0.149	0.156	0.157	0.210	0.074
	(0.011)	(0.017)	(0.016)	(0.017)	(0.028)	(0.113)
$\log(k+1)$	10.1	7.94	25.30	9.26	8.86	12.39
	(1.83)	(5.04)	(3.96)	(3.76)	(3.86)	(4.05)
$\log k$						
$\log \lambda$						
$\log \delta$						
coefficient of variation of p		-0.016				
		(0.007)				
$\log(k+1)$ in nearest region	-0.49					
	(0.65)					
R^2	0.39	0.41	0.24	0.40	0.40	0.40
# markets	206	206	206	206	206	206

Table 8: Mean wage regression results without skill heterogeneity (*cont.*) . Columns: (7) includes frictions in nearest region, (8) with coefficient of variation of p, (9) with capital correction, (10) GLS for heteroskedasticity, (11) GLS for spatial autocorrelation, (12) GLS for sectoral autocorrelation

constant	402.2
	(10.95)
Fixed assets	0.195
	(0.018)
R^2	0.04

Table 9: Regression for capital correction

$$\widehat{p}_i = \widehat{c}_0 + \widehat{\varepsilon} = p_i - \widehat{c}_1 d_i$$

where $\widehat{c}_0$ and $\widehat{c}_1$ are the the estimated regression parameters. Note that we do not explicitly model the decision process of capital investments in our analysis. We refer to Acemoglu and Shimer (2000) and Robin and Roux (2002) for models in which this process is described in a search framework.

The results of the regression are summarized in Table 9. The results for the mean wage regression are in column 9 of Table 8. (The results are very similar if we use the number of November workers instead of fte's.)

All wage regressions presented use wages in levels as the left-hand side variable. From the equations as derived in the theoretical section, this is also the most straightforward specification. However, there may be heteroskedasticity, in particular since high wage levels are often associated to higher variances of the error term. Using the Breusch-Pagan test, the null-hypothesis of no heteroskedasticity is definitely rejected. We investigate the impact of heteroskedasticity using feasible GLS. The results are in column (10) of Table 8. We find that heteroskedasticity does not have an impact on our main conclusions.

Another aspect concerning our econometric specification is that in reality there may be spatial correlation between regions and sectors that are close to each other (to some extent this may capture movements of workers between markets). This implies that we should allow for the following structure with respect to the error term

$$\varepsilon_m = \rho W \varepsilon + \nu_m$$

where W is the weighting matrix and ε is a vector containing all elements of ε_m. The scalar ρ is the parameter of serial correlation and ν_m is a remainder term that is i.i.d. among markets. Ideally we should use a semi-parametric method such as presented in Pinkse, Slade and Brett (2002) to determine the weighting matrix. However, the implementation of such techniques is difficult and in our opinion outside the scope of this paper. Instead, we only allow for correlation between regions that have common borders (for example Copenhagen has as borders Roskilde and Størstrom) and sectors that produce similar products.[27]

We start our analysis with the investigation of correlation between regions, meaning that we allow for correlation between the same sectors in different regions. Using Gauss-Newton regression, we find that there is indeed correlation between the regions (see Davidson and MacKinnon, 1993). The results of feasible GLS taking this correlation into account are reported in column (11). Although there is an increase of the standard error of $\log(1+k)$, our main conclusions are not affected.

We use a similar analysis to investigate the possibility of correlation between sectors within the same region. Here we allow for sectors in manufacturing, groceries and stores, transportation and services in transportation as well as business and other services to be serially correlated. A Gauss-Newton regression results in a test statistic equal to 1.56. Given the fact that this test statistic follows a Gaussian distribution under the null hypothesis, we cannot reject this hypothesis. Nevertheless, we estimated the model by feasible GLS taking correlation between sectors into account and the results are presented in column (12) of Table 8.

We conclude from the main results and the sensitivity analyses that there is strong evidence of a negative effect of frictions on the mean wage in the market. In the Subsection 6.4, we allow for skill heterogeneity within markets.

As explained in Subsection 3.2, one may investigate whether individual search efforts (and therefore the individual job offer arrival rates) causally depend on the individual wage, by way of a regression of the measure of frictions in a market on the coefficient of variation of wages across firms in the market. Because of the endogeneity of wages, we instrument the latter by the coefficient of variation of productivities across firms in the market (this makes no difference for the results). The results are in Table 10. They indicate a marginally significant effect, so in the words of Subsection 3.2, there is evidence of reverse causality. However, as explained in Subsection 3.2, our mean wage regression results can be argued to be insensitive to this.

6.3 Results with transitions between markets

Taking account of cross-market mobility means estimating equation (10) instead of equation (9). This involves that we first estimate the model as discussed at

[27]We used many different specifications of W to test the robustness of our results. The results did not differ much from the ones presented here.

constant	2.135
	(0.020)
Coefficient of variation of p	0.097
	(0.047)
R^2	0.019
# markets	206

Table 10: "Reverse causality" regression of measure of frictions $\log k$ on indicator of wage dispersion across firms in a market, without skill heterogeneity.

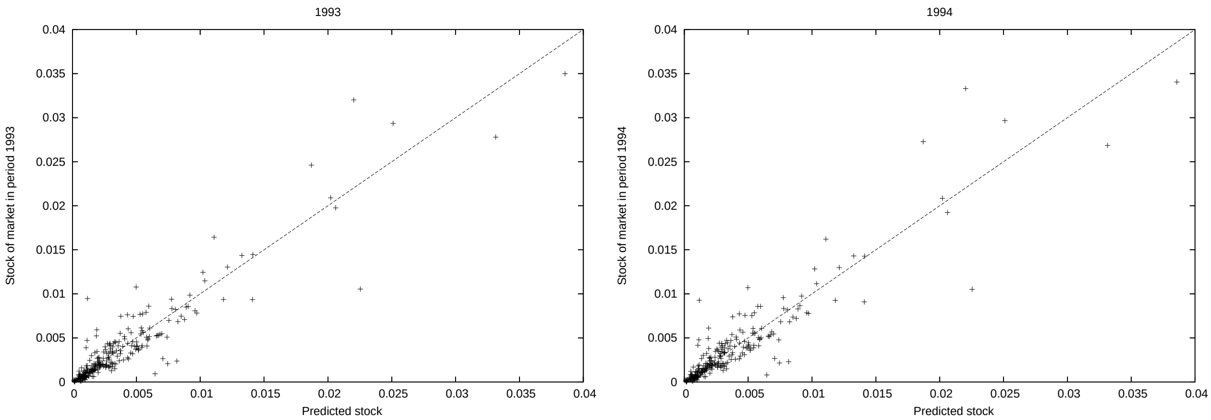

Figure 1: Illustration of the predictive power the model with transitions between markets

the end of Section 5.2 using a 10 percent sample of the dataset. In order to gain some insight into the predictive value of the transition rate estimates, we draw scatter plots of the predicted and the observed stocks in markets in 1993 and 1994. These are illustrated in Figure 1. The fit is remarkably good.

The results of the estimation of regression equation (10) are listed in Table 11. In general, we find higher estimates of α_2 than in the previous subsection. One may think of multiple explanations for this. First, there may be an attenuation bias in the results of the previous subsection. Since the measure of search frictions in the previous subsection did not take all relevant aspects into account, the real search frictions are only imperfectly related to the estimated search frictions. Hence, a measure that takes these ignored aspects into account should result in larger levels of the coefficient. Second, the misspecification may also result in a bias that does not come from random measurement error. In the previous analysis, regions with a large outflow rate are estimated to have search frictions

	(i)	(ii)	(iii)	(iv)
constant	78.5	81.6	40.5	105.1
	(31.1)	(33.9)	(20.8)	(32.5)
Productivity	0.175	0.263	0.122	0.169
	(0.015)	(0.018)	(0.013)	(0.015)
$\log(k+1)$				14.18
				(6.44)
$\log(\widetilde{k}+1)$	16.32	12.50	27.36	
	(6.49)	(6.84)	(5.10)	
Total outflow rate				-7452
				(2820)
Total inflow rate				1559
				(572)
R^2	0.397	0.502	0.341	0.430
# of Markets	206	206	206	206

Table 11: Mean wage regression results taking account of transitions between different markets, (i) baseline, (ii) # of fte units, (iii) November earnings, (iv) Estimated total outflow and inflow rates and k separately.

that are lower than the relevant level of search frictions. We now correct for this in our analysis.

Columns (ii) and (iii) of Table 11 list the results when we use fte's and November earnings instead of the baseline regression. Our final conclusions remain unchanged. This is also the case when we use k and the total out- and inflows as separate regressors. As expected, the outflow rate has a large negative impact on the wages. The inflow rate has a small positive impact on the wages. We interpret this as evidence that cross-market transitions may to a small extent be driven by differences between average wages across markets. Finally, we also looked at the other sensitivity exercises as presented in Table 8. These exercises also showed the robustness of our results.

6.4 Results with skill heterogeneity

As discussed in section 5.2, it is unfeasible to estimate the search frictions with the full sample when allowing for mobility between markets. This implies that as soon as we estimate the search frictions for different skill levels, we may end up with a low number of workers with a given skill level. Hence, we estimate our regression equations including skill heterogeneity only for the restrictive version of our measure of search frictions. Although we realize that this may bias our results, as we have seen from the previous subsection, it can be expected that the impact of search frictions on wages is larger when we would allow for cross-market mobility. Hence, our exercise can be interpreted as a worst case scenario.

Table 12 presents the mean wage regression results allowing for skill heterogeneity. Recall that we estimate equations for each skill level. The measure of frictions is based on estimates of λ and δ that take these to be proportional in sectoral, regional, and skill effects, estimated simultaneously across markets. The left-hand side variable is based on the firm average of wage earnings by worker type in November, using the number of workers in November as measure of firm size.

The most important result is that there is a negative and significant impact of the amount of frictions on the mean wage in the market, controlling for productivity, for 3 of the 6 skill levels. For the lowest and highest levels we also have a negative impact, but it is not significantly different from zero.

Note that the signs of the estimated coefficients are often not in accordance to the strict interpretation (equation (15)) of the mean wage regression equation with skill heterogeneity. In particular, this is true for 15 of the 30 estimated coefficients associated with the fractions of workers with specific skills. However, these estimates are often insignificant. We also estimated equations in which the strict interpretation is imposed on the data by way of the cross-equation restrictions on the regression parameters that are involved (see e.g. equation (16)). We perform nonlinear least squares where the criterium function equals the sum of the sum of squares of the separate equations. Although the number of parameters is reduced by the cross-equation restrictions, the computational burden is increased, in particular for the calculation of the standard errors. We therefore merge some of the skill levels. The analyses lead to nonsensical rankings of the estimated skill-specific productivity components ψ_j, unless the number of skill levels is reduced to 2 (these estimates will be used in Section 7). We conclude that the strict interpretation is incorrect unless there are only 2 skill levels in the economy. Despite this, we find in all cases, for all skill levels considered, that the effect of frictions on the mean wage across firms in the market is significantly negative.

We perform a number of sensitivity analyses. First, we include gender as an additional market characteristic. Second, we replace the education level by the occupation level as a market characteristic. In the empirical analyses, both gender

	I	II	III	IV	V	VI
Constant	57.47	-37.55	10.57	278.64	-93.76	469.1
	(41.01)	(53.13)	(33.62)	(77.27)	(119.2)	(337.9)
Productivity	0.070	0.076	0.035	0.021	0.033	0.031
	(0.013)	(0.015)	(0.010)	(0.020)	(0.032)	(0.047)
$log(1+\kappa)$	16.27	28.38	58.54	-13.80	68.78	71.60
	(14.38)	(16.94)	(11.06)	(22.97)	(35.42)	(60.27)
Elementary school	–	-5.41	-63.50	-90.00	137.36	-227.23
		(31.94)	(16.51)	(44.85)	(66.08)	(303.1)
Highschool	-34.38	–	-21.03	-50.68	-38.07	-1081.0
	(11.54)		(8.12)	(31.41)	(27.98)	(376.6)
Apprenticeship	-24.05	101.2	–	5.89	214.8	-494.1
	(22.48)	(32.56)		(48.59)	(71.52)	(288.5)
Short education	8.22	7.51	2.12	–	16.62	29.34
	(6.08)	(7.69)	(4.58)		(17.05)	(514.6)
Bachelors	-3.22	-1.94	-2.58	-62.20	–	-420.6
	(6.12)	(7.81)	(4.71)	(24.37)		(525.4)
Masters	7.10	7.58	1.95	7.46	18.19	–
	(4.50)	(5.40)	(3.47)	(9.97)	(11.00)	
R^2	0.248	0.279	0.341	0.148	0.120	0.381
Number of observations	193	174	195	121	163	71

Table 12: Mean wage regression results with skill heterogeneity

and occupational level can be treated like the level of education. In addition to these sensitivity analyses, we perform analyses analogous to those in columns 4, 5, 6, 8, and 9 of Table 8. The conclusions from all these exercises do not differ from those presented. Contrary to the results in the previous subsection, we now find that the coefficient of variation of p across firms in a combination of region and sector has a significantly negative effect on the mean skill-specific wage across firms in the market. We also estimate regressions where we add explanatory variables like the fraction of women in a market to the specification (18). Again, the results on the effect of frictions do not change.

We conclude again that there is strong evidence of a negative effect of frictions on the mean wage in the market. Informally, labor demand is more elastic than labor supply, in response to a change in frictions. The results favor models that predict this over models that predict the opposite.

6.5 The quantitative importance of search frictions

The results enable us to assess the quantitative importance of frictions as a determinant of wages, in a number of ways. First, we examine the magnitude of the effect of a change in the amount of frictions on the left-hand side of the mean wage regressions, i.e. on the mean wage across firms in a market. This represents the effect on the mean wage setting behavior of firms. For ease of exposition we only discuss the results in absence of skill heterogeneity. Consider the typical large and small values of k from Subsection 6.1, namely $k = 11$ and $k = 28$. One may envisage a market with very high frictions ($k = 11$) adopting a highly sophisticated matching technology ($k = 28$). Column 1 of Table 8 implies that the mean wage across firms in the market then increases by 4%.[28] If a market with $k = 28$ is taken to be sufficiently close to the competitive case without frictions, then the mean wage increase across firms due to an economy-wide move to a frictionless market is below 5%.[29] Note that the mean wage increase across workers is larger because of the self-selection into high wage jobs.

A second way to assess the quantitative importance of frictions is to examine the fraction of wage variation that can be explained by them. We first decompose the total wage variation across firms into variation within markets and variation between markets. In absence of skill heterogeneity, the former explains 62%, so

[28]A potential problem with such a counterfactual analysis is that an increase of k may affect the mean productivity across firms with firm size over 20 in a market in an unidentified way.

[29]It is unreasonable to take the frictionless case to be a market where the firm's wage equals the firm's observed productivity level, as the latter covers many other production costs.

sector and region explain 38% of wage variation across firms. With skill heterogeneity, we have to use wages earned by workers in November. Part-time workers then have equal weight as full-time workers, and this increases the within-market wage variation such that a comparison is uninformative. Now, we may decompose the total "between-market" variation of the market-specific mean wage into variation due to differences in frictions across markets, variation due to differences in the market-specific mean productivity, and residual variation. These decomposition results invariably state that less than 5% of the between-market variation is due to differences in frictions, while at most another 5% can be attributed to interactions between frictions and the mean productivity. In sum, inter-industry (and inter-region and inter-skill) wage differences cannot be explained by differences in the degree of frictions.

The small role of frictions in explaining between-market wage variation does not mean that frictions are quantitatively unimportant determinants of within-market variation. As demonstrated in Subsection 2.2 and the references therein, productivity variation across firms within a market may by itself not generate any wage dispersion, in the sense that wage dispersion may equal zero if frictions are infinitely large or absent. It is rather the interaction between productivity variation and frictions that provides a good fit to within-market wage distributions.

7 Two-sided sorting versus heterogeneity of frictions across skills

As set out in Section 1 and Subsection 2.5, models that integrate search frictions with heterogeneity of agent-specific productivity at both sides of the market may give very different predictions of the frictions effect on wages than most of the models considered so far. This is particularly true if the equilibrium displays two-sided sorting behavior, that is, high quality firms (workers) only want to team up with high quality workers (firms). This section investigates whether two-sided sorting behavior occurs, using within-market data. If it does then this has negative implications for the equilibrium search models we considered so far, whether they predict a negative effect of frictions on wages or not.

Obviously, two-sided sorting leads to positive assortative matching, that is, a positive correlation between the firm-specific productivity and the average productivity of its workers. We therefore start by examining the presence of positive assortative matching. However, positive assortative matching by itself is not sufficient for two-sided sorting. In particular, the former can also be explained by lower frictions in the labor markets for high-skilled workers, because then high-skilled workers move quickly to high-wage firms that have high firm-specific productivity. We distinguish between these explanations by examining whether sectors and regions where the correlation is high have a low amount of search frictions. Stated somewhat informally: if frictions for the low skilled are low then in a "two-sided productivity heterogeneity model" world they end up at low-productivity firms whereas in an "equilibrium search" world they end up at high-productivity firms.

We first carry out the empirical assessment of the extent of positive assortative matching, for each combination of sector and region. After that, we empirically distinguish between the two explanations for it. Throughout this section we restrict attention to two skill levels, covering education levels 1 and 2–6, respectively, and we redo the estimation of Section 6 accordingly.

We can not quantify the firm-specific productivity component because we effectively only have one observation of a firm's productivity. Instead, since we are only interested in the relation between the firm-specific component and the fraction of low-skilled workers, we postulate a stochastic relation between them, and attempt to determine the sign and significance of the relation in any given market. In the notation of Subsection 5.5, consider a firm i in sector $\times$ region m with firm-specific productivity component p^0_{mi} and fraction of low-skilled employees π_{mui}. We postulate

$$p^0_{mi} = \beta_{0,m} - \beta_m \pi_{mui} + \varepsilon_{mi} \tag{19}$$

with $\mathrm{E}(\varepsilon_{mi}) = 0$ and $\varepsilon_{mi} \perp \pi_{mui}$. Positive assortative matching means that $\beta_m > 0$. Aggregation of equation (12) over $j = u, s$ gives,

$$p_{mi} = p^0_{mi} + (\psi_u - \psi_s)\pi_{mui} \tag{20}$$

Substitution of (19) into (20) gives

$$p_{mi} = \beta_{0,m} + (\psi_u - \psi_s - \beta_m)\pi_{mui} + \varepsilon_{mi} \tag{21}$$

For a given m, we observe p_{mi} and π_{mui} for all i. The analysis in Subsection 6.4 with two skill levels provides an estimate of $\psi_u - \psi_s$.[30] Specifically, we use the estimate that follows from the regression analysis of equation (17).[31] As a

[30]Obviously, β_m is not identified from (21) without the estimate of $\psi_u - \psi_s$ obtained from between-market comparisons.

[31]Using alternative estimates does not lead to different results below, since the estimate of β_m is only linearly dependent on the value of $\psi_u - \psi_s$.

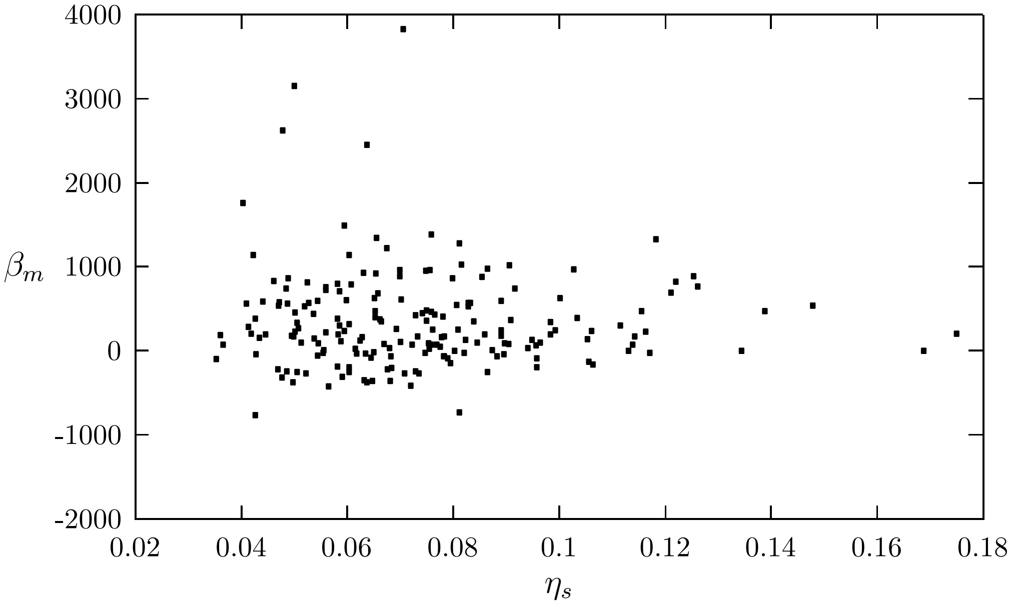

Figure 2: Scatter plot of the indicator of search frictions $1/(1+k_{ms})$ (here denoted as η_s) versus the measure of positive assortative matching β_m, across regions $\times$ sectors m.

result, we can estimate β_m in (21) by way of a regression, for each m separately. The results show that for 85% of all combinations m of region and sector, β_m is non-negative, and for most of these, β_m is significantly positive, so that positive assortative matching is a common phenomenon.

In a world with two-sided productivity heterogeneity, positive assortative matching is more likely as equilibrium outcome if there are few frictions,[32] so the magnitude of β_m should be positively correlated with k_{ms} and k_{mu}. Note that these correlations should be similar due to the additive log-linear specification of k_{mj} as a function of skill, region, and sector. Figure 2 contains a scatter plot of the friction indicator $1/(1 + k_{ms})$ versus β_m. Table 13 gives estimates of the corresponding regression. Clearly, there is no evidence at all for two-sided sorting.

[32]Strictly speaking, two-sided sorting can never be an equilibrium outcome if the workers' and firms' productivity inputs are assumed to be perfect substitutes, as in the additive linear production function of Subsection 5.5. We ignore this: we do not impose absence of two-sided sorting; we merely use the additive linear structure to design a manageable method for quantification of the amount of positive assortative matching.

	$1/(1+k_{ms})$
constant	390.02
	(4560)
β_m	-1245.2
	(847)
R^2	0.018
# region × sector	177

Table 13: Regression of the search friction measure on the measure of positive assortative matching.

8 Conclusions

The most fundamental prediction of theories of labor market frictions concerns the effect of the degree of frictions on wages. We test this using data that are longitudinal, cover the whole population, and match employers and employees. The data are from Denmark, whose geographical structure is well suited for our purposes.

The empirical results are unambiguous. Frictions have a significant effect on the mean wage in the market: higher frictions imply that the mean wage across firms is lower. Informally, labor demand is more elastic in response to a change in frictions than labor supply. This result is robust with respect to a very wide range of sensitivity checks.

The quantitative effect of frictions on the mean wage across firms is small. In case of an economy-wide move to a frictionless market, the mean wage increase across firms is estimated to be below 5 percent. Across workers the effect is larger due to worker self-selection. But it seems that frictions are sufficiently small to prevent a major exploitation of monopsony power by firms. We also find that inter-industry (and inter-region and inter-skill) wage differences cannot be explained by differences in the degree of frictions.

The within-market data on wages, productivity, and skill composition of the firm's workforce, provide evidence of positive assortative matching (which we define as a positive correlation between the firm-specific productivity component and the skill level of the firm's workforce). However, the extent of positive assortative matching seems to be unrelated to the amount (and skill distribution) of frictions in the market. We find no evidence for the claim that positive assortative matching is the result of two-sided sorting (which we define as high-productivity agents choosing to only team up with other high-productivity agents).

The results lend credence to models that predict a negative effect of frictions on wages. This includes many existing so-called equilibrium search and matching models, notably the well-known Burdett-Mortensen and Pissarides models and most of their offsprings. However, it is not clear yet whether frictions are quantitatively important determinants of the wage distribution in general.

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