The Effect of Search Frictions on Wages

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Abstract

Labor market theories that allow 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. We effectively compare different markets with different degrees of frictions and different market outcomes. 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 allow for an assessment 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. Using within-market variation, we also investigate the extent of (and explanations for) positive assortative matching. We perform separate analyses for The Netherlands and Denmark.

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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 because new firms may enter the market, and because firms may have been constrained in their labor demand because of the frictions. For examples, 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 has 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. 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. 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 productivity and wage costs in a market, and on firm characteristics. The matched data allow for an assessment 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 observed characteristics to define different labor markets. Such markets are supposed to contain all employees who compete with each other for jobs.

The estimation results are used to decompose 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 subsequently be decomposed into a part due to cross-market differences in the skill composition of the workforce and cross-market differences in the firms' productivity. By using industry 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.

We perform separate analyses for The Netherlands and Denmark. The recent literature has shown that average frictions in the Dutch labor markets are in between those of most continental European countries on the one hand and the Anglo-Saxon countries on the other (Ridder and van den Berg, 1999), whereas the flexibility and the average amount of frictions in the Danish labor market are in the same range as those in the U.S.. An advantage of the Danish data over the Dutch data is that the former enable us to follow single individuals and firms over time whereas the latter are repeated cross-sections, with only retrospective information on job mobility. In addition, the Danish data contain information on all workers employed at a firm if the firm is in the sample, whereas the Dutch data only have information on a sample of workers employed at firms in the firm sample.

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 necessarily 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 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 and models that may generate assortative matching; 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, i.e. to what extent high-productivity firms team up with high-productivity workers. For each firm we can quantify the firm-specific productivity component, and this can be used to calculate the correlation 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 certain relative amounts of search frictions for high-skilled and 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). So this enables us to perform another decomposition. In sum, whereas we use between-market variation to examine the relation between frictions and wages, we use within-market variation to examine assortative matching.

Our analysis is complementary to the analyses in Abowd, Kramarz and Margolis (1999) and its offsprings. These studies do not address the role of frictions, and they assume that mobility of individuals between firms is unrelated to the firm's characteristics, whereas we allow this mobility to be driven by differences between the old and the new firm. However, these studies allow for unobserved individual-specific productivity terms, whereas we only allow for individual heterogeneity across observable skills and other characteristics.

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 Dutch and Danish data are discussed in Section 4. Section 5 concerns the estimation and testing strategy. The results for The Netherlands are in Section 6. Section 8 deals with the empirical analysis of assortative matching. The results for Denmark are in Section 7. Section 9 concludes.

2 Theoretical considerations

2.1 The general framework

Consider a labor market with search frictions. 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 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 market 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, 2001, Abbring, 1999, and Acemoglu and Shimer, 2000). All of these models allow for an asymmetry in the environments of workers and employers, such that workers benefit more from a reduction in frictions than employers do. As a result, the competitive wage in the limiting case where frictions vanish exceeds the wage in case of frictions.

Let us examine this more closely at a general level. The most fundamental difference between a worker and a firm is that the former corresponds to a relatively long-lived physical unit whereas the latter 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, and as a result the firms benefit less than the workers. So, entry and exit of firms creates an asymmetry in the effect of frictions on employers and workers. Now 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 the next subsections we examine some specific models to illustrate the above mechanisms and to shape thoughts for the empirical analysis. It would be 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 The Bontemps, Robin and Van den Berg 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. It should be emphasized from the outset that the famous Burdett and Mortensen (1998) model is a special case of this model.

The model considers 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.[1] 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

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

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

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

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, 1999). 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 $\phi < \underline{w} \leq \underline{p}$.[2,3] In equilibrium, the profit maximizing wage for a firm of type p defines a mapping $w = K(p)$,

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

with $\overline{\Gamma} := 1 - \Gamma$, The distribution of wage offers is $F(w) = \Gamma(K^{-1}(w))$. Note that a firm always offers $w < p$.[4]

It is useful to define

$$\eta = \frac{\delta}{\delta + \lambda}$$

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[5]

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

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

[3]For expositional reasons we do not address existence and multiplicity of equilibria; see Van den Berg (2000).

[4]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.

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

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

Without firm heterogeneity, the mean wage offer is equal to the sum of the first and the second term. Thus, the *second term* in the decomposition of the mean wage represents the change in the mean wage due to search frictions. It should be emphasized that in this case wages are dispersed (Burdett and Mortensen, 1998) so that workers do move between jobs. Taken together, the first and second term are a weighted average of $\mathrm{E}(p)$ and $\underline{w}$. The latter reflect the threshold values or outside options of both parties. The precise location of the wage in between these bounds only depends on the frictional indicator η. The second term is actually always negative and it decreases in η. This is the effect that we discussed in the previous subsection. If η is small 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.[6]

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 $0 < \eta < 1$) 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.[7] If on-the-job search is impossible (i.e., $\lambda = 0$ so $\eta = 1$) 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

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

[7]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.

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. Consequently, in case of frictions, the wage is below the competitive wage.

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. As noted above, all this is intuitively plausible.

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

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

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 them to have high mean-preserving productivity dispersion.

In two recent working papers, Postel-Vinay and Robin (2000, 2001) work out a model in which it is possible to post worker-dependent wages. Moreover, they assume that it is possible for a firm to renegotiate on a wage when a worker obtains a better outside option. It can be shown that the mean wage is the same 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[8]

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

for a given fixed measure of vacancies v. The threshold values or outside options of both parties depend on the frictional indicators λ_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.[9] As such this is a better indicator of the amount of frictions than λ_0. There

[8] 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.

[9] In the model of the previous subsection this would be irrelevant, as all agents search 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 (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, in response to a change in search frictions. From an empirical point of view, this assumption certainly seems more reasonable than its opposite.

Now let us 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 intensity 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 intensity 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, and the competitive wage is below the equilibrium wage in case of frictions.

Finally, recall from the introduction 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). 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 will all agents at the other side of the market. In both cases, the mean wage strongly depends on the productivity of the matches that can be formed. We return to assortative matching in Section 8.

2.5 Reverse causality

The models considered in Subsection 2.2 and 2.3 suggest the use of λ and λ_0 (or expressions that depend on these) as measures of friction. 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 intensity is high. This creates a positive causal effect from the mean wage to λ_0. This in turn creates a negative relation between the mean wage and the amount of frictions as captured by λ_0. An empirical analysis on this relation may therefore have difficulties in identifying the causal effect of frictions on wages.

We now argue that this issue is less problematic if we use a measure of frictions based on the job offer arrival rate for employed workers. If there is no wage dispersion then the optimal search intensity for employed workers is zero (see e.g. Albrecht, Holmlund and Lang, 1991), irrespective of the actual wage level. If the wage variance is positive then the optimal search intensity for an employed worker may be positive. Whether it depends on the wage depends on the way in which direct (utility equivalents of) search costs depend on the current wage.

If they decrease in the current wage then the optimal search intensity may be a constant. Remember, however, that we are only interested in market averages. In general, the mean search intensity and the resulting average arrival rate are very sensitive to the wage variance but not to the mean wage. Intuitively, this is because a change in the mean wage also affects the relative income position of the average employed searcher. For unemployed searchers, the situation is different: if the mean wage increases then the gap with the instantaneous income flow increases, and this increases the search intensity.

3 Measure of frictions

To measure the amount of frictions in a market, we focus on the ease with which workers can make job-to-job transitions. This is inspired by the equilibrium models that allow for on-the-job search. Specifically, in the notation of the Bontemps, Robin and Van den Berg (2000) model, we use λ and λ/δ as our measure or "index" of search frictions. We define

$$k := \frac{\lambda}{\delta}$$

Note that this is related to η defined above by way of $\eta = 1/(1+k)$. The higher λ is, the easier it is to find another job. The measure k equals the mean number of job offers in a spell of employment, which may cover multiple consecutive job spells. It equals the rate at which job opportunities arise as a fraction of the rate at which they are needed. In other words, it is informative on the speed at which workers can climb the job ladder.

In many equilibrium models, the parameter 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. Note also that in all of those equilibrium models, the wage distributions F and G and their means depend on λ only by way of k.

In empirical studies, the estimates of λ and k are often positively correlated across markets with the estimate of λ_0 (see e.g. Ridder and Van den Berg, 1997). Therefore, λ and k may also capture the amount of frictions for the unemployed. However, as noted in Subsection 2.5, the use of λ and k is less sensitive to reverse causality problems than the use of λ_0.

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. One may think of at least three factors. First, by relating λ to an aggregate matching function (as in Subsection 2.3) it becomes 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. To the extent that these determinants differ across markets, λ also differs across markets (see Amable and Gatti, 2001, for a recent overview of empirical evidence on this).

4 The Dutch and Danish data

4.1 The Dutch data

For the years 1993 and 1994, we have access to two survey data sets of Statistics Netherlands: the Production Survey and the Wage and Employment Survey. Firms are legally obliged to respond and give sufficient answers to the different questions of these surveys when sampled.

In the *Production Survey (PS)*, all manufacturing firms with 20 or more employees are surveyed and a sample is drawn from the firms with less than 20 employees. The total number of sampled firms is about 6000 per year. Many firms are present in both years. We use information on the registration number of the firm, the industry type, the firm size (labor force), the revenue product, the wage costs, and the depreciation costs of the firm. We now examine the variables in more detail.

The registration number of the firm is a unique identifier. The industry type (or sector) of the firm is based on the first two digits of the 1993 Standard Industry Classification (SIC). The PS data contain firms in the manufacturing industry with 2-digit SIC numbers ranging from 15 to 37. We delete the firms of the tobacco industry and the recycling industry because these are very small industries with characteristics that deviate a lot from the other industries. The remaining 21 industries are: Food / Textiles / Wearing apparel / Leather / Products of wood / Pulp and paper / Publishing / Refined petroleum / Chemicals / Rubber and plastic / Other non-metallic / Basic metals / Fabricated metal / Machinery / Office machinery / Electrical machinery / Radio, tv / Medical instruments / Motor vehicles / Other transport / Furniture.

Firm size is the number of individuals who were working in the firm at the end of September of the year of observation. Total value added of the firm is the total sales of the firm minus the monetary value of all purchases. 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. Total wage costs of the firm concern the total wage bill of the firm. It includes wage and labor taxes and social security payments for both employers and employees. Finally, depreciation costs are the depreciation costs as they appear on the firms' balance sheets. They are roughly equal to a fixed percentage of the historical price of the fixed assets.

The *Wage and Employment Survey (WES)* is based on a two-stage sample design. Statistics Netherlands takes a sample of firms to ask questions about total employment of the firm in the first stage. The sample is not random but takes account of firm size. All firms with 20 or more employees are drawn, while a sample is taken from the firms with less than 20 employees. The latter sample is purely random and does not depend on firm size. The sample in this second stage is a subsample of the ultimate sample of the first stage. All firms with 100 or more employees are drawn, while a sample is taken of the firms with less than 100 employees. Additionally, the number of employees being sampled within the firm depends on firm size as well. Firms with less than 20 employees provide data for all employees, while firms with 20 or more employees provide data for only a fraction of their employees. This fraction depends again on the firm size and varies from 7 to 50 percent. The actual percentage decreases in the number of employees. The total number of individuals in the WES is about 78,000 per year.

The probability of an individual worker being sampled within the WES is equal to the probability that the firm is sampled, multiplied by the probability that the individual worker is sampled, given that the firm is sampled. The first term of the product is decreasing with firm size and the second is increasing with firm size. We take account of this sampling device in our empirical implementation.

We use variables from the WES concerning the registration number of the firm, the 2-digit SIC number of the firm, the firm size, the city of the firm's head office, the worker's tenure, the worker's hourly wage, and the worker's skill level (high or low). The registration number of the firm and the firm size are defined as in the PS. The city where the firm's head office is situated is used to create regional indicators for the following 7 regions: (1) north, (2) east, (3) center, (4) northern west coast, (5) southern west coast, (6) south, and (7) southeast. These regions are depicted in Figure 1.

The worker's hourly wage includes extra payments for overtime hours. This is the gross wage, including wage taxes and social security payments for the employee, but excluding the wage and labor taxes and social security payments that are borne by the employer. The occupational classification for the worker is

Figure 1: Regional classification of The Netherlands as used in the empirical analysis.

not based on the International Standard of Occupation Classification, but is based on a question about the worker's main activities in the job. Statistics Netherlands classifies the answers that were given into 19 categories. We reduce this to two levels: high skilled and low skilled. The first applies to workers with at least a master's degree as well as workers with an administrative job and managers. The second applies to jobs that do not require special skills. Finally, the tenure is measured by way of the year in which the worker started in his current job.

Table 1 lists some descriptive statistics of the most important variables for the years 1993 and 1994.

One of the drawbacks of the data set used for the first two years of analysis is the relative lack of information on the characteristics of the worker. Additionally, the original setup of the Wage and Employment Survey ended in 1994 and a new survey started in 1995 with even less information on worker characteristics.[10] Since this type of information is essential for our analysis, we use another data set to obtain information of the workers for the years 1995 to 1997. This data set is the *Structure of Earnings Survey (SES)*. This data set is created by

[10]For example, the question about the skills of the labor force was deleted from the WES in 1995.

Variable	Mean value
Wage and Employment Survey	
Hourly wage (guilders)	24.35
	(10.10)
Tenure (elapsed job duration; months)	148.08
	(111.69)
High skilled (fraction)	0.45
Production Survey	
Productivity (1000 guilders per year)	114.21
	(84.63)
Wage costs (1000 guilders per year)	69.01
	(15.92)
Wage floor (1000 guilders per year)	31.04
	(1.20)

Table 1: Summary statistics for the PS and WES data, averaged over 1993 and 1994 (The Netherlands).

matching three data sources: the (new) Wage and Employment Survey (WES), the Register System of the Social Security Funds (RSS) and the Dutch Labor Force Survey (LFS). The records of the WES and the RSS are matched with the LFS on the variables address, postal code, city, date of birth and gender. Only the records from the RSS that match with the LFS are considered for inclusion in the SES data set. Some observations of the data set are imputed by Statistics Netherlands. The number of observations is only around 22,000 for individuals working in the manufacturing industry. This is considerably lower than the number of observations in the original Wage and Employment Survey. More details about the SES data set can be found in Schulte Nordholt (1998).

We use the following variables. Like in the WES data, we have the registration number of the firm, the 2-digit SIC number of the firm, the city where the firm's head office is situated, and the hourly wage including extra payments for overtime hours. The tenure variable is in months, so it is more precise than in the old WES. We also use variables on gender and level the education, based on the highest level of education obtained from the International Standard Classification of Education.

Table 2 summarizes statistics on the most important variables of the data set. We emphasize that this data set is particularly useful when we look at the impact of worker characteristics on labor market frictions and its relation with offered wages. We use the PS data of 1995 to 1997 merge with the SES data. The number of firm observations is around 4000. The reduction of observations compared to earlier years is a result of a smaller subsample of firms with less than 20 employees.

4.2 The Danish data

We use the Pay and Performance data set for Denmark. This is a part of the Integrated Database for Labour Market Research (IDA). The Danish Bureau of Statistics has collected the data from a variety of sources used in the production of official statistics. The data set is all-encompassing, all Danish establishments and all Danish residents are included. The information is on a yearly basis, from 1980 to 1995. For our analysis, data from all Danish citizens is matched with information on the establishments to which they were affiliated each year.

A specific feature of the data set is that it enables us to group workers as employees at a specific establishment, while the labor market history of a worker can be described by a sequence of establishments. The labor market status, including establishment affiliation, for each person is evaluated at a specific date in November. The matching of establishments and workers is possible because establishments on an annual basis report the income of each employee, who is identified by his or her "personnummer" (personal number). This is a numeric code that each Dane is given at birth and which is the registration number for individuals in all governmental (and many private) databases. When information is collected for statistical purposes, the "personnummers" are used as identifiers, which enables the Danish Bureau of Statistics to match information from different sources.

An establishment is basically a production unit at a specific location and information on the market is limited to a detailed industrial code. In the construction of the database considerable attention has been paid to cases where establishments have moved or undergone other major changes. For example, if most workers at an establishment move to another physical location and the owner and industrial code for those workers are unchanged, then the establishment is considered a continuing establishment with another physical location. Attrition of individual persons is for all practical purposes not present in IDA, the Danish Bureau of Statistics keeps track of every single Danish resident and assigns him or her one and only labor market state and establishment in each year.

Variable	Mean
Tenure (elapsed job duration; months)	134.42
	(113.35)
Hourly wage	29.68
	(15.28)
Female	0.184
Education levels	
No completed primary education	0.009
Only primary education	0.113
Lower secondary education	0.275
Upper secondary education	0.442
Higher vocational	0.124
Masters degree	0.035
Ph.D.	0.002
Regions	
North	0.093
East	0.228
Center	0.049
Northern west coast	0.110
Southern west coast	0.142
South	0.262
Southeast	0.117
Number of individuals	21716

Table 2: Summary statistics for the SES data (The Netherlands).

The first set of variables that we use is related to individual worker information. This includes the worker, firm, and establishment identifiers, and information on occupation, level of education, sector, residence, labor market state, and earnings. The firm identifier changes over time when the ownership of the firm changes or when it changes location. Recall that the establishment identifier does not necessarily change at such instances.

There are six different occupation types: CEO, high-level management, low-level management, office worker, skilled blue collar worker and unskilled blue collar worker. Based on the type and years of education, we distinguish 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. It was not possible to obtain an accurate measure of the eduction level for all workers. We deleted these individuals when education level is taken into account for the analysis. The sector classification of the firm is based on the 1993 Standard Industry Classification (SIC). The place of residence gives one of the 276 cities (*kommune*). We aggregate this into regions (*amt*). The yearly earnings concern the job held at November, 1st.

We exclude individuals who were self-employed, out of the labor force or working for the public sector for some years between 1980 and 1995. It is likely that the behavior of such individuals, at least in a certain period, deviates substantially from the behavior that the model intends to describe. Moreover, we delete individuals who work in the industries agriculture, fishery, mining, financial services, education and medical services. These industries do not have information about firms and therefore inclusion of individuals who work in these industries does not add anything to our analysis.

The total number of observations in our data set is equal to 612,701 observations when we do not include education levels in our analysis. The number of observations is equal to 533,628 when we take this into account.

Table 3 lists the descriptives of the main variables of the data set. The first column describes the raw data set. The second column describes our sample before we created the education levels. The final columns describes our sample after deleting the observations without an accurate education level. We find that around half of the Danes only have primary education. This figure is much higher as was found from the Dutch data set. However, primary education in the Netherlands is only six years instead of up to ten years in Denmark. Moreover, we find that almost one third of the Danes live in Copenhagen. The second largest urban area is Århus, where around 10% of all Danes are living.

The second set of variables contains the business statistics of the firms. Only firms that have over 20 employees are included. There are observations for the years 1992 to 1997. The variables are basically the same as in the Dutch PS data. Specifically, we have the firm identifier, the total wage costs, the total value added, the firm size in November, both in number of employees and in number of full time equivalents (fte), and we have the value of the fixed assets.

Both the productivity level per worker and the wage costs per worker can be measured in either the physical unit or the number of full time equivalents. Note that both are averages for the whole company. Using the data from the individual workers, it is also possible to obtain wage costs per worker type. This can be done by taking the sum of earnings in the November job over all individuals with this type who are working in the firm in November. Table 4 summarizes the descriptive statistics for the business statistics of the firms.

There are two important differences between this data set and the Dutch data set. First, the Danish data set is a register based data set, while the data set for The Netherlands is based on a survey. The former can be expected to have a higher level of accuracy. A second important difference is the panel structure of the Danish data set. Since every Dane that ever worked in the private sector between 1980 and 1995 is in the data set, it is possible to follow these individuals over time. We use this in our empirical implementation. A third difference is that for each firm the Danish data contain records for all of its workers.

5 Estimation strategy

5.1 Identification of labor markets

The empirical analysis is based on a comparison of different markets. We therefore have to decide on a segmentation of the total labor market into unrelated (sub)markets. Initially, we assume that workers are homogeneous within a market and that a firm can only be active in one market, and we require that we can identify (i.e., observe the defining characteristics of) the market to which firms in the PS data belong. This is convenient because we only observe the total value added by a firm, and not the separate contributions to this by employees who may belong to different labor markets. We therefore assume that markets are defined by industry sector and region. We distinguish between 20 industries and 7 regions. We omit markets with less than 6 firms in the PS data or less than 26 workers in the WES data. This gives 66 different markets. For later purposes it is

Variable	Original	Homogenous workers	Heterogenous workers
Education levels			
Less than 7 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
Århus	0.119	0.112	0.114
Viborg	0.042	0.043	0.044
Nordjylland	0.089	0.091	0.092
Total number of observations	2870756	612701	533628

Table 3: Summary statistics for the individuals data set (Denmark).

Variable	Mean
Overall 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)
Distribution over 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
Århus	0.111
Viborg	0.046
Nordjylland	0.084

Table 4: Summary statistics for the firms' data set (Denmark).

[a]In Danish Kroner per year

relevant to point out that we remove those firms from the data that do not have workers who participated in the WES, because we cannot assign a region to such firms.

There are several reasons for why this characterization of what constitutes a separate labor market may be incorrect. First, each of these markets contains workers with different skill levels, and the sector and region specific labor market for high-skilled workers may be separated from (or 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 a specific industry sector. Since our data set is based on repeated cross sections of workers, it cannot be used to observe the numbers of workers who change industry over time. Instead, we use the Dutch Social Economic Panel (SEP) of Statistics Netherlands to investigate this. The SEP is a longitudinal panel survey of around 5000 families in The Netherlands. It started in 1984. Participants were interviewed twice a year until 1990. Since then, interviews are once a year. All members of the household who are 16 years or older are surveyed about their educational attainment, labor market behavior, income and wealth. In 1984, 3744 participants provided a valid response on the question concerning their industry sector. In 19% of these cases this is the manufacturing industry. When we follow this last group of workers over time, we find that in 1989 around 76% of them worked in a firm with the same 2-digit SIC code as the firm they worked for in 1984. For 1994 this reduces to 68%. It is difficult to obtain a very clear picture from these figures, because they include workers who did not change jobs at all. At most, they give an indication of the attachment to a particular industry. We are not able to identify the residence or the workplace of the respondents and therefore we are not able to investigate the attachment to the region.

In Denmark we distinguish more regions than in The Netherlands. This is justified by the geographical structure of Denmark, with many islands.

5.2 Estimation of the measure of frictions

The empirical analysis consists of two steps. In the first step, the measure of frictions is estimated for each market, using in the case of The Netherlands the WES data on individual wages and tenures.

Consider an on-the-job search model (recall that this describes the behavior of employed workers in the model of Subsection 2.2 and many equilibrium search models). For a job with a given time-invariant wage w, the exit rate out of the present job 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. As a result, the duration of a job with a given wage w has an exponential distribution with this parameter θ.[11] Ridder and Van den Berg (1999) show that the tenure (*i.e.* the elapsed job duration at the survey date), given the current wage, also has an exponential distribution with parameter θ, provided that two additional conditions are met: worker flows are in a steady state, and unemployed workers accept all wage offers. As discussed in Subsection 2.2, the latter is satisfied in equilibrium if workers are homogeneous or if the workers' reservation wages are below the wage floor in the market. Also, as we have seen in Subsection 2.2, under the two additional conditions, there is a simple relation between the wage offer distribution $F(w)$ and the distribution $G(w)$ of wages in a sample of currently employed workers. Consequently, the joint density of a worker's wage and tenure at the survey date can be expressed in terms of λ, δ and G.

For the years 1993 and 1994, the distribution of G within a market is estimated by using the empirical distribution of the wage data

$$\widehat{G}(w) = \sum_i s_i 1(w_i \leq w) \qquad \text{with } \sum_i s_i = 1$$

where the w_i's are the observed wages and the s_i's are the weights for the observations in the market under consideration. These weights are obtained by using information about the exact way in which the data is sampled. More precisely, the relative weights should be equal to 1 divided by the probability that an individual employee is sampled.[12] From the discussion of the previous paragraph, we know that the probability that an individual employee is sampled is equal to the probability that the firm is sampled multiplied by the probability that the worker is sampled from the file of the firm.

[11]In reality, making a job-to-job transition may involve costs. The empirical analysis in Van den Berg (1992) shows that these costs are only a minor determinant of the optimal strategy, and that they only have a small effect on θ.

[12]We have to divide by the total sum of these weights to guarantee that the weights sum up to one.

The log likelihood function for λ and δ within a market is based on the conditional distribution of tenure given the wage,

$$\log L = \sum_i -(\delta + \lambda\overline{F}(w_i))t_i + \log(\delta + \lambda\overline{F}(w_i))$$

where $\overline{F} := 1 - F$ can be expressed in terms of G, δ and λ, and where t_i denotes the tenure of individual i in the market under consideration. We have to take account of the fact that we only observe the year in which the employee started to work for his firm, so we have to aggregate over time intervals. Estimates of λ and δ are obtained by maximization of this likelihood. One may argue that the likelihood does not take account of the earnings distribution G and the exact way in which workers and firms are sampled. However, it is possible to show that taking this into account only adds terms that are dependent on G but not on λ or δ.

With the Danish data, the estimation of the transition parameters is somewhat different. We use the panel structure of the data set by following individuals over the time period 1992 to 1994. In these years, we observe the employment status of this individual (*i.e.* employed or unemployed) and when employed, we are able to identify the establishment of this individual. We make the assumption that individuals change job whenever their establishment changes. This requires some discussion, as the empirical analyses in the second stage are based on firm data instead of establishment data. However, as mentioned in Subsection 4.2, firm identifiers may change from year to year even when the firm remains essentially the same. This makes it difficult to establish whether an individual makes a transition on the basis of these identifiers. 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.

Based on the above information, it is possible to distinguish thirteen different employment histories. For example, an individual can be observed to be employed in 1992, employed in another establishment in 1993 and unemployed in 1994. The probabilities of these complete histories are dependent on the probabilities of the initial states, employment and unemployment. These are equal to $\lambda_0/(\delta+\lambda_0)$ and $\delta/(\delta + \lambda_0)$. In addition, the probabilities of complete histories are dependent on the distributions of the duration of an unemployment spell and a job spell. These are both exponential with parameters equal to λ_0 and $\delta+\lambda\overline{F}(w)$. We do not have any information on the exact transition date or on the new wage. This implies that we have to integrate over the conditional distributions of the durations of the unemployment and job spells. We demonstrate this procedure in Appendix 1 to this paper.[13] To obtain the likelihood equation, we define $P_i(\lambda_0, \lambda, \delta)$ as the probability that an individual is in state i and let N_i be the number of individuals observed that are in state i. The likelihood is equal to

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

Note that λ_0 is a nuisance parameter here. Also note that 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. Also note that the results for Denmark can be expected to be less sensitive to the assumption that the labor markets are in stead state than the Dutch results, which are solely based on retrospective tenures.

If we allow for skill heterogeneity, then we require measures of frictions for each combination of industry sector, region, and skill level. In both the Dutch and the Danish 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 industry, regional, and skill effects (e.g., $\lambda \equiv x'\beta_\lambda$), and we estimate them simultaneously for all markets.

In case of the Dutch data, a small number of observations per market also complicates the non-parametric estimation of G. We therefore take a semi-parametric approach when we use the SES data to allow for detailed skill heterogeneity. Specifically, we specify F along the lines of Gallant and Nychka (1987) as a Hermite series (see Gabler, Laisney and Lechner, 1993, Koning, Van den Berg and Ridder, 2000, and Van der Klaauw and Koning, 2001, for other applications). We assume that $\log w = \mu + \epsilon$, where the density of ϵ is given by

$$h(\epsilon) = \left(\sum_{i=0}^{K} \alpha_i \epsilon^i \right)^2 \exp\left(-\left(\frac{\epsilon}{\gamma}\right)^2 \right) \Big/ S$$

[13]The procedure has been used before by Koning et al. (2000). They analyze the Danish individual data by regressing the mean earned wage on friction indicators. They do not have firm data, and they examine the mean wage across workers instead of firms. Bunzel et al. (2000) also use the Danish individuals data to estimate frictional parameters, as part of the structural estimation of a specific equilibrium search model.

where K is an integer and S is simply a normalizing constant. Additionally, $\alpha_0 = \pi^{-1/4}$, α_1 is chosen such that $\mathrm{E}(\epsilon) = 0$, and $\alpha_i; i = 2, \ldots K$ and γ are parameters to be estimated. A very wide range of shapes can be obtained for $h(\epsilon)$ even when K is not very high. In this case, $\log \mu$ is also taken to be additive in the three market identifiers x.

The SES data contain elapsed job durations in months, so we do not have to aggregate the likelihood function over yearly time intervals.

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 i and k denote the market i and the firm k. The endogenous variable is then denoted by $\mathrm{E}_k(w_{ik})$ and the explanatory variables are $\mathrm{E}_k(p_{ik})$, $\log \eta_i$ and the wage floor $\underline{w}_i$ in market i. The wage floor is the maximum of the national minimum wage and the sector-specific minimum wage. Both $\mathrm{E}_k(w_{ik})$ and $\mathrm{E}_k(p_{ik})$ are obtained from the firm data (wage costs and average revenue product averaged over the two years for each market).

The basic specification of the regression equation is:

$$\mathrm{E}_k(w_{ik}) = \alpha_0 + \alpha_1 \mathrm{E}_k(p_{ik}) + \alpha_2 \underline{w}_i + \alpha_3 \log \eta_i + \varepsilon_i \qquad (9)$$

The parameter of interest is α_3, and we test whether it is negative. Specification (9) is ad hoc (or "reduced-form"). To some extent it 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 $\mathrm{E}_k(p_{ik})$ and the measure of frictions, and we separately allow for λ_i and δ_i (instead of only by way of η_i).

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 $\mathrm{E}_k(w_{ik}), \mathrm{E}_k(p_{ik})$, and η_i are estimated instead of observed (albeit they are estimated from very large samples). We take this into account when we estimate the standard deviations of the regression parameters. Appendix 1 to this paper explains a method to estimate the standard deviations of λ and δ when we use a non-parametric distribution of G. The standard deviations of the regression estimates are derived by using the delta method. We also estimate standard errors using bootstrapping.

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 above results are biased. 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, consider the mean wage regression equation for market[14] i, j, specified analogously to equation (9),

$$\mathrm{E}_k(w_{ijk}) = \alpha_{0j} + \alpha_{1j}\mathrm{E}_k(p_{ijk}) + \alpha_{2j}\underline{w}_{ij} + \alpha_{3j}\log\eta_{ij} + \varepsilon_{ij} \tag{10}$$

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

$$\mathrm{E}_k(w_{ik}) = \alpha_0 + \alpha_1\mathrm{E}_k(p_{ik}) + \alpha_2\mathrm{E}_j(\underline{w}_{ij}) + \alpha_3\mathrm{E}_j(\log\eta_{ij}) + \varepsilon_i$$

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, $\underline{w}_i \equiv \mathrm{E}_j(\underline{w}_{ij})$. This is unlikely to be true since in the data $\underline{w}_i = \min_j\{\underline{w}_{ij}\}$. Thirdly, the amount of frictions $\log\eta_{ij}$ is the same for all skill groups (otherwise the η_i 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

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

be dealt with by using the worker data. With the Dutch data, we estimate the wage distribution G of all workers with skill type j in market i (i as before defines the industry and region) and use the relation between F and G to estimate the mean of the skill-specific F, for each i, j. In particular, we exploit that

$$\mathrm{E}_{F_{ij}}(w) = \underline{w}_{ij} + \int_{\underline{w}_{ij}}^{\infty} \frac{1 - G_{ij}(w)}{1 + kG_{ij}(w)} dw \tag{11}$$

In the Danish data, we observe all workers in the firm, so we can directly quantify $\mathrm{E}_k(w_{ijk})$, which is an advantage over the Dutch data. In both cases we replace the mean wage costs by the mean gross wage, as the endogenous variable. The wage costs are the price of labor from the perspective of the employer, whereas the gross wage is the price of labor from the perspective of the worker.

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

$$p_{ijk} = p_{ik}^0 + \psi_j \tag{12}$$

where p_{ik}^0 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 industries and regions. In fact, we only need an aggregated version of (12),

$$\mathrm{E}_k(p_{ijk}) = \mathrm{E}_k(p_{ik}^0) + \psi_j \tag{13}$$

By aggregating this over j we obtain,

$$\mathrm{E}_k(p_{ik}) = \mathrm{E}_k(p_{ik}^0) + \sum_j \pi_{ij}\psi_j \tag{14}$$

where π_{ij} is the fraction of workers with skill j in market i. Note that the left-hand side and the π_{ij}'s are observable, while the ψ_j's are parameters, and the $\mathrm{E}_k(p_{ik}^0)$ terms are unobserved and potentially different across markets.

By substituting (13) and (14) into equation (10) we obtain

$$\mathrm{E}_k(w_{ijk}) = \alpha_{0j} + \alpha_{1j}\mathrm{E}_k(p_{ik}) + \sum_{x \neq j} \alpha_{1j}(\psi_j - \psi_x)\pi_{ix} + \alpha_{2j}\underline{w}_{ij} + \alpha_{3j}\log \eta_{ij} + \varepsilon_{ij} \tag{15}$$

for all j. Note that we may normalize $\psi_1 := 0$. For two skill levels, equation (15) simplifies to

$$\mathrm{E}_k(w_{iuk}) = \alpha_{0u} + \alpha_{1u}\mathrm{E}_k(p_{ik}) + \alpha_{1u}(\psi_u - \psi_s)(1 - \pi_i) + \alpha_{2u}\underline{w}_{iu} + \alpha_{3u}\log\eta_{iu} + \varepsilon_{iu} \tag{16}$$

$$\mathrm{E}_k(w_{isk}) = \alpha_{0s} + \alpha_{1s}\mathrm{E}_k(p_{ik}) + \alpha_{1s}(\psi_s - \psi_u)\pi_i + \alpha_{2s}\underline{w}_{is} + \alpha_{3s}\log\eta_{is} + \varepsilon_{is} \tag{17}$$

where subscripts u and s denote low skill and high skill, respectively, and π_i denotes the fraction of low skilled workers in market i.

Equation (15) is very similar to (9), the only substantial difference being that the π_{ij}'s are added as explanatory variables. The parameters of interest are the α_{3j}'s for the different skill levels. An equation-by-equation analysis of identification suggests that one needs to have more values of i (i.e., more combinations of sectors and regions) than skill levels. However, since the $\psi_j - \psi_x$ parameters appear in equations for different j, 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 sectors and regions. For example, one may adopt a more flexible factor loading structure.

An alternative motivation for equation (15) is as follows: start with equation (9), take $\mathrm{E}_k(w_{ijk})$ as the endogenous variable, and add the π_{ix} as explanatory variables in the hope that these correct for the effects of skill heterogeneity within market i. This gives an ad hoc interpretation to equation (15). In this case, there are no cross-equation parameter restrictions. Of course, one may test whether these restrictions hold.

6 Results for The Netherlands

6.1 Results without skill heterogeneity

We estimated the labor market friction parameters for each market separately, where we use a non-parametric specification for G. Most of the estimates of λ, δ and η are in the ranges $(0.004, 0.02)$, $(0.004, 0.006)$ and $(0.20, 0.65)$ per month, respectively. Table 5 summarizes the estimates in more detail. We find that the variance in the friction parameters over regions is somewhat smaller than the variance over sectors. The difference is not very large.

We present plots of the residuals of the estimated friction parameters in Figure 2. When the dots in this picture are on the 45 degrees line, then it indicates a

	λ	δ	k	η
Simple means of the raw estimates				
Over all markets	0.012	0.005	2.64	0.478
	(0.034)	(0.0018)	(6.83)	(0.2949)
Over regions	0.014	0.006	2.73	0.478
	(0.010)	(0.0003)	(1.92)	(0.1032)
Over sectors	0.012	0.006	2.50	0.479
	(0.012)	(0.0009)	(2.31)	(0.1033)
Means, weighted by market size				
Over all markets	0.006	0.005	1.38	0.559
	(0.010)	(0.0014)	(2.08)	(0.284)
Over regions	0.006	0.005	1.38	0.559
	(0.002)	(0.0007)	(0.45)	(0.1232)
Over sectors	0.006	0.005	1.38	0.559
	(0.004)	(0.0007)	(0.71)	(0.1245)

Table 5: Means of the estimated friction parameters (standard deviations of the distribution of the estimated parameters in parentheses)

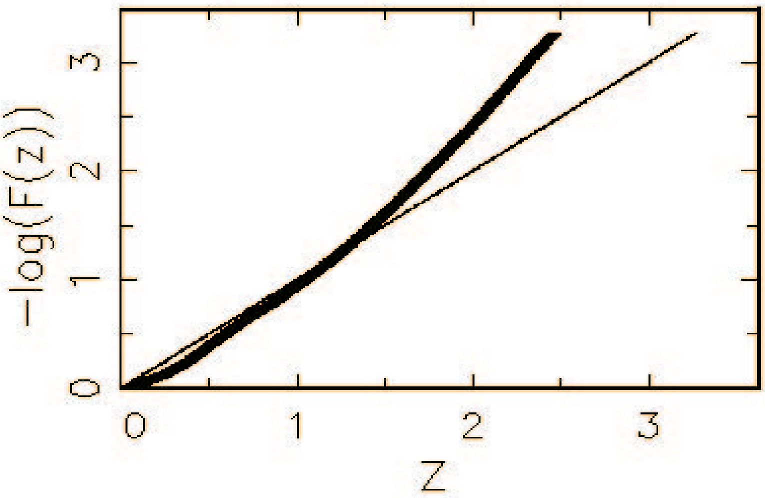

Figure 2: Residual plots of the elapsed job durations, where $z = (\delta + \lambda\overline{F}(w))t$ is the integrated hazard. Note that over 90% of the observations satisfy the restriction that the integrated hazard is smaller than 2

good fit of the model (Lancaster, 1990). We find that the deviation with the 45 degrees line is not very large as long as the values of the integrated hazard are lower than 2. This inequality is true for around 91 percent of the observations. The deviation with the 45 degrees line becomes substantial for larger values. Although these observations can be interpreted as outliers, it may also indicate that (elapsed) job durations are either not exponentially distributed or that there is a lot of heterogeneity that is ignored in our analysis. Later on we deal with the second problem.

The estimation results of our original equation are in the first column of Table 6. The measure of the wage and productivity levels is in hours. The regression estimate of the frictions indicator is negative as expected, but obviously it is insignificant. Additionally, we find that the effect of the productivity level is positive and significant, though the level of the estimate is low. The effect of the minimum wage is insignificant.

We perform a range of sensitivity analyses. First, we allow for interaction terms between $\mathrm{E}_k(p_{ik})$ and η_i. Secondly, we include higher moments of the distribution of p within markets. Both modifications are supported by the theoretical model of Bontemps, Robin and Van den Berg (2000). The first sensitivity check is illustrated in the second column of Table 6. We find that the effect of the

	Original	Sensitivity analysis		
Constant	17.70	20.05	17.31	19.47
	(4.15)	(4.07)	(4.58)	(4.69)
Productivity	0.291	0.358	0.337	0.394
	(0.045)	(0.088)	(0.065)	(0.108)
Minimum wage	0.258	0.197	0.232	0.211
	(0.174)	(0.181)	(0.205)	(0.207)
$\log \eta$	-0.289	2.92	-0.494	2.43
	(0.632)	(2.64)	(0.748)	(2.91)
$\eta(\mathrm{E}_k(p_{ik}) - \underline{w})$	–	-0.151	–	-0.137
		(0.125)		(0.141)
$\mathrm{sd}(p_{ik})/\mathrm{E}_k(p_{ik})$	–	–	-9.13	-8.45
			(8.16)	(7.05)
R^2	0.76	0.78	0.78	0.80
Number of observations	66	66	66	66

Table 6: Mean wage regression results without skill heterogeneity

interaction term is negative, but insignificant. The effect of $\log \eta$ turns from a negative into a positive value, and therefore frictions might either have a positive or negative effect on wages, depending on the value of η and the difference between the productivity level and the minimum wage. The third column of Table 6 summarizes the results of the second sensitivity analysis. We find a negative impact of the coefficient of variation on the wages, but the effect is insignificant as well. This goes against the theoretical prediction of Bontemps, Robin and Van den Berg (2000). The final column illustrates the results of a combination of both sensitivity checks. The additional terms are invariably insignificant, and the main result is not affected.

Figure 3 graphically illustrates the relationship between the labor market frictions and the mean profit margin per sector. This picture shows the relatively weak evidence for the hypothesis that frictions have a negative impact on the mean wage.

The results obtained in the previous paragraph could be due to differences in the capital stock of firms. Firms with larger capital stocks need to make bigger investments in order to keep their stock at the same level. Therefore, the productivity level as measured up till now might not be a good indicator of what is left for workers after costs are deduced from the sales. We do not have any

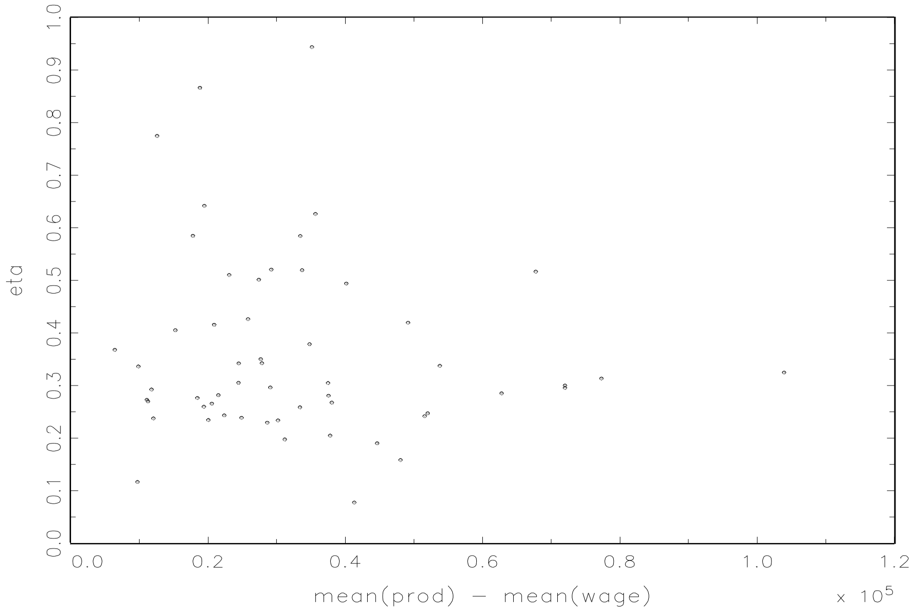

Figure 3: Scatter plot of the relationship between $\mathrm{E}_k(p_{ik}) - \mathrm{E}_k(w_{ik})$ and η_i.

information about the capital stock of a firm, but we know the value of the depreciation costs. In order to correct for the costs of capital, we run a regression of productivity on the deprecation costs. We derive the 'alternative' productivity levels, $\widehat{p_i}$, from

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

where $\widehat{c}_0$ and $\widehat{c}_1$ result from the regression of the deprecation costs, d_i on the value added, p_i. We expect that $\widehat{c}_1$ is equal to one, but this does not necessarily have to hold when firms use different accounting techniques to value their fixed assets or when firms use different techniques to calculate their depreciation costs. 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 (1999) for models in which this process is described in a search framework. The results of the regression are summarized in Table 7. We find the regressor of the depreciation costs to be significantly bigger than one.

Table 8 lists the results using the capital correction term. We find that the absolute value of the regressor of the labor market frictions increases sharply, but it is still insignificant.[15]

[15]Note that we did not make the assumption that variance of productivity levels is the same among markets. However, when these are different, the OLS estimates of the regression of the

Variable	Estimate
Constant	60.889
	(4.894)
Depreciation costs	2.594
	(0.327)
R^2	0.425
Standard deviation of regression	30.596

Table 7: Results of the regression of productivity on deprecation costs.

Variable	Estimate
Constant	36.628
	(5.06)
Productivity	0.251
	(0.028)
Minimum wage	-0.584
	(0.236)
$\log \eta$	-0.814
	(0.677)
R^2	0.71
Number of observations	56

Table 8: Mean wage regression results without skill heterogeneity, using capital correction.

6.2 Results with limited skill heterogeneity

We start with the inclusion of heterogeneity in our analysis by looking at the data of the Wage and Employment Survey. We use the classification of workers in high and low skilled, as discussed in the data section. We use the subscript s to label parameters that are related to the high skilled workers. Similarly, we use the subscript u for low skilled workers. Tables 9 and 10 present results of the means of our estimated values. We find λ to be larger and δ to be lower for high skilled workers using the means of the raw estimates. The difference is not very large and disappears when we take the market size into account.

Tables 11 and 12 list the estimation results. We find a positive rather than a negative effect of search frictions on wages. This relationship is significant for the high skilled workers. We perform the same sensitivity analyses as in Table 6. These are listed in columns 2 to 4 in Tables 11 and 12. The relationship between frictions and offered wages is not significant in most specifications. Hence, the main result is not affected. In addition, we include the frictions indicator for one skill level into the equation for the other skill level and vice versa. These terms are insignificant, and again the main result is not affected.

The value of $\psi_s - \psi_u$ can be derived from dividing the regression estimates of π_u (or minus the estimate of $1 - \pi_u$) in the equation for high (low) skilled workers by the regression estimates of $\mathrm{E}_k(p_{ik})$. This provides us with two estimates of $\psi_s - \psi_u$ for any of the model specifications and hence our analysis is overidentified in that respect. For example, we find that $\psi_s - \psi_u$ is equal to 33.94 from the first column of Table 11. It is equal to 16.58 using the estimates of the first column of the table for the low skilled workers. We test whether these estimates significantly differ from each other. These tests are found in Table 13. Although the differences in the values of $\psi_s - \psi_u$ are substantial, we find that the t-values do not indicate that these are significant.

Table 14 lists the results of the regression of high and low skilled workers using the capital correction method described earlier in this section. Again, there is no significant impact of the search frictions on the offered wages.

6.3 Results with detailed skill heterogeneity

As stated before, the Wage and Employment Survey does not contain many variables on worker characteristics. Therefore, we use the Structure of Earnings Survey to further investigate the impact of worker heterogeneity. We include two

productivity level on the depreciation costs does not lead to efficient estimates. Additionally, the standard errors as presented in Tables 7 and 8 are biased. We do not elaborate on this.

	λ	δ	k	η
Simple means of the raw estimates				
Over all markets	0.014	0.006	3.04	0.463
	(0.024)	(0.0024)	(5.76)	(0.3121)
Over regions	0.014	0.005	3.02	0.458
	(0.008)	(0.0005)	(1.78)	(0.1225)
Over sectors	0.013	0.005	2.93	0.459
	(0.011)	(0.0010)	(2.70)	(0.1266)
Means, weighted by market size				
Over all markets	0.008	0.005	1.89	0.559
	(0.010)	(0.0016)	(2.61)	(0.2703)
Over regions	0.008	0.005	1.89	0.559
	(0.005)	(0.0008)	(1.16)	(0.1866)
Over sectors	0.008	0.005	1.89	0.559
	(0.005)	(0.0009)	(1.06)	(0.1479)

Table 9: Means of the estimated friction parameters for high skilled workers (standard deviations of the distribution of the estimated parameters in parentheses)

	λ	δ	k	η
Simple means of the raw estimates				
Over all markets	0.013	0.006	2.94	0.465
	(0.026)	(0.0021)	(6.99)	(0.3070)
Over regions	0.014	0.006	3.30	0.459
	(0.009)	(0.0004)	(2.55)	(0.1145)
Over sectors	0.013	0.006	2.90	0.457
	(0.009)	(0.0008)	(2.57)	(0.1201)
Means, weighted by market size				
Over all markets	0.008	0.005	1.84	0.510
	(0.013)	(0.0014)	(3.36)	(0.2872)
Over regions	0.008	0.005	1.84	0.510
	(0.004)	(0.0005)	(0.84)	(0.1606)
Over sectors	0.008	0.005	1.84	0.510
	(0.005)	(0.0006)	(1.06)	(0.1466)

Table 10: Means of the estimated friction parameters for low skilled workers (standard deviations of the distribution of the estimated parameters in parentheses)

	Original	Sensitivity analyses			
Constant	17.57	17.56	17.39	17.30	17.54
	(5.15)	(5.37)	(4.57)	(4.79)	(8.08)
Productivity	0.033	0.032	0.007	0.005	0.032
	(0.022)	(0.062)	(0.085)	(0.092)	(0.033)
Minimum wage	0.504	0.504	0.504	0.504	0.505
	(0.225)	(0.220)	(0.215)	(0.215)	(0.350)
$\log \eta_s$	5.79	5.79	5.58	5.47	5.81
	(2.78)	(3.28)	(3.00)	(1.90)	(4.91)
Share of unskilled workers	1.12	1.12	1.26	1.27	1.12
	(3.04)	(2.97)	(0.97)	(2.98)	(3.05)
$\eta_s(\mathrm{E}_k(p_{ik}) - \underline{w})$	–	0.0005	–	-0.006	
		(0.161)		(0.140)	
$\mathrm{sd}(p_{ik})/\mathrm{E}_k(p_{ik})$	–	–	5.03	5.06	
			(15.60)	(15.68)	
$\log \eta_u$	–	–	–	–	-0.020
					(4.64)
R^2	0.72	0.72	0.73	0.73	0.72
Number of observations	56	56	56	56	56

Table 11: Mean wage regression results for high skilled workers

	Original	Sensitivity analyses			
Constant	18.42	17.30	18.41	17.30	18.25
	(5.89)	(4.12)	(3.16)	(3.68)	(6.72)
Productivity	0.038	0.009	0.037	0.010	0.035
	(0.016)	(0.047)	(0.034)	(0.049)	(0.023)
Minimum wage	0.077	0.108	0.076	0.109	0.126
	(0.206)	(0.169)	(0.158)	(0.049)	(0.262)
$\log \eta_u$	3.11	1.74	3.10	1.74	3.01
	(2.20)	(2.73)	(0.59)	(1.84)	(3.73)
Share of skilled workers	-0.63	-1.33	-0.61	-1.35	-1.73
	(1.80)	(2.41)	(1.80)	(2.68)	(2.42)
$\eta_u(\mathrm{E}_k(p_{ik}) - \underline{w})$	–	0.062	–	0.062	–
		(0.107)		(0.077)	
$\mathrm{sd}(p_{ik})/\mathrm{E}_k(p_{ik})$	–	–	0.267	-0.189	
			(6.09)	(11.89)	
$\log \eta_s$	–	–	–	–	0.160
					(2.25)
R^2	0.56	0.58	0.56	0.58	0.56
Number of observations	59	59	59	59	59

Table 12: Mean wage regression results for low skilled workers

	Original	Sensitivity analyses			
T-statistic	0.159	-0.116	0.070	0.025	-0.126

Table 13: T-statistics for the test of equality of the effect of the difference between productivity levels, using the estimates for high and low skilled workers

Variable	High-skilled	Low-skilled
Constant	9.227	13.704
	(5.726)	(4.209)
Productivity	0.034	0.023
	(0.037)	(0.026)
Share of unskilled workers	2.835	·
	(2.116)	
Share of skilled workers	·	1.810
		(0.786)
Minimum wage	0.828	0.316
	(0.335)	(0.172)
$\log \eta_s$	4.80	·
	(3.77)	
$\log \eta_u$	·	2.66
		(1.94)
R^2	0.70	0.45
Number of observations	43	45

Table 14: Mean wage regression results with skill heterogeneity, using capital correction.

main characteristics in our analysis: education level and gender. For the education level, we use the seven different levels that can be derived from the first digit of the International Standard Classification of Education (ISCED) as summarized in Table 2. Since there are only a few individuals in manufacturing with a Ph.D., we take levels 6 and 7 together.

(P.M.)

7 Results for Denmark

We replicated our main analysis for Denmark. Table 15 summarizes the results of our estimates of the friction parameters. In contrast to our results for The Netherlands, we find that the job offer arrival rate of employed workers increases with education level. The job offer arrival rate is higher for workers with at least 8 years of primary schooling and it stays rather constant for the other education levels. The job separation rate is the highest for those with exactly 8 years of primary schooling and it decreases for higher education levels. Compared with the remainder of Denmark, Copenhagen has low job offer arrival rates for the unemployed, while they are high among 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 in the textiles industry as well is in the construction sector and the hotels and restaurants sector.

Table 16 summarizes the results for the mean wage regression equation for homogeneous workers (*i.e.* equal education levels). In contrast with our results from the Netherlands, we find a negative and significant impact of search frictions on wages. The influence is stronger for the equation where we use wage costs as measured in full time equivalents. The productivity level has a positive and significant influence on the wage offer.

Table 17 lists the results for the regression equation with heterogeneous workers. We find that most education levels (*i.e.* 7 out of 10) predict a negative and significant relationship between wages and search frictions. The relationship is strongest for individuals with a masters degree. It is insignificantly negative for the individuals with a public exam and it is insignificantly positive for individuals with a short education or bachelors degree. There is a positive relationship between wage costs and productivity.

We did some additional analysis for heterogeneous workers. First, we included gender in the analysis. Second, we looked at different occupation levels. The conclusions from these exercises do not deviate substantially from those presented.

	$\log \lambda_0$	$\log \lambda$	$\log \delta$
Constant	-3.224	-3.411	-5.118
	(0.019)	(0.027)	(0.012)
Education levels			
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)

Table 15: Estimation results for the friction parameters (Denmark).

	$\log \lambda_0$	$\log \lambda$	$\log \delta$
Regions			
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)
Århus	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 15: Estimation results for the friction parameters (Denmark; continued).

	$\log\lambda_0$	$\log\lambda$	$\log\delta$
Industries			
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 of likelihood =	-773480		

Table 15: Estimation results for the friction parameters (Denmark; continued).

Variable	Number of workers	Full time equivalents
Constant	112.1	128.3
	(9.85)	(7.19)
Productivity	0.185	0.134
	(0.017)	(0.021)
$\log \eta$	-8.66	-19.60
	(4.64)	(3.12)
R^2	0.36	0.38
Number of observations	235	235

Table 16: Mean wage regression results without skill heterogeneity (Denmark).

	1	2	3	4	5	6	7	8	9	10
Constant	230.4	-40.25	-127.3	97.01	-115.8	180.3	914.2	297.2	1165	25.83
	(36.11)	(225.3)	(110.9)	(48.91)	(55.37)	(22.97)	(1713)	(324.5)	(951.2)	(8517)
Productivity	0.0846	0.0706	0.0661	0.0844	0.0776	0.0534	0.0849	0.0871	0.0973	0.1446
	(0.0259)	(0.0204)	(0.0216)	(0.0213)	(0.0251)	(0.018)	(0.0302)	(0.024)	(0.0685)	(0.0935)
Shares in workforce										
Less than 8 years in primary	·	349.3	389.5	108.5	250.6	-49.87	-738.5	-158.5	-689.6	-72.22
		(253.6)	(129.2)	(49.27)	(55.98)	(21.9)	(1784)	(341.6)	(924.3)	(8470)
8 years in primary school	-262	·	-10.76	59.57	-7.79	198.5	-546.4	-354.2	-1230	399.1
	(142.8)		(179.6)	(100.3)	(118.9)	(82.81)	(1632)	(303.7)	(1188)	(8391)
9 years in primary school	-259.2	-120.4	·	-411	305	-246.9	-1013	-136.3	-968.9	-332.1
	(96.93)	(276.4)		(101.9)	(117.1)	(56.94)	(1740)	(275)	(954.9)	(8098)
10 years in primary school	-255.4	-56.8	50.49	·	272.9	-94.7	-832.9	-247.6	-1115	-515.8
	(54.73)	(236.5)	(146)		(70.21)	(34.59)	(1708)	(330.3)	(954.9)	(8831)
Highschool	-291.2	-64.94	39.47	-125.5	·	-13.75	-887.2	-182.3	-892.8	-346.5
	(40.03)	(245.2)	(109.9)	(63.15)		(26.94)	(1663)	(349.9)	(947.1)	(8698)
Apprenticeship	-106.1	140.4	175.8	-9.652	277.9	·	-769.8	-73.33	-686.3	67
	(32.92)	(226.2)	(120.6)	(47.39)	(52.74)		(1692)	(328.5)	(1004)	(8467)
Public exam	-525	-295.6	-28.55	-359.3	401.2	-35.52	·	254.7	-181.4	847.8
	(372)	(366.8)	(328.3)	(266.3)	(320.5)	(242.1)		(577.8)	(1668)	(11440)
Short education	159.2	266.7	405.5	-144.4	101.5	-360.7	-1089	·	-685.8	962.9
	(179.1)	(241.2)	(141.9)	(141.2)	(164.3)	(119.6)	(2022)		(1436)	(7155)
Bachelors degree	159.5	259.4	483.1	533.1	832.8	506.2	-662.6	119.7	·	72.89
	(179.7)	(373.1)	(166.8)	(138.3)	(159.5)	(137.6)	(2015)	(417.5)		(9631)
Masters degree	-1074	-593.7	-1204	-1083	-307.2	-1555	-725.2	-909.6	-2950	·
	(673.1)	(596.9)	(518.1)	(536.5)	(617.2)	(505.8)	(2873)	(425.6)	(3058)	
$\log \eta$	-25.58	-18.95	-28.93	-22.98	-18.17	-22.72	-8.959	3.282	26.86	-83.05
	(7.29)	(6.992)	(7.952)	(9.037)	(9.905)	(10.75)	(12.99)	(7.706)	(28.03)	(41.58)
R^2	0.501	0.608	0.631	0.546	0.498	0.518	0.415	0.567	0.378	0.419
Number of observations	193	193	194	194	194	194	168	192	161	77

Table 17: Mean wage regression results with skill heterogeneity (Denmark).

8 Investigation of assortative matching

As set out in Section 1 and Subsection 2.4, models with two sided sorting do not always agree with our hypothesis that wages decline with search frictions. This section investigates whether two sided sorting is relevant in the Dutch markets that we analyze. The most likely form of two sided sorting, and the one that is discussed most in the literature, is positive assortative matching. This section investigates the possible existence of positive assortative matching in the Dutch labor market. In addition, with a positive empirical relation between average skill level and firm-specific productivity, we make an effort to distinguish between an explanation for this based on two-sided sorting and an explanation based on self-selection of workers. It should be stressed that the inference in this section is more speculative than in the rest of the paper, in the sense that we do not aim to impose the same degree of consistency between theoretical concepts and relations on the one hand, and empirical specifications on the other.

We emphasize that positive assortative matching is an equilibrium outcome instead of an assumption in the literature of models with two sided sorting. The basic result is that positive assortative matching occurs whenever two types (in our case workers and firms) are complements. We refer to Shimer and Smith (2000) for a more detailed analysis of this supermodularity assumption. For our analysis, this implies that high skilled workers are more productive at high productive firms than they are at low productive firms. In addition, low skilled workers may be more productive at high productive firms, but the difference must be lower than the difference of high skilled workers. This implies that in our analysis, in which the workers' and firms' productivity inputs are assumed to be perfect substitutes, (denoted by ψ_j and p_0), assortative matching can never be an equilibrium outcome. In fact, workers will be indifferent in matching with a low productive firm or search further for a high productive firm, since they are always able to bargain over the wage level. We ignore this problem in this section and focus on the existence of assortative matching from the data, maintaining our assumption of perfect substitutes. In that sense, we only test whether there is a possibility for positive assortative matching and this would imply that the model versions of the previous sections were misspecified. However, we are not able to conclude anything from this with respect to its consequences on the relationship between wages and search frictions.

For our analysis, this implies that high p^0_{ik} firms match with skilled workers. We investigate this as follows: consider two firms: k_1 and k_2. According to equation (12),

$$p^0_{ik_1} - p^0_{ik_2} = p_{ik_1} - p_{ik_2} + (\psi_s - \psi_u)(\pi_{ik_1} - \pi_{ik_2}) \tag{18}$$

where π_{ik_1} is the share of unskilled workers in firm k_1. Additionally, we specify the following relationship

$$p^0_{ik_1} - p^0_{ik_2} = \beta_0 + \beta_1(\pi_{ik_2} - \pi_{ik_1})$$

This equation states that there is a direct relationship between the firms' productivity levels and the share of high skilled workers. Positive assortative matching would imply that $\beta_1 > 0$. Now, substitute this equation into equation (18). This gives

$$p_{ik_1} - p_{ik_2} = \beta_{0_i} + (\beta_{1_i} + \psi_s - \psi_u)(\pi_{ik_2} - \pi_{ik_1}) \tag{19}$$

To test whether β_{1_i} is positive, we can proceed as follows: we take one firm as being the k_1 firm and the other firms are the k_2 firms. This implies that we observe the difference of productivity levels on the right hand side of equation 19. It is less straightforward to obtain observations of the differences in the percentage of unskilled workers. This is due to the problem that in most cases only a few observations of the individual workers in the firm are given. Although this might bias the results somewhat, we neglect this problem and take the observed percentages of unskilled workers in the firms' samples as estimates for the total percentage of low skilled workers. At this stage, the sampling procedure of individuals in firms, *i.e.* small firms have to provide information of all their workers, is somewhat fortunate for our analysis.

The above procedure gives an estimate of β_1 for each segment i. This says for each segment to what extent high-skilled workers are at high-productivity firms. This can indicate that we are in a "two-sided sorting model" world with positive assortative matching (i.e., a demand driven explanation), but it could also result from $\eta_{is} < \eta_{iu}$ in an equilibrium search model world, where high-skilled workers move quickly to high-wage firms which have high p^0_{ik} (i.e., a supply driven explanation). Note that if the demand driven explanation dominates then this is difficult to reconcile with the empirical analyses in the previous sections that show that frictions have a negative effect on wages. This is because we interpret the latter as evidence that firms are constrained in their labor demand.

In the first world, positive assortative matching is more likely as equilibrium outcome if there are few frictions. So the magnitude of β_{1_i} should be negatively

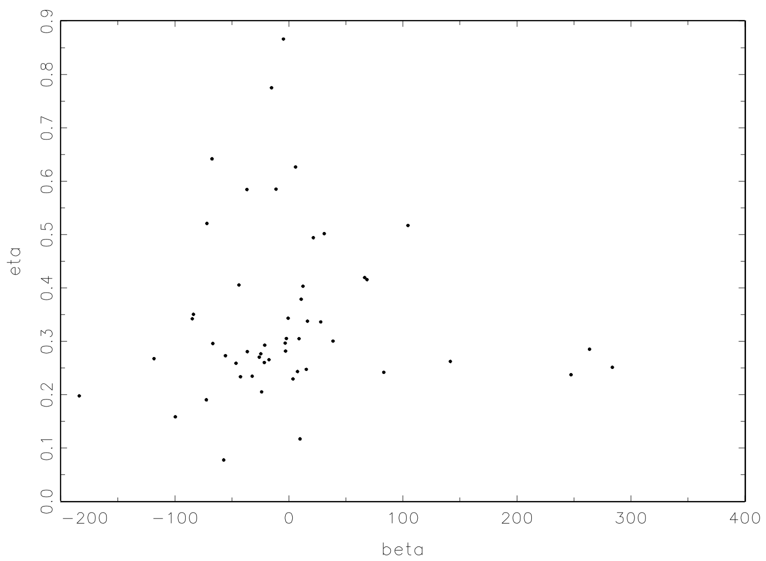

Figure 4: Results for the assortative matching analysis, with $\widehat{\beta}_1$ based on the estimated value of $\psi_s - \psi_u$ for the high skilled individuals and η being the overall labor market frictions

correlated with (the average of) η_{is} and η_{iu}. In the second world, positive assortative matching is more likely as equilibrium outcome if there are much fewer frictions for the high skilled than for the low skilled. So the magnitude of β_{1_i} should be negatively correlated with say the difference of η_{is} and η_{iu}. Note that the effect of the amount of frictions for the low skilled η_{iu} is particularly informative on which explanations fits the data best. Stated somewhat informally: if frictions for the low skilled are low then in a "two-sided sorting model" world they end up at low-productivity firms whereas in an "equilibrium search" world they end up at high-productivity firms.

Figures 4, 5 and 6 show the relationship between β_1 and the friction parameter η. We use the levels of $\psi_s - \psi_u$ using the regression estimates for the high skilled workers only. Using those of the low skilled workers would not give very different results, since the estimates of the β_1's are only linearly dependent on the level of $\psi_s - \psi_u$. Therefore, it would only lead to a horizontal transformation of the results. From the figures, it is possible to see that there is indeed a negative relationship. The relationship does not seem to be very strong.

We investigate this relationship somewhat further by using regression analysis. Table 18 lists the results of this exercise. We find a significantly negative relationship when the friction indices of the homogeneous model are used. There is no effect in the other two cases. (To be completed.)

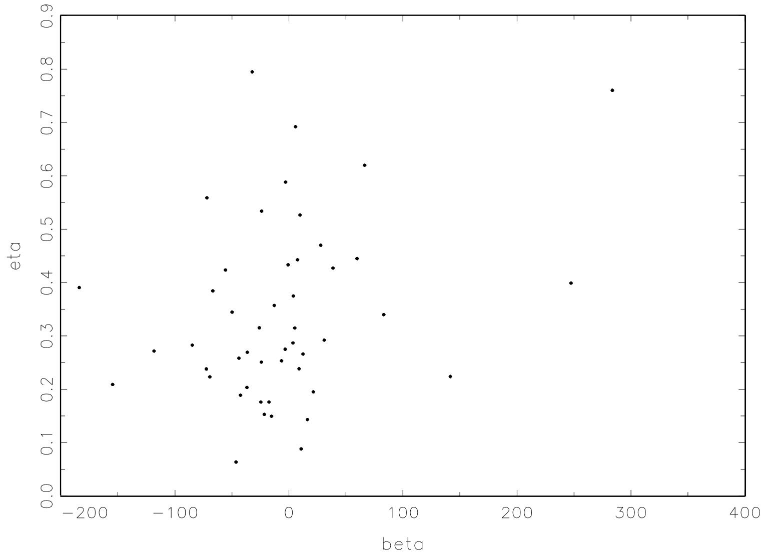

Figure 5: Results for the assortative matching analysis, with $\widehat{\beta}_1$ based on the estimated value of $\psi_s - \psi_u$ for the high skilled individuals and η being high skilled labor market frictions

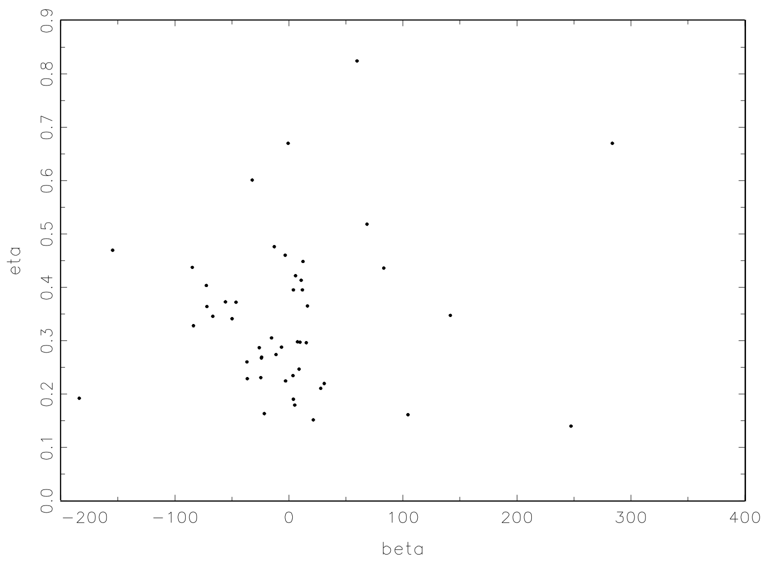

Figure 6: Results for the assortative matching analysis, with $\widehat{\beta}_1$ based on the estimated value of $\psi_s - \psi_u$ for the high skilled individuals and η being the low skilled labor market frictions

	Using estimates of η from		
	Over all	High skilled	Low skilled
Constant	0.481	0.513	0.511
	(0.037)	(0.040)	(0.039)
$\widehat{\beta}_1(\times 1000)$	-0.779	0.297	-0.185
	(0.386)	(0.410)	(0.404)
R^2	0.060	0.082	0.033
Number of observations	66	66	66

Table 18: Results of the regression of the measure of frictions η on $\widehat{\beta}_1$ (The Netherlands).

9 Conclusions

The most fundamental prediction of theories of labor market frictions concerns the negative effect of the degree of frictions on wages. Despite the popularity of these theories, this has never been tested. In this paper we performed tests with matched worker-firm data. We effectively compared different markets with different degrees of frictions and different market outcomes.

Our results do not support the prediction of a negative relationship between search frictions and wages in The Netherlands. On the contrary, we found positive relationships for particular types of workers. There are a number of reasons for this surprising result. First, the Dutch labor market may not match with the standard monopsony models described in the literature. These assume either free entry of firms or make the assumption that firms are always willing to expand and therefore take on any worker. Models that do not make these asymmetry assumptions of workers and firms do not necessarily make this prediction. We investigated this by looking at the possible existence of two-sided sorting. We found that this may indeed be a possible source of the surprising results found in our analysis. Therefore, a more elaborate investigation is a good opportunity for future research. Second, the Dutch data set used in this paper may not be as accurate as necessary for our empirical analysis. In particular, it contained a survey of firms about their wage costs and productivity levels. It is quite essential that these are correct, but especially for the smaller firms, there is no easy way to check the answers. Third, our estimation techniques may not be as accurate as necessary to obtain good results. We estimated the friction parameters by using the relationship between elapsed job durations and the (relative) wage level earned in the job. This procedure makes a lot of restrictive assumptions. For example, search costs should be equal among all types of workers. This assumption may have a dramatic impact on the levels of estimated search frictions and hence on the regression parameters.

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Appendix 1: Construction of the likelihood contributions from the Danish data

We estimate the friction parameters from the marginal distribution of job and employment durations, together with the assumption that workers move from lower to higher paying jobs. In the fitted duration distribution we integrate over the wage distribution. This method has been developed in Koning et al. (2000).

To demonstrate the marginalization that is used, we first define z_i as the job leaving rate out of a job with wage w_i, which equals

$$z_i = \delta + \lambda \overline{F}(w_i) \tag{20}$$

The job leaving rate consists of the layoff rate and the transition intensity to new jobs. Given the distribution of w_i, it is possible to derive the distribution of z_i, the mixture distribution of the hazard of a job duration. We first derive a general expression for the mixture distribution of z_i:

$$H(z_i) = \Pr\left(\delta + \lambda\overline{F}(w_i) \leq z_i\right) = \Pr\left(w_i \geq F^{-1}\left(\frac{\lambda + \delta - z_i}{\lambda}\right)\right) \tag{21}$$

Several distributions of (sequences of) wages may prevail. If the distribution of w_i is F, *i.e.* if the job spell follows an unemployment spell, the c.d.f. and the p.d.f. of z_i are, respectively

$$H(z_i) = \frac{z_i - \delta}{\lambda} \quad \Rightarrow \quad h(z_i) = \frac{1}{\lambda} \quad z_i \in [\delta, \delta + \lambda] \tag{22}$$

Thus z_i is uniformly distributed on the interval $[\delta, \delta + \lambda]$. Note that the mixture distribution of z_i only depends on δ and λ, irrespective of any assumed distribution of p.

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

$$H(z_i) = \frac{(\lambda + \delta)(z_i - \delta)}{\lambda z_i} \quad \Rightarrow \quad h(z_i) = \frac{(\lambda + \delta)\delta}{\lambda z_i^2} \quad z_i \in [\delta, \delta + \lambda] \tag{23}$$

In this case, the mixture distribution of z_i is skewed to the left. This stems from the fact that individuals have less opportunities to find better paying jobs as they climb the job ladder. Hence, the average job leaving rate of a cross-section of workers is smaller than the average job leaving rate of those workers who start climbing the job ladder.

We also may observe durations of jobs which are drawn from a flow sample of jobs that follow another job. Then, w_{i+1} is a draw from F, with $w_{i+1} > w_i$, and the distribution of z_{i+1}, conditional on $z_{i+1} \leq z_i$, is

$$H(z_{i+1}|z_i) = \frac{z_{i+1} - \delta}{z_i - \delta} \quad \Rightarrow \quad h(z_{i+1}|z_i) = \frac{1}{z_i - \delta} \quad z_{i+1} \in [\delta, z_i] \tag{24}$$

Just like in the first case, z_{i+1} is uniformly distributed, but now on the interval $[\delta, z_i]$.

The distributions of multiple job-to-job transitions can be easily derived from this. When the first job spell has a wage which is drawn from F.

$$h(z_1, z_2) = \frac{1}{\lambda} \frac{1}{z_1 - \delta} \quad z_2 \leq z_1 \tag{25}$$

When the first job spell has a wage which is drawn from G:

$$h(z_1, z_2) = \frac{\delta(\delta + \lambda)}{\lambda z_1^2 (z_1 - \delta)} \quad z_2 \leq z_1 \tag{26}$$

We are now in the position to derive the likelihood contributions of the employment and job spells, which is in two steps. First, we derive the likelihood which is conditional on a particular sequence of values of z, the consecutive job leaving rates within an employment spell. Next, we integrate with respect to the mixture distribution of this sequence to obtain the integrated likelihood. The possible mixture distributions of a sequence of N job leaving rates are as in (25) and (26).

Our empirical analysis is on a monthly basis. If we observe a worker who is employed at a particular establishment in year T, then either the establishment code remains unchanged until the end of the year, $T + 12$ (*i.e.* one year later), or it changes at time t, with $T \leq t \leq T + 12$. The likelihood of the first event is, conditional on survival until T, and z_i

$$\exp(-12 z_i) \tag{27}$$

The likelihood of a job-to-job transition is, conditional on survival until T, and the consecutive job leaving rates, z_i and z_{i+1},

$$\int_T^{T+12} (z_i - \delta) \exp(-z_i(t-T)) \exp(-z_{i+1}(T+1-t)) \mathrm{d}t =$$

$$= \frac{z_i - \delta}{12z_i - 12z_{i+1}} [\exp(-12z_{i+1}) - \exp(-12z_i)] \tag{28}$$

Finally, the likelihood of a transition into unemployment, and conditional on survival until T, is

$$\frac{\delta}{z_i - \lambda_0} [\exp(-12\lambda_0) - \exp(-12z_i)] \tag{29}$$

For each year we know the density of z_i, and, if a job-to-job transition occurs, the joint density of z_i and z_{i+1}. The conditional likelihood contributions as in (27) and (28) can be integrated over the mixture distributions of the (consecutive) job leaving rates.

As an example, let us consider the case of an individual worker, who is employed at time T, finds a new job in $[T, T+12]$, and becomes unemployed in period $t \in [T+12, T+24]$. The conditional likelihood of these events is

$$\frac{z_1 - \delta}{(z_1 - z_2)(z_2 - \lambda_0)} \; [\exp(-12z_2) - \exp(-12z_1)] \; \times \; [\exp(-12\lambda_0) - \exp(-12z_2)] \; \delta \tag{30}$$

We integrate the conditional likelihood over the joint density of z_1 and z_2. This density follows from (26) and the integrated likelihood is

$$\frac{\delta^2(\delta+\lambda)}{\lambda} \int_\delta^{\delta+\lambda} \int_\delta^{z_1} \frac{[\exp(-12z_2) - \exp(-12z_1)]}{z_1^2(z_1 - z_2)(z_2 - \lambda_0)} \times \; [\exp(-12\lambda_0) - \exp(-12z_2)] \; dz_2 dz_1 \tag{31}$$

Appendix 2: Derivation of the standard deviations of the estimates of λ and δ

This appendix illustrates how the standard deviations of λ and δ can be derived when we use the empirical distribution of the observed wages. For convenience, the analysis presented here is somewhat less complex than is dealt with in our particular application. It still captures the main ideas. We deal with the extension that is used to derive the standard deviations for this paper at the end of the appendix. For the moment, we assume that observed wages are the offered wages from firms. Additionally, we ignore the problem that the elapsed job duration is observed only once a year. The log-likelihood contributions are equal to[16]

$$\log L_i = \log(\delta + \lambda\overline{F}(w_i)) - (\delta + \lambda\overline{F}(w_i))t_i \tag{32}$$

where t is the observed elapsed job duration of the individual job spell i. We substitute F by the empirical distribution of observed wages

$$\widehat{F}(w) = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}(w_i \leq w)$$

Since $F(w)$ is consistently estimated by this estimator for any value of w, λ and δ are also consistently estimated by using maximum likelihood. The individual log-likelihood contributions are as defined above. However, the estimation of $F(w)$ has an influence on the asymptotic distribution of these estimators. This problem can be solved by using the results as discussed by Newey and McFadden (1994)[17] (see also Andrews, 1994). Using their analysis, we come to the following theorem

Theorem 1 *Assume that λ, $\delta > 0$. Define $\beta(w,t)$ as*

$$\beta(w,t) = \begin{pmatrix} \beta_1(w,t) \\ \beta_2(w,t) \end{pmatrix} \tag{33}$$

and

$$\beta_1(w,t) = \frac{1}{\lambda}\left(\frac{\delta}{\delta + \lambda\overline{F}(w)} + \log\left(\frac{\delta + \lambda\overline{F}(w)}{\delta}\right) - \frac{2\delta+\lambda}{\lambda}\log\left(\frac{\delta+\lambda}{\delta}\right) + 1\right) \tag{34}$$

and

[16]The complete contribution to the likelihood is $\log L_i = \log(\delta + \lambda\overline{F}(w_i)) - (\delta + \lambda\overline{F}(w_i))t_i + \log f(w_i)$, where $f(w_i)$ is the density of the wage offer distribution in w_i (or the probability $\mathbb{P}(W = w_i)$ when w_i is a mass point). However, the latter term does not vary with the structural parameters of the model.

[17]In particular, Theorem 8.1, page 2196 of Newey and McFadden deals with this problem. The remainder of this appendix derives heavily from their result.

$$\beta_2(w,t) = -\frac{1}{\delta + \lambda\overline{F}(w)} + \frac{1}{\lambda}\log\left(\frac{\delta+\lambda}{\delta}\right) \tag{35}$$

Additionally, define the log-likelihood function as

$$\log L = \sum_{i=1}^{n} \log(\delta + \lambda\widehat{\overline{F}}(w)) - (\delta + \lambda\widehat{\overline{F}}(w))t \tag{36}$$

where $\widehat{\overline{F}} = 1 - \widehat{F}(w)$ *and* $\widehat{F}$ *is the empirical distribution of the observed offered wages. Let* $H_{\lambda,\delta}$ *be the matrix of second order derivatives of equation (36) and* $\widehat{H}_{\lambda,\delta}$ *a consistent estimate of this matrix. Maximization of this equation with respect to* λ *and* δ *leads to consistent estimates and* $\sqrt{n}((\widehat{\lambda},\widehat{\delta}) - (\lambda,\delta)) \rightsquigarrow N(0, \widehat{H}_{\lambda,\delta}^{-1}\widehat{\Omega}\widehat{H}_{\lambda,\delta}^{-1})$. $\widehat{\Omega}$ *is equal to*

$$\widehat{\Omega} = \frac{1}{n}\sum_{i=1}^{n}\left(\widehat{\psi}(w_i,t_i;\widehat{F}) + \beta(w_i,t_i)\right)\left(\widehat{\psi}(w_i,t_i;\widehat{F}) + \beta(w_i,t_i)\right)^T$$

where ψ *is the vector of the first order derivatives of the log-likelihood contributions. The hats above* ψ *and* β *indicate that we use estimated values of* λ *and* δ.

We sketch the proof of theorem 1. According to Newey and McFadden (1994), we need to find a function Ψ such that for $\|\widehat{F} - F\|$ small enough, $\|\psi(z,\widehat{F}) - \psi(z,F) - \Psi(z, F-\widehat{F})\| \leq b(z)\|\widehat{F}-F\|^2$. For our application, the following function satisfies this inequality for $\gamma = F - \widehat{F}$

$$\Psi(w,t,\gamma) = \begin{pmatrix} \Psi_1(w,t,\gamma) \\ \Psi_2(w,t,\gamma) \end{pmatrix} \tag{37}$$

where

$$\Psi_1(w,t,\gamma) = \delta\frac{\gamma}{(\delta+\lambda\overline{F}(w))^2} - \gamma t \tag{38}$$

and

$$\Psi_2(w,t,\gamma) = -\lambda\frac{\gamma}{(\delta+\lambda\overline{F}(w))^2} \tag{39}$$

Additionally, for all $\left\|\widehat{F} - F\right\|$ small enough $\int \Psi(z, \widehat{F} - F) dF(z) = \int \beta(z).d\widehat{F}(z)$.[18] It is possible to show that the function β as defined above satisfies this equality.

As stated above, we observe a random sample of wages among individuals instead of a random sample of wages paid by firms. We find that

$$\delta + \lambda \overline{F}(w) = \delta \frac{\delta + \lambda}{\delta + \lambda G(w)}$$

where G is defined as in the main text of the paper. Substitution of this equation into the log-likelihood contributions, *i.e.* the right hand side of equation (32), leads to

$$\log L_i = \log(\delta) + \log(\delta + \lambda) - \log(\delta + \lambda G(w_i)) - \frac{\delta(\delta + \lambda)}{\delta + \lambda G(w_i)} t_i \tag{40}$$

where G is estimated by the empirical distribution. Although the calculus of this problem is quite complex, the underlying mechanism of deriving the asymptotic distribution stays the same.[19]

Simulations using a log normal distribution of the offered wages indicate that the approximation is close even if the number of observation is not extremely large. Additionally, we find that the errors that are made by using the inverse hessian of the log likelihood is quite substantial for the application of this paper. For example, the estimated standard deviations using the inverse hessian is for most sectors at least 30% lower than the actual asymptotic standard deviations. The error that is made in the calculation of the standard deviation of δ is in most cases much lower.

[18] The results of Newey and McFadden (1994) are more generally applicable, but this is not necessary for our application. Note that $\int \beta(z) d\widehat{F}(z) = \frac{1}{n} \sum_{i=1}^{n} \beta(z_i)$.

[19] Derivations and final results are provided by the authors upon request.