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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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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 expected 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.

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.

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, but this is a partial (supply) effect and not an equilibrium effect. The mean wage across workers may be negatively correlated to the amount of frictions, but this does not imply that firms take frictions into account when they set wages.

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 the survey in

[1] Alternatively, one may follow one labor market over time. However, the time span of the data does not cover different steady-state equilibria, and the theoretical literature on the dynamics of going from one steady-state equilibrium to another is not well developed.

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.

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. By using sector as a market characteristic, the 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.

The paper is organized as follows. The next section discusses the theoretical framework. 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

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 m 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.[2] 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 $G(w)(m-u)$. 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, $\delta G(w)(m-u)$ and those who receive a job offer that exceeds w, $\lambda(1-F(w))G(w)(m-u)$. In the steady state, the flows into and out of the stock are equal, so

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

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

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 $m, n, \delta, \lambda_0, \lambda$ 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) productivity 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, 2003). 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 $\phi < \underline{w} \leq \underline{p}$.[3,4] In equilibrium, the profit maximizing wage for a firm of type p defines a mapping $w = K(p)$,

[3]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 $\lambda_0 \leq \lambda$.

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

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

with $\overline{\Gamma} := 1 - \Gamma$, The distribution of wage offers is $F(w) = \Gamma(K^{-1}(w))$. Note that a firm always offers $w < p$.[5]

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[6]

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

with $k := \lambda/\delta$. 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

[5] 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.

[6] These results are not in Bontemps, Robin and Van den Berg (2000).

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.[7]

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 among firms.[8] 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

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

[8] 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.

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),

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

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

2.3 The Pissarides model

We start by listing the differences between the "prototype" Pissarides (1990) model (see also Pissarides, 1984, 1986) and the model of the previous subsection. 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[9]

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

[9]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.

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.[10] 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:

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

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.

2.4 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

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

(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[11]). 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

[11] 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.

depends on the productivity of the matches that can be formed. We return to assortative matching in Section 7.

3 Measures of frictions

3.1 Definitions

It is nowadays 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.

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 2.3) 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[12], although the amount of this turbulence

[12]See Amable and Gatti, 2001, for a recent overview of empirical evidence on this.

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 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).[13] In the empirical analysis we also examine the relation between the coefficient of variation of wages across firms and the measure of frictions.

[13]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).

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. (2001) 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 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 10 education levels: (1) less than 7 years of primary schooling, (2) between 7 and 8 years of primary schooling, (3) between 8 and 9 years of primary schooling, (4) between 9 and 10 years of primary schooling, (5) high school, (6) apprenticeship, (7) public exam, (8) short education, (9) bachelors degree and (10) masters degree and higher. For some individuals the level of education increases by more than two levels in consecutive years. We deleted such individuals whenever this variable is used as an explanatory variable.

Table 1 lists some descriptives. The first column concerns the raw data set. The second column concerns our sample without requiring observation of the education level (612,701 individuals). The final column describes our sample after removing the individuals without a reliable observation of the education level (533,628 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 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 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

Variable	Original	Baseline selection	Observed level of education
Education levels			
Less than 8 years of primary education	–	–	0.154
8 years of primary education	–	–	0.039
9 years of primary education	–	–	0.344
10 years primary education	–	–	0.159
Highschool	–	–	0.153
Apprenticeship	–	–	0.326
Public exam	–	–	0.014
Short education	–	–	0.033
Bachelors degree	–	–	0.026
Masters degree	–	–	0.004
Regions			
Copenhagen	0.303	0.286	0.282
Roskilde	0.046	0.048	0.048
Vestjælland	0.054	0.054	0.054
Storstrom	0.046	0.049	0.048
Fyn	0.008	0.008	0.008
Bornholms	0.087	0.088	0.088
Sonderjylland	0.047	0.051	0.051
Ribe	0.042	0.044	0.044
Vejle	0.065	0.072	0.073
Ringkoping	0.053	0.056	0.056
Aarhus	0.119	0.112	0.114
Viborg	0.042	0.043	0.044
Nordjylland	0.089	0.091	0.092
Gender	0.453	0.314	0.298

Table 1: Summary statistics of individuals.

Variable	Original	Baseline selection	Observed level of education
Sectors			
Food & Tobacco	0.030	0.077	0.075
Textiles, wearing, leather	0.009	0.027	0.027
Wood & paper	0.008	0.017	0.018
Publishing	0.014	0.035	0.035
Chemicals, petroleum	0.022	0.053	0.053
Metals	0.018	0.046	0.047
Machines	0.034	0.085	0.086
Cars, trucks etc.	0.012	0.034	0.035
Furniture	0.011	0.022	0.023
Construction	0.004	0.136	0.142
Trade in cars, etc.	0.017	0.051	0.053
Groceries	0.047	0.121	0.122
Stores	0.050	0.110	0.103
Hotels and restaurants	0.020	0.025	0.023
Transportation	0.026	0.053	0.053
Services in transportation	0.008	0.015	0.015
Real estate	0.009	0.013	0.013
Business services	0.038	0.071	0.071
Other services (non medical)	0.004	0.009	0.008
Occupation levels			
Unskilled workers	0.234	0.343	0.334
Skilled workers	0.094	0.262	0.273
Office workers	0.186	0.243	0.238
Managers	0.163	0.151	0.154

Table 1: Summary statistics of individuals (continued).

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.

A distinguishing feature of the data set 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. See also Appendix 1.

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 (all) 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 depreciation costs 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 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[14]).

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

[14]The category with the lowest level of education does not have the lowest average wage across firms because it mostly concerns older experienced workers whose amount of education may have been rationed. The compulsory level is nowadays higher.

	Average	Standard deviation
Education levels		
Less than 8 years in primary school	158.33	43.70
8 years in primary school	112.78	43.57
9 years in primary school	124.60	44.81
10 years in primary school	146.60	35.76
Highschool	184.16	40.19
Apprenticeship	210.29	30.46
Public exam	169.08	42.01
Short education	175.34	32.83
Bachelors degree	276.73	81.96
Masters degree	236.74	131.81
Occupation levels		
Unskilled workers	133.57	36.50
Skilled workers	178.11	32.93
Office workers	160.00	24.31
Managers	261.35	39.62

Table 2: Skill-specific wage across firms.

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

5.1 Identification of labor markets

We have to decide on a segmentation of the total labor market into (sub)markets. In the analyses we assume that a worker is in one single labor market throughout the observation window. Initially, we make the same assumption for firms. The latter is convenient because we only observe the total value added by a firm, and

Variable	Average (standard deviation)
Firm characteristics	
Average firm size	86.2
	(276.0)
Average firm size (fte)	72.1
	(229.2)
Wage costs (x1000)[a]	200.37
	(132.95)
Wage costs (fte) (x1000)[a]	233.31
	(56.51)
Productivity (x1000)[a]	403.27
	(497.26)
Productivity (fte) (x1000)[a]	482.13
	(1338)
Fixed assets per worker (x1000)[a]	253.72
	(988.79)
Fixed assets per worker (fte) (x1000)[a]	286.32
	(465.64)
Regions	
Copenhagen	0.335
Roskilde	0.032
Vestjælland	0.043
Storstrom	0.031
Fyn	0.006
Bornholms	0.078
Sonderjylland	0.044
Ribe	0.044
Vejle	0.076
Ringkoping	0.070
Aarhus	0.111
Viborg	0.046
Nordjylland	0.084

Table 3: Summary statistics of firms.

[a]In Danish Kroner per year

Variable	Average
Sectors	
Food & Tobacco	0.041
Textiles, wearing, leather	0.030
Wood & paper	0.030
Publishing	0.035
Chemicals, petroleum	0.054
Metals	0.066
Machines	0.089
Cars, trucks etc.	0.028
Furniture	0.039
Construction	0.129
Trade in cars, etc.	0.058
Groceries	0.167
Stores	0.062
Hotels and restaurants	0.026
Transportation	0.040
Services in transportation	0.015
Real estate	0.004
Business services	0.078
Other services (non medical)	0.005

Table 3: Summary statistics of firms (continued).

not the separate contributions to this by employees who may belong to different labor markets. Specifically, 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 235 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 5.4 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. 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. 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. Indeed, 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.

	Copenhagen	Roskilde	West Zealand	Storstrøm	Funen	Bornholm	South Jutland	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
West Zealand	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
Størstrom	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
Funen	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
Bornholm	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
Southern Jutland	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
Aarhus	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.

	Food & tobacco	Textiles, wearing	Wood & paper	Publising	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
Publising	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.

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. 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 of frictions λ and k 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, 2003, for an overview). However, at this stage we are not interested in F, and the individual data on earnings may be insufficiently reliable 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 slightly more complicated than in Ridder and Van den Berg (2003) due to the fact that we observe consecutive job spells. Appendix 1 provides details.

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.[15] 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.

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. In that case 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.

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. (2001) 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).

[15]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.

5.3 Estimation of the mean-wage regression without skill heterogeneity

The endogenous variable of interest is the mean wage 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 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).[16] See Appendix 2 for details.

[16]We also estimated standard errors using bootstrapping, and the results are very similar.

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. 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 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[17] i, j, specified analogously to equation (9), and with wage floor $\underline{w}$,

$$\mathrm{E}_i(w_{mji}) = \alpha_{0j} + \alpha_{1j}\mathrm{E}_i(p_{mji}) + \alpha_{2j}\log(k_{mj}+1) + \alpha_{3j}\underline{w}_{mj} + \varepsilon_{mj} \tag{10}$$

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 (10) 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 (10) 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 $\mathrm{E}_i(w_{mji})$.[18]

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,

$$p_{mji} = p^0_{mi} + \psi_j \tag{11}$$

[17] 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.

[18] 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.

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.[19] In fact, we only need an aggregated version of (11),

$$\mathrm{E}_i(p_{mji}) = \mathrm{E}_i(p^0_{mi}) + \psi_j \tag{12}$$

By aggregating this over j we obtain,

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

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 (12) and (13) into equation (10) (and removing $\underline{w}$ for convenience) we obtain

$$\mathrm{E}_i(w_{mji}) = \alpha_{0j} + \alpha_{1j}\mathrm{E}_i(p_{mi}) + \sum_{x \neq j} \alpha_{1j}(\psi_j - \psi_x)\pi_{mx} \ + \alpha_{2j}\log(k_{mj}+1) + \varepsilon_{mj} \tag{14}$$

for all j. Note that we may normalize $\psi_1 := 0$. For two skill levels, equations (14) simplify to

$$\mathrm{E}_i(w_{mui}) = \alpha_{0u} + \alpha_{1u}\mathrm{E}_i(p_{mi}) + \alpha_{1u}(\psi_u - \psi_s)(1-\pi_m) + \alpha_{2u}\log(k_{mu}+1) + \varepsilon_{mu} \tag{15}$$

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

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.

Equations (14) 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

[19] 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.

way.[20] Using the same criteria as in Subsection 5.1, we now use data on 1760 different markets.

The derivation of equations (14) determines the signs of the effects of π_{mx} on $\mathrm{E}_i(w_{mji})$. For example, in equation (16) 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 (14): 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:

$$\mathrm{E}_i(w_{mji}) = \alpha_{0j} + \alpha_{1j}\mathrm{E}_i(p_{mi}) + \sum_{x \neq j} \gamma_{xj}\pi_{mx} + \alpha_{2j}\log(k_{mj}+1) + \varepsilon_{mj} \qquad (17)$$

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.[21]

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 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.

[20] 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 (11) 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}.

[21] In equations (14), 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.

6 Estimation results

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.

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 is rather constant 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 job separation rate is relatively high in Copenhagen. The construction and the transportation sectors have relatively high job offer arrival rates. High job separation rates are found for the textiles industry as well as for the construction sector and the hotels and restaurants 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 $(0.03, 0.15)$ per month and $(3, 20)$, 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 over education levels.

We also estimated λ, λ_0 and δ with less than 10 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.[22]

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 their size in fte's in November. We find a negative and significant impact of the

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

	$\log \lambda_0$	$\log \lambda$	$\log \delta$
constant	-3.224	-3.411	-5.118
	(0.019)	(0.027)	(0.012)
Education levels (< 8 years is baseline)			
8 years of primary schooling	0.223	0.481	0.153
	(0.021)	(0.038)	(0.017)
9 years of primary schooling	0.295	0.647	0.148
	(0.015)	(0.030)	(0.012)
10 years of primary schooling	0.361	0.666	-0.048
	(0.014)	(0.027)	(0.010)
Highschool	0.216	0.688	-0.254
	(0.016)	(0.026)	(0.011)
Apprenticeship	0.258	0.499	-0.210
	(0.012)	(0.018)	(0.008)
Public exam	0.233	0.769	-0.257
	(0.043)	(0.070)	(0.029)
Short education	0.356	0.828	-0.429
	(0.032)	(0.072)	(0.023)
Bachelors degree	0.289	1.153	-0.479
	(0.033)	(0.086)	(0.024)
Masters degree	0.249	1.114	-0.427
	(0.117)	(0.216)	(0.058)
Regions (Copenhagen is baseline)			
Roskilde	0.085	0.020	-0.097
	(0.220)	(0.037)	(0.013)
Vestjælland	0.161	0.063	0.087
	(0.019)	(0.037)	(0.015)
Storstrom	0.037	-0.232	0.076
	(0.019)	(0.030)	(0.014)
Fyn	-0.087	-0.821	-0.019
	(0.036)	(0.081)	(0.022)
Bornholms	0.075	-0.304	-0.051
	(0.017)	(0.029)	(0.012)
Sonderjylland	0.188	-0.159	-0.300
	(0.024)	(0.036)	(0.015)
Ribe	0.205	-0.089	-0.212
	(0.020)	(0.048)	(0.016)
Vejle	0.179	-0.223	-0.182
	(0.017)	(0.030)	(0.014)
Ringkoping	0.339	0.037	-0.295
	(0.023)	(0.031)	(0.015)
Aarhus	0.088	-0.194	-0.059
	(0.014)	(0.025)	(0.009)
Viborg	0.314	-0.218	-0.201
	(0.022)	(0.038)	(0.015)
Nordjylland	0.007	-0.434	0.088
	(0.015)	(0.025)	(0.010)

Table 6: Estimation results for the friction parameters.

	$\log\lambda_0$	$\log\lambda$	$\log\delta$
Sector (food and tobacco is baseline)			
Textiles, wearing, leather	-0.002	-0.195	0.265
	(0.031)	(0.051)	(0.022)
Wood & paper	0.027	-0.056	-0.083
	(0.037)	(0.063)	(0.026)
Publishing	-0.079	-0.119	-0.012
	(0.026)	(0.046)	(0.017)
Chemicals, petroleum & rubber	0.092	0.081	-0.032
	(0.028)	(0.039)	(0.019)
Metals	0.096	0.021	0.038
	(0.024)	(0.046)	(0.020)
Machines	0.079	0.067	-0.013
	(0.022)	(0.031)	(0.013)
Cars, trucks etc.	0.094	0.127	0.120
	(0.026)	(0.050)	(0.016)
Furniture	0.144	0.020	-0.012
	(0.034)	(0.060)	(0.024)
Construction	0.333	0.253	0.389
	(0.020)	(0.026)	(0.011)
Trade in cars, etc.	0.213	0.249	-0.142
	(0.031)	(0.055)	(0.019)
Groceries	0.082	0.244	-0.070
	(0.021)	(0.034)	(0.013)
Stores	0.106	0.174	-0.011
	(0.021)	(0.035)	(0.015)
Hotels and restaurants	0.092	0.250	0.334
	(0.030)	(0.052)	(0.021)
Transportation	0.225	0.620	0.054
	(0.025)	(0.044)	(0.015)
Services in transportation	0.173	0.387	0.079
	(0.036)	(0.063)	(0.021)
Real estate	0.070	0.264	-0.187
	(0.061)	(0.099)	(0.036)
Business services	0.132	0.256	-0.112
	(0.024)	(0.046)	(0.018)
Other services (non medical)	0.149	0.059	-0.085
	(0.048)	(0.114)	(0.036)
Log likelihood =	–773480		

Table 6: Estimation results for the friction parameters (continued).

		λ_0	λ	δ	k	$1/(k+1)$
Simple statistics of the estimates						
Over all markets:	mean	0.065	0.068	0.005	15.91	0.082
	standard deviation	0.012	0.029	0.002	9.98	0.048
	minimum	0.034	0.012	0.002	1.56	0.014
	maximum	0.112	0.207	0.011	69.3	0.390
Over regions:	standard deviation	0.008	0.014	0.001	4.12	0.024
Over sectors:	standard deviation	0.006	0.013	0.001	3.75	0.018
Over education levels:	standard deviation	0.006	0.020	0.001	7.75	0.036
Statistics weighted by number of workers in the market						
Over all markets:	mean	0.081	0.078	0.007	14.90	0.115
	standard deviation	0.022	0.029	0.002	7.28	0.050
Over regions:	mean	0.079	0.089	0.006	20.20	0.098
	standard deviation	0.019	0.023	0.002	5.80	0.028
Over sectors:	mean	0.083	0.087	0.006	20.00	0.101
	standard deviation	0.020	0.024	0.002	6.01	0.029
Over education levels:	mean	0.042	0.047	0.003	11.56	0.052
	standard deviation	0.018	0.027	0.001	8.11	0.038

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

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 number of individuals in November as a measure of firm size in the construction of the left-hand side variable. This results in a negative but insignificant effect of frictions. the wage offers. 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 significantly positive effect of λ and an insignificantly 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 nearest region (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. However, the estimated effect is insignificantly different from zero.

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)	(7)	(8)	(9)
constant	128.3	112.1	88.03	135.4	215.4	140.00	116.23	127.8	148.7
	(14.5)	(19.7)	(14.2)	(14.3)	(157)	(14.5)	(30.2)	(15.1)	(16.5)
Productivity	0.134	0.185	0.103	0.134	0.135	0.141	0.130	0.134	0.009
	(0.025)	(0.036)	(0.025)	(0.025)	(0.026)	(0.036)	(0.024)	(0.017)	(0.017)
$\log(k+1)$	19.60	8.66	20.94			13.18	16.95	19.76	35.26
	(6.38)	(8.84)	(6.74)			(5.11)	(10.0)	(6.48)	(7.15)
$\log k$				17.35					
				(5.96)					
$\log \lambda$					23.83				
					(10.7)				
$\log \delta$					-5.75				
					(62.8)				
coefficient of variation of p								0.35	
								(3.23)	
$\log(k+1)$ in nearest region							8.57		
							(11.8)		
R^2	0.38	0.36	0.34	0.38	0.38	0.37	0.39	0.38	0.12
# markets	235	235	235	235	235	235	235	235	235

Table 8: Mean wage regression results without skill heterogeneity.
Columns: (1) baseline, (2) # November workers, (3) November earnings, (4) with k, (5) with λ, δ, (6) k separately estimated by market, (7) includes frictions in nearest region, (8) with coefficient of variation of p, (9) with capital correction.

constant	184.4
	(2.56)
Fixed assets	0.998
	(0.002)
R^2	0.83

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. We expect $\widehat{c}_1$ to be equal to one. 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 (2003) 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.)

We conclude from the main results and the sensitivity that there is strong evidence of a negative effect of frictions on the mean wage in the market. In the next subsection 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 skill heterogeneity

Table 11 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,

constant	2.135
	(0.020)
Coefficient of variation of p	0.097
	(0.047)
R^2	0.019
# markets	235

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

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. For the two highest skill levels, the number of skill-specific workers in the firm and the number of firms in a market are often small. As a result, the results for the mean wage are uninformative, and we do not report them here.

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 6 of the 8 skill levels. For the two highest levels we consider here, the effect is insignificantly different from zero.

Note that the signs of the estimated coefficients are often not in accordance to the strict interpretation (equation (14)) of the mean wage regression equation with skill heterogeneity. In particular, this is true for 36 of the 72 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 (15)). 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

skill level	1	2	3	4	5	6	7	8
constant	230.4	-40.3	-127	97	-116	180	914	297
	(51.3)	(255)	(135)	(64.4)	(72.4)	(28.9)	(1749)	(347)
Productivity	0.085	0.071	0.066	0.084	0.078	0.053	0.085	0.087
	(0.03076)	(0.02624)	(0.026)	(0.026)	(0.030)	(0.022)	(0.035)	(0.027)
Skill shares in region $\times$ sector								
Less than 8 years in primary	·	349	390	108.5	250.6	-49.87	-739	-159
		(288)	(159)	(67.9)	(76.1)	(32.3)	(1822)	(365)
8 years in primary school	-262	·	-10.76	59.57	-7.79	198.5	-546.4	-354
	(206)		(232)	(151)	(172)	(121)	(1671)	(331)
9 years in primary school	-259	-120	·	-411	305	-246.9	-1013	-136
	(143)	(322)		(143)	(161)	(89.4)	(1779)	(299)
10 years in primary school	-255	-56.8	50.49	·	272.9	-94.7	-832.9	-248
	(77.7)	(270)	(179)		(95.8)	(50.1)	(1745)	(354)
Highschool	-291	-64.94	39.47	-126	·	-13.75	-887.2	-182
	(60.4)	(279)	(136)	(86.5)		(39.6)	(1698)	(374)
Apprenticeship	-106	140	176	-9.652	278	·	-770	-73.33
	(47.1)	(257)	(148)	(64.3)	(71.2)		(1728)	(351)
Public exam	-525	-296	-28.55	-359	401	-35.52	·	255
	(502)	(490)	(444)	(385)	(443)	(334)		(644)
Short education	159.2	267	405.5	-144	102	-360.7	-1089	·
	(262)	(310)	(208)	(214)	(241)	(177)	(2071)	
Bachelors degree	159.5	259	483.1	533	832.8	506.2	-663	120
	(242)	(443)	(227)	(200)	(225)	(186)	(2064)	(456)
Masters degree	-1074	-594	-1204	-1083	-307.2	-1555	-725	-910
	(886)	(817)	(726)	(738)	(832)	(652)	(2988)	
$\log(k+1)$	25.58	18.95	28.93	22.98	18.17	22.72	8.959	-3.282
	(10.7)	(10.2)	(10.3)	(11.0)	(12.0)	(11.9)	(14.9)	(9.08)
R^2	0.50	0.61	0.63	0.55	0.50	0.52	0.42	0.57
# region $\times$ sector	193	193	194	194	194	194	168	192

Table 11: Mean wage regression results with skill heterogeneity

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 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 (17). 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.

6.4 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 $k = 3$ and $k = 20$. One may envisage a market with very high frictions ($k = 3$) adopting a highly sophisticated matching technology ($k = 20$). Column 1 of Table 8 implies that the mean wage across firms in the market then increases by 14%.[23] If a market with $k = 20$ 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 10%.[24] Note that the mean wage increase across

[23]Calculation of this and other statistics in this subsection requires non-reported sample averages of the regression variables. A potential problem here 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.

[24]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.

workers is larger because of the self-selection into high wage jobs. These results are within the range of what is commonly found if equilibrium search models are structurally estimated (see e.g. Van den Berg and Ridder, 1998, and Ridder and Van den Berg, 2003), giving further credence to these models.

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 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 2.4, 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 now proceed with 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 1–4 and 5–10, respectively.

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 some stochastic relation between them and attempt to determine the sign and significance of the relation in any given market. In the notation of Subsection 5.4, consider a firm i in sector × region m with firm-specific productivity component p^0_{mi} and fraction of low-skilled employees π_{mui}. We postulate

$$p^0_{mi} = \beta_{0,m} - \beta_m \pi_{mui} + \varepsilon_{mi} \tag{18}$$

with $\mathrm{E}(\varepsilon_{mi}) = 0$ and $\varepsilon_{mi} \perp \pi_{mui}$. Positive assortative matching means that $\beta_m > 0$. Aggregation of equation (11) over $j = u, s$ gives,

$$p_{mi} = p^0_{mi} + (\psi_u - \psi_s)\pi_{mui} \tag{19}$$

Substitution of (18) into (19) gives

$$p_{mi} = \beta_{0,m} + (\psi_u - \psi_s - \beta_m)\pi_{mui} + \varepsilon_{mi} \tag{20}$$

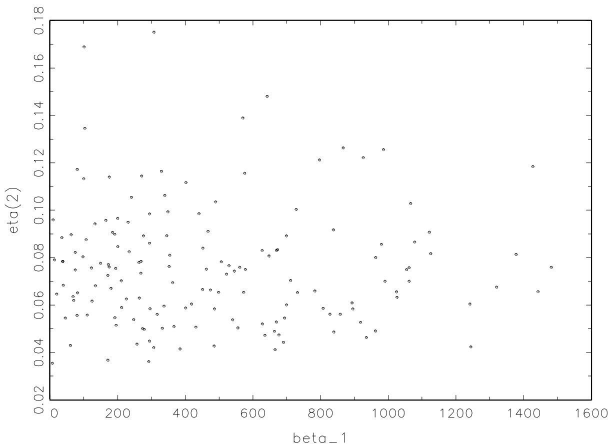

Figure 1: Scatter plot of the measure of positive assortative matching β_m versus the indicator of search frictions $1/(1+k_{ms})$, across regions $\times$ sectors m.

For a given m, we observe p_{mi} and π_{mui} for all i. The analysis in Subsection 6.3 with two skill levels provides an estimate of $\psi_u - \psi_s$.[25] Specifically, we use the estimate that follows from the regression analysis of equation (16).[26] As a result, we can estimate β_m in (20) 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,[27] 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 1 contains a scatter plot of β_m versus the friction indicator $1/(1+k_{ms})$. Table 12 gives estimates of the corresponding regression. Clearly, there is no evidence at all for two-sided sorting.

[25] Obviously, β_m is not identified from (20) without the estimate of $\psi_u - \psi_s$ obtained from between-market comparisons.

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

[27] 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 5.4. 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 12: 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 use unique Danish data to test this. These data are useful for our purposes because they are longitudinal, they cover the whole population, and they match employers and employees. Moreover, the geographical structure of Denmark 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 10%. Across workers the effect is larger due to worker self-selection. But it seems that frictions are sufficiently small to prevent major monopsony power exploitation 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 strong 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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Appendix

Appendix 1 Unconditional inference estimation of the measures of frictions

The individual likelihood contributions can be constructed out of the individual sequence of labor market states and earnings. Due to the assumptions listed in Subsection 5.2, the probabilities of being employed and unemployed at the beginning of the observation window are equal to $\lambda_0/(\delta+\lambda_0)$ and $\delta/(\delta+\lambda_0)$, respectively.

To proceed, it is useful to first consider the joint distributions of earnings w in consecutive jobs. As we choose not to observe earnings, we may replace them by the corresponding job exit rate θ which is a monotonic function of w by way of $\theta = \delta + \lambda\overline{F}(w)$, with $\overline{F} = 1 - F$. The distribution H of θ (i.e. the distribution of the job exit rate) follows from

$$H(\theta) = \Pr\left(\delta + \lambda\overline{F}(w) \leq \theta\right) = \Pr\left(w \geq F^{-1}\left(\frac{\lambda+\delta-\theta}{\lambda}\right)\right)$$

Several distributions of (sequences of) wages may prevail. If the job spell follows an unemployment spell then the distribution of w is F, and as a result the c.d.f. and the p.d.f. h of θ are, respectively

$$H(\theta) = \frac{\theta-\delta}{\lambda} \quad \Rightarrow \quad h(\theta) = \frac{1}{\lambda} \quad \theta \in [\delta, \delta+\lambda] \tag{21}$$

Thus θ is uniformly distributed on the interval $[\delta, \delta+\lambda]$. Note that the distribution of θ only depends on δ and λ and not on (the determinants of) F.

If the distribution of w is G, *i.e.* if the corresponding job spell is a draw from the stock distribution of job spells, then the distribution of θ is

$$H(\theta) = \frac{(\lambda+\delta)(\theta-\delta)}{\lambda\theta} \quad \Rightarrow \quad h(\theta) = \frac{(\lambda+\delta)\delta}{\lambda\theta^2} \quad \theta \in [\delta, \delta+\lambda] \tag{22}$$

Now consider the job exit rates θ_1, θ_2 in two consecutive jobs with earnings w_1 and w_2. According to the on-the-job search model, w_2 is a draw from F truncated from below at w_1, so

$$H(\theta_2|\theta_1) = \frac{\theta_2-\delta}{\theta_1-\delta}, \qquad h(\theta_2|\theta_1) = \frac{1}{\theta_1-\delta} \quad \theta_2 \in [\delta, \theta_1) \tag{23}$$

so θ_2 is uniformly distributed on the interval $[\delta, \theta_1)$.

The distributions of the job exit rates of N consecutive jobs can be easily derived from this. If θ_1 concerns a job following unemployment,

$$\begin{aligned} h(\theta_1, \theta_2, ..\theta_N) &= \frac{1}{\lambda}\Pi_{i=1}^{N-1}\frac{1}{\theta_i-\delta} \\ &\quad \delta \leq \theta_N < \theta_{N-1} < \cdots < \theta_2 < \theta_1 \leq \delta+\lambda, \qquad N \geq 1 \end{aligned}$$

whereas if θ_1 concerns a job in the stock of employed,

$$\begin{aligned} h(\theta_1, \theta_2, ..\theta_N) &= \frac{(\delta+\lambda)\delta}{\lambda\theta_1^2}\Pi_{i=1}^{N-1}\frac{1}{\theta_i-\delta} \\ &\quad \delta \leq \theta_N < \theta_{N-1} < \cdots < \theta_2 < \theta_1 \leq \delta+\lambda, \qquad N \geq 1 \end{aligned} \tag{24}$$

Other cases follow analogously.

We are now in the position to derive the likelihood contributions of the unemployment and job spells, in two steps. First, we derive the likelihood conditional on a particular sequence of values of θ. Next, we integrate with respect to the distribution of this sequence. Note that the sequence of values of θ does not depend on the sojourn times. It suffices to give some examples.

Our empirical analysis uses the month as the unit of time. A worker who is employed at a particular establishment in month T either changes job during the year or not. In the first case, let t denote the moment of job change, with $T \leq t \leq T+12$. The probability of exactly one job-to-job transition in $[T, T+12]$, conditional the consecutive job exit rates θ_1 and θ_2 equals,

$$\begin{aligned} &\int_T^{T+12} (\theta_1 - \delta)\exp(-\theta_1(t-T))\exp(-\theta_2(T+12-t))\mathrm{d}t = \\ = \; &\frac{\theta_1-\delta}{\theta_1-\theta_2}[\exp(-12\theta_2)-\exp(-12\theta_1)] \end{aligned} \tag{25}$$

Similarly, the probability of a transition into unemployment with a subsequent unemployment spell that lasts at least to $T+12$, conditional on θ_1, is

$$\frac{\delta}{\theta_1-\lambda_0}[\exp(-12\lambda_0)-\exp(-12\theta_1)] \tag{26}$$

in the generic case where $\lambda_0 \neq \theta_1$.

Also, consider the case of an individual worker who is employed at time T, finds a new job in $(T, T+12]$, becomes unemployed in $t \in (T+12, T+24]$, and does not move to employment before $T+24$. The probability of these events, conditional on θ_1 and θ_2, is

$$\frac{\theta_1-\delta}{(\theta_1-\theta_2)(\theta_2-\lambda_0)}\;[\exp(-12\theta_2)-\exp(-12\theta_1)] \;\times\; [\exp(-12\lambda_0)-\exp(-12\theta_2)]\;\delta \tag{27}$$

The probabilities as in (25), (26) and (27) can now be integrated over the relevant distributions of the (consecutive) job exit rates. In case of (27), the latter distribution follows from (24). We obtain,

$$\begin{aligned} &\frac{\delta^2(\delta+\lambda)}{\lambda}\int_\delta^{\delta+\lambda}\int_\delta^{\theta_1} \quad \frac{[\exp(-12\theta_2)-\exp(-12\theta_1)]}{\theta_1^2(\theta_1-\theta_2)(\theta_2-\lambda_0)} \\ &\qquad \times\;[\exp(-12\lambda_0)-\exp(-12\theta_2)]\;\; d\theta_2 d\theta_1 \end{aligned} \tag{28}$$

For computational convenience, we exclude the possibility that individuals make more than one transition between two consecutive observations (i.e., between two consecutive Novembers). Sensitivity analyses that allow for more transitions did not give very different results.[28] As a result, there are 13 qualitatively different employment histories in the data. For example, an

[28] The assumption leads to underestimation of λ, and, to a lesser extent, of δ. As a result, k is underestimated, and the estimated coefficients of k and λ in mean wage regressions may therefore be too large in absolute value. The estimated coefficient of $\log(k+1)$ may be less affected.

Variable	Percentage
unemployed throughout	0.017
job, unemployed, unemployed	0.019
unemployed, job, unemployed	0.008
unemployed, unemployed, job	0.016
job, same job, unemployed	0.017
job, different job, unemployed	0.005
job, unemployed, job	0.025
unemployed, job, same job	0.017
unemployed, job, different job	0.010
job, same job, same job	0.665
job, different job, same job	0.079
job, same job, different job	0.082
job, different job, different job	0.041

Table 13: Distribution of labor market histories.

individual can be observed to be employed in 1992, employed in another establishment in 1993 and unemployed in 1994 (see Table 13).

To express the likelihood function, we define $P_i(\lambda_0, \lambda, \delta)$ as the probability that an individual has a sequence i of events ($i = 1, \ldots, 13$) and define $\mathcal{N}_i$ to be the number of individuals observed with sequence i. The likelihood function is equal to

$$\log L = \sum_{i=1}^{13} \mathcal{N}_i \log P_i(\lambda_0, \lambda, \delta)$$

The number of computations to calculate the likelihood does not increase with sample size. Based on the fact that we have over half a million observations, this is a very convenient property.

Appendix 2 Estimation of standard errors in the mean-wage regressions

Let I be the total number of markets and K_m be the total number of firms observed within market m. In addition, let M_m be the total number of observed workers in a market and let σ_{p_m} and σ_{w_m} be the variances of the productivity levels and offered wages in market m.

We denote $\phi(\alpha, \mathrm{E}_i w_{mi}, \mathrm{E}_i p_{mi}, \eta_m)$ the error of the regression and we use hats for the estimated parameters $\mathrm{E}_i w_{mi}, \mathrm{E}_i p_{mi}, \eta_m$ that are estimated in the first stage of the estimation procedure. This implies that our regression estimates of α can be defined as follows

$$\widehat{\alpha} = \arg\min \frac{1}{I} \sum_m \phi^2(\alpha, \widehat{\mathrm{E}}_i w_{mi}, \widehat{\mathrm{E}}_i p_{mi}, \widehat{\eta}_m)$$

Using well-known Taylor series expansions, we have

$$\sqrt{I}(\widehat{\alpha} - \alpha) \rightsquigarrow N(0, \Sigma_\alpha)$$

where

$$\Sigma_\alpha = H^{-1}\Omega H^{-1}$$

with H the Hessian of the criterium function (in this case equal to the cross-correlation matrix of the right hand side variables), and with Ω equal to

$$\begin{aligned}
\Omega = H\sigma^2 &+ \mathrm{E}\left(\frac{\partial^2\phi(\alpha, \mathrm{E}_i w_{mi}, \mathrm{E}_i p_{mi}, \eta_m)}{\partial\alpha\partial \mathrm{E}_i p_{mi}}\right)\Sigma_p\left[\mathrm{E}\left(\frac{\partial^2\phi(\alpha, \mathrm{E}_i w_{mi}, \mathrm{E}_i p_{mi}, \eta_m)}{\partial\alpha\partial \mathrm{E}_i p_{mi}}\right)\right]^T \\
&+ \mathrm{E}\left(\frac{\partial^2\phi(\alpha, \mathrm{E}_i w_{mi}, \mathrm{E}_i p_{mi}, \eta_m)}{\partial\alpha\partial \mathrm{E}_i w_{mi}}\right)\Sigma_w\left[\mathrm{E}\left(\frac{\partial^2\phi(\alpha, \mathrm{E}_i w_{mi}, \mathrm{E}_i p_{mi}, \eta_m)}{\partial\alpha\partial \mathrm{E}_i w_{mi}}\right)\right]^T \qquad (29) \\
&+ \mathrm{E}\left(\frac{\partial^2\phi(\alpha, \mathrm{E}_i w_{mi}, \mathrm{E}_i p_{mi}, \eta_m)}{\partial\alpha\partial\eta}\right)\Sigma_\eta\left[\mathrm{E}\left(\frac{\partial^2\phi(\alpha, \mathrm{E}_i w_{mi}, \mathrm{E}_i p_{mi}, \eta_m)}{\partial\alpha\partial\eta}\right)\right]^T
\end{aligned}$$

where $\sigma^2 = \mathrm{var}(\varepsilon)$ and

$$\Sigma_p = \begin{pmatrix} \sigma^2_{p_1}/K_1 & 0 & \dots & 0 \\ 0 & \sigma^2_{p_1}/K_2 & \dots & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & \dots & \sigma^2_{p_1}/K_I \end{pmatrix}$$

and

$$\Sigma_w = \begin{pmatrix} \sigma^2_{w_1}/K_1 & 0 & \dots & 0 \\ 0 & \sigma^2_{w_1}/K_2 & \dots & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & \dots & \sigma^2_{w_1}/K_I \end{pmatrix}$$

and

$$\Sigma_\eta = \begin{pmatrix} \sigma^2_{\eta_1}/K_1 & 0 & \dots & 0 \\ 0 & \sigma^2_{\eta_1}/K_2 & \dots & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & \dots & \sigma^2_{\eta_1}/K_I \end{pmatrix}$$

where σ_{η_m} is the standard error from the first stage estimation of the friction parameter η_m.

The method as described above can be easily extended to the regression approach of Subsection 5.4 and to the method that imposes the cross-equation restrictions.[29] Consistent estimates of Σ_p, Σ_w, Σ_η and Ω can be derived using estimated values of σ_{p_m}, σ_{w_m}, σ_{η_m}, $\mathrm{E}_i(p_{mi})$, $\mathrm{E}_i(w_{mi})$, η_m and α. Hence, a consistent estimate for Σ_α can be easily derived. Except when the cross-equation restrictions are imposed, the analytical derivatives of equation (29) are easy to derive. We use numerical derivatives for the expressions in equation (29) in the cross-equation restrictions case.

[29] In the latter case, the Hessian is no longer equal to the cross-correlation matrix and H in the definition of Ω should be replaced by the cross-correlation matrix $\left(\left(\frac{\partial\phi}{\partial alpha}\right)\left(\frac{\partial\phi}{\partial alpha}\right)^T\right)$.