# Wage Effects of Labor Market Tightness*

Christian Philip Hoeck

University of Copenhagen and Danmarks Nationalbank

January 2023

**Abstract**

I study the impact of labor market tightness on wages. Using Danish data on vacancies and unemployment at the occupational level and firm-level data on the occupational composition of employees, I construct novel firm-specific measures of labor market tightness. Using these measures, I estimate the causal impact of labor market tightness on wages at the firm level. I find an elasticity of wages with respect to tightness of 0.014, which implies an increasing but relatively flat wage-setting curve. The results are in line with the qualitative implications of the canonical search-and-matching model of the labor market.

**JEL Classification:** E24; J31; J63

*Email: christian.hoeck@econ.ku.dk. The viewpoints and conclusions stated are the responsibility of the author, and do not necessarily reflect the views of Danmarks Nationalbank. I thank my advisors Daniel Le Maire and Søren Hove Ravn for their invaluable advice and support. I also thank Jesper Bagger, Antoine Bertheau, Adrien Bilal, Simone Bonin, Edouard Challe, Jeppe Druedahl, Niklas Engbom, Mike Elsby, Renato Faccini, Ana Figueiredo, Rasmus Lentz, Pascal Michaillat, Espen Moen, Laura Pilossoph, David Pinkus, Morten Ravn, Pontus Rendahl, Daphné Skandalis, Antonella Trigari, David Wiczer, seminar participants at the EALE annual conference, the Dale T. Mortensen Centre Conference and colleagues at Danmarks Nationalbank and the Danish Research Center for Economic Modelling and Analysis for thoughtful discussions and comments. I gratefully acknowledge financial support from the Danish Research Center for Economic Modelling and Analysis.

# 1 Introduction

How do aggregate labor market conditions affect wages? Standard search-and-matching models such as the ones developed by Diamond, Mortensen, and Pissarides (Pissarides (2000)) (the DMP model) predict that higher labor market tightness makes it easier for job searchers to find a new job. This improves their outside option and in turn, they demand a higher wage.

There is a large literature on the aggregate co-movements of wages and tightness, such as Shimer (2005), Pissarides (2009) and more recently Domash and Summers (2022). Others have looked at how individual wages covary with aggregate unemployment and changes in labor market flows. However, evidence of the causal effect from tightness to wages is lacking. One reason for this is that aggregate wages and tightness are usually modeled as equilibrium variables, determined simultaneously by a wage-setting curve and a vacancy-creation curve. The causal effect from tightness to wages is therefore not well defined in the aggregate. On the other hand, more disaggregated measures of tightness that would provide the needed variation have also been lacking.

In this paper, I document the effect of tightness on wages at the firm level using Danish administrative datasets. To study the effect of labor market tightness on wages at the firm level, I use that different firms hire from different occupations. I argue that the differential exposure to changes in aggregate occupational tightness must affect firm-level wages and not vice versa, since the individual firms take aggregate tightness in each occupation as given, i.e, they do not account for their own vacancies increasing tightness. Conducting the analysis at the firm level, therefore, blocks the feedback mechanism from the vacancy-creation curve in the DMP model. From the firm's perspective, wages are determined by the job-match productivity and aggregate exogenous labor market conditions through bargaining. Given the wages, the firm then decides how many vacancies to open. Firm-level data, therefore, allows me to disentangle the vacancy-creation curve and the wage-setting curve, and I show that my estimates pin down the slope of the wage-setting curve in a DMP model. This relies on the assumption that firms are small compared to the labor markets they hire from and that the relevant labor market for each firm can be characterized by the occupational composition of its employees. I motivate these assumptions using existing literature and use several robustness checks when estimating the effect, such as excluding firms that are large employers in an occupation.

I obtain the estimates of the effect of tightness on wages using the assumptions above and a shift-share design as in Adão et al. (2019). Specifically, I use a weighted average of changes in occupation-level tightness to measure the change in firm-specific tightness, where the weights are given by the occupational composition of workers at the individual firm. This measure exploits that different firms hire employees from different sub-markets of the labor market and provides firm-level variation in labor market tightness. Firm-level variation in tightness is key to disentangling the effects from the wage-setting and vacancy-creation curves.

I estimate the effect of labor market tightness on wages using specifications that examine 1-year differences and 3-year differences in average log daily earnings and the constructed tightness measures at the firm level. I find wage earnings elasticities with respect to tightness ranging from around 0.014-0.020 in the 1-year-difference specification to 0.017-0.025 in the 3-year-difference specification. I also show that the estimates are robust to a range of extensions and robustness checks. This includes constructing alternative versions of the labor market tightness measures that allow for on-the-job search, occupational mobility or adjust for occupational substitution and examining the effect on the wages of new hires and stayers separately. As a validation of the constructed tightness measure, I also examine the effect of tightness on the firm-level Employer-to-Employer separation rate (EE), which many models also predict should be increasing in tightness (Pissarides, 2000; Moscarini and Postel-Vinay, 2018; Mercan and Schoefer, 2020). I find that this also holds empirically.

I highlight three implications of these estimates. First, the positive estimates imply an upward-sloping wage-setting curve, which is in line with the qualitative implications of the DMP model. Secondly, the estimates are relatively small and imply a relatively flat wage-setting curve. Using my estimates, I recover values for key parameters for the DMP model. These differ substantially from the values used in the calibration in Shimer (2005) and imply that the slope of the wage-setting curve is much lower and close to the calibration in Hagedorn and Manovskii (2008).

Finally, the estimates in this paper have implications for larger macroeconomic models where the labor market is modeled as a DMP-type framework. Ravn and Sterk (2021), Bilbiie (2021) and Challe (2020) argue that the volatility of unemployment in these models depends on whether the earnings risk is countercyclical, where earnings risk is defined as the probability of losing your job and not finding a new job multiplied by the drop in income when unemployed. Intuitively, tightness affects earnings risk through two effects in opposite directions. There is a positive effect through the job-finding rate since a fall in tightness makes it harder to find a job, but a negative one through wages, since the fall in earnings when unemployed is diminished. A relatively flat wage-setting curve makes it more likely that the increase in unemployment risk is larger than the fall in the earnings difference between employed and unemployed when tightness falls, making earnings risk countercyclical. I show that this is likely the case for Denmark. The feedback between earnings risk and precautionary savings could therefore lead to a contractionary spiral.

The two main contributions in this paper are the following: First, I develop a novel measure of labor market tightness at the firm level. Papers such as Azar et al. (2020) and Turrell et al. (2021) have calculated occupation-specific tightness using vacancy data, but to the best of my knowledge, I am the first to combine it with data on the firm-level composition of employees, to get firm-level variation in tightness. Secondly, I use the tightness measures to obtain causal estimates of the effect of tightness on wages, i.e. the slope of the wage-setting curve. Solon et al. (1994), Beaudry and DiNardo (1991) and Moscarini and Postel-Vinay (2017) investigate the similar relationship between wages and the unemployment rate and find that aggregate unemployment has a moderate negative effect on individual wages. Jäger et al. (2020) exploit natural experiments in Austria to show that the value of non-employment, the other main driver of wages through outside options in the DMP model, has little effect on wages. However, to the best of my knowledge, no evidence on the causal relationship between tightness and wages at the firm level exists.

The rest of the paper is organized as follows: Section 2 contains a description of a simple extension of the canonical model DMP model that includes different occupations and heterogeneous firm productivity. This model is used to motivate the identification strategy. The shift-share method used for obtaining the estimates of the effect is outlined in Section 3. The vacancy data is described in Section 4 along with the additional administrative data used, and the results and their implications are described in Section 5.

# 2 Theoretical Background

This section contains a simple extension of the canonical DMP model from Pissarides (1985, 2000), by allowing for different occupations and heterogeneous firm productivity. This model is used to highlight why conducting the empirical analysis at the firm level helps to identify the slope of the wage-setting curve.

Time is continuous. There exist a continuum of firms with measure $K$ indexed by $k$ and $H$ different types of occupations indexed by $h$. I assume that the occupation of a worker is predetermined, i.e. occupational mobility is not present. Firms create vacancies in order to hire workers. Vacancies are specific to an occupation, but each firm can create several vacancies for each different occupation. The market tightness for each occupation is given by $\theta_h = \frac{V_h}{U_h}$, where $V_h$ is the number of vacancies for occupation $h$, and $U_h$ is the number of unemployed job seekers of occupation $h$. In each occupation-specific labor market, the number of matches is governed by a matching technology such that the hazard rate of filling a vacant position for occupation $h$ is $q(\theta_h)$, and the hazard rate for a job seeker getting a job is $\theta_h q(\theta_h)$. Within each occupation-specific labor market, matching between firms and unemployed is random. Furthermore, each individual firm is small and does not take its own effect on the labor market into account.

I assume that each firm simply has a constant firm-specific productivity for each occupation, $y_{h,k}$, which is known prior to creating the vacancy, with the occupation-specific distribution across firms denoted by $G_h(y_{h,k})$. This implies that no complementarities between labor types are present in the firm's production function.

In steady-state, the value of a filled vacancy of occupation $h$ for the individual firm $k$ is denoted $\Pi^e_{h,k}$ and is determined by

$$r\Pi^e_{h,k} = y_{h,k} - w_{h,k} + \delta\left(\Pi^v_{h,k} - \Pi^e_{h,k}\right) \tag{1}$$

where $\Pi^v_{h,k}$ is the value of a vacancy, $y_{h,k}$ is the marginal product, $w_{h,k}$ is the corresponding wage and $\delta$ is the job destruction rate, which for simplicity is assumed to be homogeneous. The value of a vacancy is determined by

$$r\Pi^v_{h,k} = -c_{h,k} + q(\theta_h)\left(\Pi^e_{h,k} - \Pi^v_{h,k}\right) \tag{2}$$

where $c_{h,k}$ is the instantaneous cost of posting a vacancy of occupation $h$ for firm $k$. I assume that hiring costs are increasing in the number of vacancies posted by the firm, i.e., $c_{h,k} = f(V_{h,k}) > 0$, where $f'(V_{h,k}) > 0$. This ensures that the firm with the highest constant productivity is not the only firm that creates vacancies. Combining equations (1) and (2) and using the free-entry condition, which states that firms will open vacancies until the expected discounted profit of a filled vacancy equals the expected vacancy costs, i.e $\Pi_v^h = 0$, results in the firm-specific vacancy creation curve of firm $k$ for occupation $h$,

$$\frac{y_{h,k} - w_{h,k}}{r + \delta} = \frac{c_{h,k}}{q(\theta_h)} \tag{3}$$

Note that while this firm-specific vacancy-creation curve appears identical to the aggregate vacancy-creation curve in the canonical DMP model, its implications are somewhat different. It still implies a negative partial relationship between wages and vacancies posted by the firm, as higher wages decrease the gain of filling a vacancy. Firms are atomistic and do not take their own effect on tightness into account. Instead, hiring costs, $c_{h,k}$, are increasing in the number of vacancies posted. The firm creates vacancies until hiring costs, $c_{h,k}$, have increased so much that they equal the expected gain of filling a vacancy. Note, that this difference between a firm-specific and aggregate vacancy creation curve also holds in the canonical DMP model, but due to firms being homogeneous they coincide.[1]

The value of employment for a worker of occupation $h$, $V_{h,k}^e$, is given by

$$rV_{h,k}^e = w_{h,k} + \delta\left(V_h^u - V_{h,k}^e\right) \tag{4}$$

and the value of unemployment for a worker of occupation $h$, $V_h^u$, is given by

$$rV_h^u = z + \theta_h q(\theta_h)\left(E_k\left(V_{h,k}^e\right) - V_h^u\right) \tag{5}$$

where $z$ is the instantaneous utility of unemployment, which is assumed to be homogeneous

[1] The homogeneity of firms also remove the need for increasing vacancy costs.

across occupations. $E_k\left(V^e_{h,k}\right)$ is the expected value of employment for a worker of type $h$, with the expectation taken over the firm dimension, i.e. $E_k\left(V^e_{h,k}\right) = \int \psi_h(j)V^e_{h,k}dj$, where $\psi_{h,k}$ is the share of the total number of vacancies for occupation $h$ posted by firm $j$. The value of employment is uncertain since unemployed do not know the productivity of their future employer. The expected value of employment is given by the value of employment at each firm $k$ and the probability of getting a job at firm $k$, which is determined by the share of vacancies for occupation $h$ posted by firm $k$. Note that because all matches will result in jobs, as no firm will post a vacancy where the resulting wage would be below the workers' reservation wage.

When a match is made, the surplus is distributed according to a generalized Nash Bargaining solution. Using this assumption and the stated equations results in the following wage equation,

$$w_{h,k} = (1-\beta)z + \beta y_{h,k} + \beta\theta_h q(\theta_h)E_j(\Pi^e_{h,j}) \tag{6}$$

where $\beta$ is the relative bargaining power of workers.[2] Note that the expected value of a filled vacancy enters the last term, which captures the effect of the outside option on wages. Even if a firm has low productivity, it is still affected by the general productivity level in its wage setting. Finally, inserting equation (2) results in the following wage equation

$$w_{h,k} = (1-\beta)z + \beta\left(y_{h,k} + E_j(c_{h,j})\theta_h\right) \tag{7}$$

which is similar to the wage-setting curve in the DMP model, with the only difference coming from the firm-level heterogeneity in productivity and hiring costs. This equation shows a clear connection between tightness and wages. As tightness increases, the outside option of the worker increases, and she, in turn, receives a higher wage. It is important

[2]See Appendix A for the derivation. Note that $j$ is being used to differentiate the future employer from the current, $k$.

to note that none of the wage determinants in equation (7) are affected by the number of vacancies created by the individual firm, since $E_j(c_{h,j})$ is unaffected by the individual firm's actions. In the aggregate, wages, tightness, and vacancies are equilibrium variables that are determined simultaneously. However, for the firm, tightness is an exogenous aggregate variable. Therefore, the result of the wage bargaining process only depends on exogenous variables. Focusing the analysis at the firm level disentangles the wage-setting curve and the vacancy creation curve. The wages of matches are determined by the productivity and aggregate labor market conditions through bargaining. The bargained wage then determines the number of vacancies created by the firm through the firm-specific vacancy creation curve in equation (3). It is, therefore, possible to examine the effects of tightness on wages at the firm level, even if tightness and wages are equilibrium variables in the aggregate. Furthermore, the effect examined will correspond to the slope of the wage-setting curve.

For simplicity, I assume that the average instantaneous cost is the same across occupations, i.e. $E_j(c_{h,j}) = c$. Thus, I only assume dispersion in hiring costs within an occupation. However, differences in total hiring costs between occupations are still present, as the hazard rate for filling a vacancy depends on occupational tightness. Using this, the wage equation, (7), can be written as

$$w_{h,k} = (1-\beta)z + \beta\left(y_{h,k} + c\theta_h\right) \tag{8}$$

The direct effect of tightness on wages at the firm level is given by $\beta c$, which is positive. The model, therefore, implies an increasing wage-setting curve.

# 3 Shift-Share Design

In this section, I describe the empirical method used to estimate the effect of tightness on wages highlighted in the previous section. Following the empirical literature on wage determinants, e.g. Mincer (1974) and Abowd et al. (1999), the empirical model is a reduced-form log-linear wage equation. This can be seen as a reduced-form log-linear approximation of equation (8) from the theoretical model. I estimate the parameter of interest using a shift-share design as described in Adão et al. (2019) and Bartik (1991). In Section 5.3, I consider how to recover parameter values for the theoretical model presented in Section 2 using the estimates obtained from the reduced-form model in this section.

I specify a reduced-form model for log wages at the worker level in the following way:

$$\ln w_{i,t} = \rho \ln \theta_{h(i,t),t} + \lambda \ln y_{k(i,t),h(i,t),t} + a\mathbf{x}_{k(i,t),t} + \epsilon_{i,t} \tag{9}$$

Here $\ln w_{i,t}$ denotes log individual daily earnings, $\ln \theta_{h(i,t),t}$ denotes log labor market tightness of worker $i$'s occupation $h$ and $\ln y_{k(i,t),i,t}$ denotes the log productivity for worker $i$ at firm $k(i,t)$. Finally, $a\mathbf{x}_{k(i,t),i,t}$ includes firm and year fixed effects as well as industry and region linear trends.

As noted in Section 2, it is important to control for productivity when estimating the effect of tightness on wages. I have access to data on value added per worker at the firm level, which can be used as a proxy for firm-level productivity. I, therefore, aggregate the analysis to the firm level. Additionally, I also express the model in first differences. This removes the firm fixed effects and changes the region and industry trends to fixed effects. The resulting reduced-form model at the firm level used for the analysis is then given by:

$$\hat{w}_{k,t} = \rho\hat{\Theta}_{k,t} + \lambda\hat{y}_{k,t} + a\hat{\mathbf{x}}_{k,t} + \hat{\epsilon}_{k,t} \tag{10}$$

where $\hat{w}_{k,t}$ denotes the change in average log daily earnings at firm $k$ from period $t$ to $t+\Delta t$, i.e. $\hat{w}_{k,t} = \frac{1}{n_{k,t+\Delta t}}\sum_i \ln w_{i,t+\Delta t} - \frac{1}{n_{k,t}}\sum_i \ln w_{i,t}$, where $n_{k,t}$ denotes the number of workers in firm $k$ at time $t$. Additionally, $\hat{y}_{k,t}$ denotes the change in average log productivity and $\hat{\Theta}_{k,t} = \sum_{h\in H} s_{h,k,t}\left(\ln \theta_{h,t+\Delta t} - \ln \theta_{h,t}\right)$, i.e. a weighted average of changes in occupational log tightness, with the weights given by the initial occupational composition at firm $k$, $s_{h,k,t}$. The tightness measure, $\hat{\Theta}_{k,t}$, is a firm-specific measure of the change in labor market tightness. It captures the notion that different firms hire different types of labor, and therefore in reality hire from different labor sub-markets with varying conditions. For example, if a firm produces a good or service that heavily relies on the labor input of engineers, the corresponding occupation share, $s_{h,k,t}$, will be large, and the labor market tightness for engineers will have a larger effect on the firm-specific labor market tightness. This novel measure allows me to disentangle the effects of the wage-setting curve from the vacancy creation curve, as discussed in Section 2.

The measure of change in tightness, $\hat{\Theta}_{k,t}$, is similar in form to the shift-share measures described in Adão et al. (2019). Recently, two different approaches to the shift-share design have emerged. Goldsmith-Pinkham et al. (2020) establish identification through the assumption of exogenous initial shares $s_{h,k,t}$, while Adão et al. (2019) and Borusyak et al. (2022) rely on an assumption of exogenous shifters, $\ln \theta_{h,t+\Delta t} - \ln \theta_{h,t}$. Goldsmith-Pinkham et al. (2020) provide guidelines for which approach to choose. They argue that one should use the share approach if one wants to achieve identification from units having different exposure to a common shock. On the other hand, one should choose the approach with exogenous shifters if the case for identification is based on many different shocks. The latter is the case in this paper, with different occupation-specific shocks to tightness, and I, therefore, follow the approach of Adão et al. (2019).

Intuitively, the relevant pool of candidates from each occupation for the individual firm must be well proxied by the aggregate pool in order to argue that $\hat{\Theta}_{k,t}$ captures the changing state of the labor market that a specific firm is facing. There are two obvious potential objections to this assumption, geographical and sectoral. Firms located in different regions might not have access to the same pool of candidates. However, due to the small size of Denmark, I assume that each occupation-specific labor market covers the entire country. I relax this assumption in Appendix E.8 and the resulting estimates are similar. Additionally, the pool of candidates may vary between sectors or industries. This would, for example, be the case if an engineer who has worked in one industry has obtained markedly different skills compared to an engineer in a different industry. Kambourov and Manovskii (2009) show that the return to human capital is stable when switching to jobs of the same occupation in a new industry, but not in the case with a new occupation within the same industry in the U.S. This finding is confirmed in data from the UK and Portugal by Zangelidis (2008) and Lagoa and Suleman (2016). This supports the credibility of the assumption that firms from different industries hire from the same pool of candidates for each occupation. When these assumptions hold, all vacancies and job seekers within an occupation are potential matches. All firms wishing to hire a worker from a specific occupation, therefore, face the same occupation-specific tightness.

Even if all firms hire from the same occupation pools, the ratio of vacancies to unemployed might still not be the best measure of tightness for each occupation. I therefore also construct alternative measures of labor market tightness and use them in robustness checks that allow for on-the-job search, occupational mobility, adjust for occupational substitution and examine the effect on hires and stayers separately. I describe these specifications and the resulting estimates in detail in Section 5.2. As a validation of the constructed tightness measure, I also examine the effect of tightness on another outcome which many models also predict should be increasing in tightness: The Employer-to-Employmer transition rate (EE) (Pissarides, 2000; Moscarini and Postel-Vinay, 2018; Mercan and Schoefer, 2020).

If the constructed measures capture the labor market tightness faced by the firms, a number of additional assumptions are needed for the shift-share design to provide consistent estimation of the effect of tightness on wages, $\rho$, using OLS, and for valid inference. The most important assumption is that the log change in occupational tightness, $\ln \theta_{h,t+\Delta t} - \ln \theta_{h,t}$, is as good as randomly assigned across occupations conditional on the controls.[3] Essentially, changes in tightness should be uncorrelated with unobserved shocks that affect wages through other channels than tightness itself conditional on controls.

This assumption includes ruling out simultaneity bias. I, therefore, need to block the feedback mechanism from the vacancy creation curve. Based on the arguments in Section 2, I achieve this by conducting the estimation at the firm level using the firm-specific measures of labor market tightness. This would, however, not be sufficient if the individual firm is large enough to affect aggregate tightness. In Section 4, I report the average occupational Herfindahl index, which indicates that employer concentration is low.[4]

Productivity shocks will likely both affect wages directly and indirectly through tightness. This is the case in the model described in Section 2. If I do not properly control for productivity, the assumption of as-good-as-randomly assigned shocks will not hold. As mentioned above, productivity will be proxied by the value added per worker at each firm. If the variation in the change in productivity that is not captured by the proxy is uncorrelated across firms, it will not affect the estimation of the effect from tightness, as long as the assumption that firms are small holds. Similarly, if the variation not captured by value added is driven by the aggregate business cycles, industry trends or regional trends it would be captured by the included fixed effects. For the measurement error in productivity to bias the estimate, it would require that firms with measurement errors, that are not driven by aggregate business cycles, industry trends or region trends, also hire in systemically different occupations than their industry and region, and that this effect is large enough to affect occupational tightness.

In this paper, I am agnostic about the source of variation in tightness, as long as it does not also affect wages directly. However, it is still worthwhile to consider where the

[3]Changes are allowed to be correlated within occupations across different periods. All of the needed assumptions are stated in Appendix B.

[4]This is compared to the thresholds in horizontal merger guidelines from the U.S. Department of Justice and Federal Trade Commission (Azar et al., 2020).

variation originates from, for example in the framework presented in Section 2. In the model, changes in tightness could originate from occupational shocks to productivity, separation rates, or matching efficiency. According to the model the variation in tightness that is used for the estimation, therefore, stems from changes in separation rates or matching efficiency, conditional on controlling properly for productivity.

A problem with regard to inference when using shift-share designs is that any shift-share structure in the residual will lead to units with similar shares having correlated residuals. This will lead to the usual standard errors being invalid. Adão et al. (2019) show that not accounting for correlation across share composition can lead to substantially inflated rejection rates, even as high as 50 percent. To handle this I estimate standard errors using the estimator developed by the authors, which is robust to this type of correlation.[5]

Hall (2005) highlight that wage rigidity may be important in the DMP model. I, therefore, estimate the elasticity of wages with respect to tightness, $\rho$, in equation (10), using specifications based on changes over 1 year and 3 years.[6]

# 4 Data

In this section, I present the different data sources used in the analysis and provide descriptive statistics, and the sample restrictions. Table C.1 also provides an overview of the data sources.

[5] All the assumptions needed for consistent estimation and valid inference are stated in Appendix B.

[6] Note that the simple extended DMP model presented in Section 2 does not feature wage rigidity since both wages and tightness are jump variables.

## 4.1 Data Sources and Institutional Setting

**Institutional setting:** The Danish labor market is characterized by a high degree of flexibility, both in terms of employment flows and wage setting. Employment, long-term unemployment, and labor market turnover are comparable to the U.S. (Kreiner and Svarer, 2022). Most workers in the private sector are covered by collective agreements (87 pct.). However, 80 percent of those covered by these agreements only face a bargained wage floor, which is not binding for most workers, or no bargained wage at all. In practice, the wages for these workers are negotiated locally at the firm (DA, 2018).

**Vacancies:** The creation of the firm-specific tightness measure is made possible due to data on vacancies across occupations. The data is drawn from the Labor Market Balance database (Arbejdsmarkedsbalancen) created by the Danish Agency for Labor Market and Recruitment (STAR). In Denmark, all individuals receiving unemployment benefits are required to register at a recruitment center (Jobcenter). As part of their efforts to increase matching between employers and job seekers, STAR facilitates a vacancy database, where most firms post open positions, which the recruitment centers and the unemployed have access to. Importantly, the vacancies are categorized based on occupations from the International Standard Classification of Occupations (ISCO-08). I aggregate these into 2-digit ISCO codes. The data from STAR is available for 2013-2019.

**Unemployment:** I calculate unemployment across occupations using Danish administrative data on employment status and the occupation of the previously held jobs. The required data is drawn from the IDA database, which is maintained by Statistics Denmark. This database contains information on the employment status and an occupation code if employed for all danish inhabitants. If an individual is currently unemployed and has held a job in a certain occupation, he counts as one unemployed individual of that occupation. This means that an unemployed, who from 2010 to the year of unemployment, have had different occupations will count as an unemployed in all these occupations. This is intended, as such an individual is a potential applicant for vacancies in these occupations. Again, occupations are defined at the level of 2-digit ISCO codes.

**Wages and occupation shares:** I also use information from IDA for wages and occupation shares for each firm. As the wage measure, I use log daily earnings, calculated using annual individual earnings at the firm divided by days worked at the firm, and these earnings are then deflated using the Danish consumer price index from Statistics Denmark. Earnings include all taxable income paid by the firm (including bonuses), mandatory pension contributions and fringe benefits. I then calculate the average log daily earnings for each firm as my main outcome of interest. Using the occupation of each employee, I can also calculate the occupation shares at the 2-digit ISCO level for each firm. I then construct the firm-specific tightness measures by interacting the shares with aggregate occupational tightness, i.e. $\Theta_{k,t} = \sum_{h \in H} s_{h,k,t}\theta_{h,t}$.

**Employer-to-Employer transitions:** The EE-separation rate is based on BFL which contains monthly matched employer-employee data and is maintained by Statistics Denmark. I construct worker-firm spells and identify an EE-separation as the end of a worker-firm spell, where a new worker-firm spell starts with a new employer in the same or the next month. I then calculate the yearly EE separation rates for each firm.

**Accounting data:** The data on value added and revenue is drawn from the FIRM and FIRE databases, which are also maintained by Statistics Denmark. These datasets also contain information on the industry, sector and region of the firm.

## 4.2 Sample Restrictions

I conduct the following sample selection: I need to know the occupation of employees to create the occupation shares. I, therefore drop all employments which do not have an ISCO-classification. This results in an initial sample of 18,208,290 worker-firm-year observations. Additionally, I only keep primary employments for workers between the age of 18 and 67 not undergoing education, who are employed in full-time jobs with positive wages and at least 30 days of employment in the given year.[7] I also drop employments within managerial occupations due to problems with representativity for these occupations and drop observations within the highest and lowest wage percentile each year.[8] Finally, I restrict the analysis to private-sector firms with at least 5 employees.[9] This results in 5,829,446 worker-firm-year observations from 2013 to 2019 across 1,433,950 workers and 39,132 firms. I drop all firms with imputed value-added data. In general, data for smaller firms are more likely to be imputed. Accounting data is not available for all firms each year. Merging the wage and accounting data results in a final sample of 118,962 firm-year observations across 29,748 firms. Since I use 1-year and 3-year differences for the estimation, a firm-year observation is only used if data for the next year-step also exist.

## 4.3 Descriptive Statistics

Table I contains descriptive statistics for the firms in the sample including the firm-specific tightness, while Figure I shows the distribution of 1-year tightness shocks. Real wages and productivity have grown somewhat over the sample period, and so have the variances. Mean firm-specific tightness and the variance of firm-specific tightness have also increased over the sample period. The size of firms and the number of occupations at each firm are stable in the sample period. Finally, market concentration, measured by the average Herfindahl-Hirschman index for occupations, is low during the sample period.[10]

[Table I about here.]

[7]Days of employment in a given job is calculated using the spell data from BFL.

[8]STAR has stated that the coverage of vacancies in these occupations is small.

[9]A firm is defined as a corporate entity corresponding to a unique firm identification number (CVR-number). These identify firms and not individual establishments.

[10]See note for Table I for definition of Herfindahl-Hirschman index. Moderate concentration would correspond to an HHI of 0.15-0.25 (Azar et al., 2020).

[Figure I about here.]

In the DMP-type model presented in Section 2, the effect of tightness on wages comes through the outside option. Specifically, higher tightness makes it more likely to get a new job when you are unemployed and less likely to fill a vacancy, and this shifts the relative bargaining power. I start the empirical analysis by examining whether these connections between vacancies and unemployment also are present in the data. Figure II shows the Beveridge curve in a binned scatter plot of firm-year observations. It shows a negative slope of -0.437 between vacancies and unemployment as ratios of the labor force. This is in line with the DMP model where more vacancies per worker lead to more unemployed getting a job.

[Figure II about here.]

Figure II supports the qualitative implications of the DMP model concerning the flows of unemployment and vacancies. However, the main focus of this paper is the connection between wages and tightness. As seen from the wage equation (8) in Section 2, the DMP-type model presented implies a positive connection between wages and tightness at the firm level. Figure IIIa shows the correlation between wages and tightness at the firm level. The figure shows a clear positive correlation between firm-level tightness changes and changes in the firm average log daily earnings. This supports the predictions of the DMP model and motivates the further analysis conducted in Section 5. In Figure IIIb we also see that an increase in tightness is associated with an increase in the EE-separation rate. This is also in line with the predictions from Section 4. The graphs seem to indicate that the connection between wages and tightness is weaker than between EE-separations and tightness: A doubling of tightness is associated with an increase in earnings of around 1.7 percent and an increase in the EE-separation rate of 1.6 percentage points, approximately 11 pct. of the average rate. Appendix D also includes figures of the correlation between wages and EE-separations and the two elements of tightness, i.e.

vacancies and unemployment. These figures also show the expected positive and negative correlation, respectively.

[Figure III about here.]

# 5 Results

In this section, I first present the estimation results obtained using the regressions described in Section 3. I then describe the main macroeconomic implications of the estimates, both with regard to the calibration of DMP models, and the use of this type of model as a component in a larger macroeconomic model.

## 5.1 Estimation Results

The baseline estimates are shown in Table II. For all specifications, I find a positive and statistically significant effect on earnings from an increase in tightness. The estimated elasticities using 1-year differences range from 0.014-0.019. This corresponds to a 100 percent increase in tightness leading to a 1.5 percent increase in wages. The estimates from these specifications can be seen as the short-run impact of increased tightness. The specifications including on-the-job search are very similar to those obtained using the baseline definition. The specifications with no controls tend to result in slightly larger elasticities, but all estimates are similar.

[Table II about here.]

The estimates obtained when using 3-year differences are also shown in Table II. The estimates are in the range of 0.017-0.025 and are for the most part larger than their 1-year difference equivalents. This fits well with the stylized fact that wages tend to be more rigid in the short run, discussed in Section 3.

## 5.2 Extensions of Tightness Measure and Robustness Checks

Even if all firms hire from the same occupation pools, the ratio of vacancies to unemployed might still not be the best measure of tightness for each occupation. In this section, I describe several extensions to the firm-level tightness measure and additional robustness checks. The results are shown in Figure IV and in the corresponding appendices.

**On-the-job Search:** A large part of the search-and-matching literature has focused on the presence of on-the-job search (Lise and Robin, 2017; Moscarini and Postel-Vinay, 2018). To examine whether the results are robust to the inclusion of on-the-job seekers, I include a specification where occupation-level tightness is calculated as in Bilal et al. (2022), i.e. $\theta_{h,t} = \frac{V_{h,t}}{S_{h,t}}$ where the number of searchers is given by $S_{h,t} = U_{h,t} + \xi_h E_{h,t}$, where $E_{h,t}$ and $\xi_h$ denotes the number of employed in occupation $h$ and the search effort of employed relative to unemployed in occupation $h$. I calculate a proxy for $\xi_h$ using the observed number of transitions from unemployment to employment and from employment to employment for each occupation. The results are included in Table II and are similar to the ones using only unemployed job-seekers.

On-the-job search of course implies Employment-to-Employment separations (EE). Assuming that employed and unemployed search in the same labor market, the job-finding rate of an employed (or at least the rate at which an employed meet vacancies) will be $\xi_h \theta_h q(\theta_h)$.[11] The EE-separation rate at the firm is therefore also expected to be increasing in tightness. As validation of the firm-level tightness measures, I will therefore also examine whether this is the case.

**Occupational Mobility:** Until now, I have also assumed that no occupational mobility is present when calculating occupational tightness. This assumption is observably false, and

[11]This a common feature of DMP models with on-the-job search such as Moscarini and Postel-Vinay (2018) and Mercan and Schoefer (2020).

it can lead to mismeasurement in the number of effective job-seekers in an occupation, which in turn affects tightness. As a robustness check, I try to account for occupational mobility using the observed transition probabilities. The approach is inspired by Schubert et al. (2021), where the authors calculate occupation-specific outside-option accounting for occupational mobility. My implementation is the following: Let $\pi_{h,p}$ denote the probability that a worker switches from occupation $p$ to $h$ conditional on switching to a new job, where occupation $p$ is defined as the occupation of the last held job. I then calculate the mobility-adjusted number of job-seekers in occupation $h$ as

$$S_{h,t}^{om} = \sum_{p} \pi_{h,p} S_{p,t} \tag{11}$$

where $S_{p,t}$ is the number of job-seekers in occupation $p$ calculated as described in Section 4. The mobility-adjusted number of job-seekers is then used to calculate the tightness and estimate the slope of the wage-setting curve analogously to the specification not allowing for occupational mobility. I calculate a proxy for $\pi_{h,p}$ using the observed transition probabilities averaged over the sample period. The results are found in Appendix E.1 and are similar to the ones shown in Table II.

**Occupational Substitution:** The initial occupation share of employees must also represent the current needed occupational composition, to argue that the tightness measure captures the state of the labor market that the individual firm is facing. If changes in tightness lead firms to substitute towards other occupations, this changes the interpretation of the estimates. This assumption can, however, be relaxed, by using the tightness measure based on initial shares as an instrument for tightness based on current shares. I do this as a robustness check in Appendix E.2 and obtain similar results to the main specification.

**Hires and Stayers:** In Table II, I have included a specification that uses 1-year differences and one that uses 3-year differences in case wages are rigid over time. Following Pissarides

(2009) one could instead study the earnings of new hires. I, therefore, also examine the effect of tightness on earnings for hires and stayers separately. The results are shown in Appendix E.3.

**Hire-Based Shares:** It is also possible that the occupational composition of hires better reflects the needed composition instead of the composition of all employees. As another robustness check, I conduct the same analysis using hires to create the occupation shares. The results are shown in Appendix E.4, and they are similar to the ones shown in the main analysis in Table II.

**Small Aggregate Occupation Share:** My identification strategy relies on the individual firm not being large enough to affect aggregate occupational tightness. In Section 4, I already argued that the average concentration is low, based on the Herfindahl index. As a robustness check, I also conduct the estimations on samples where firms that employ non-negligible shares of the total number of workers in an occupation are excluded. I conduct this robustness check using both less than 5 pct. and less than 0.5 pct. of total employees in an occupation as thresholds. The results are shown in Appendix E.5.

**Only Use Latest Occupation:** When calculating the number of unemployed I have until now used all previous occupations to determine which occupations an unemployed belongs to. As a robustness check, I also construct the tightness measure where only the latest held job is used to determine occupation. The results are shown in use Appendix E.6, and they are similar to the ones found using the baseline definition.

**Revenue-based Productivity:** As highlighted in Section 3, it is important that I properly control for differences in productivity. As a robustness check, I also conduct the estimation using productivity measures based on revenue per worker instead of value added per worker. The results are similar to those obtained using the main specifications and can be found in Appendix E.7.

All the estimates from the listed robustness checks are shown in Figure IV. Regression tables that also include on-the-job search versions of the robustness checks can be found in the corresponding subsections in Appendix E. From the figure, it is clear that the estimates are fairly stable across the different specifications. The 1-year difference estimates tend to be around 0.015 and the 3-year difference estimates tend to be in the range of 0.02-0.025. The most noteworthy differences are for the Hires only and Stayers only specifications. The estimated elasticity for new hires is higher than for all employees, especially in the 1-year difference specification (Though they are not statically significantly different). Even though the estimated elasticity is smaller for stayers, it is still statistically significant for the 1-year difference specification. The 3-year difference stayer specification stands out for being insignificant and smaller than the corresponding 1-year difference specification. Note, however, this specification is based on employees that stayed at the same firm for three years, which may differ from the average employee. The results from the split into hires and stayers, fit well with Pissarides (2009) where the wages of new hires are flexible.

[Figure IV about here.]

As mentioned above, I also validate the firm-level tightness measure, by examining how it varies with the firm-level yearly EE-separation rates. Table III contains the estimates of the effect of tightness on the firm-level EE-separation rates. Again, I find positive and statistically significant estimates, for all specifications, in line with the prediction made in Section 3. I find that a doubling of tightness will lead to an increase in the firm-level yearly EE-separation rate between 0.7 and 1.7 percentage points. These estimates indicate sizable effects on EE-separation rates compared to the effect on wages, considering that the average EE-separation rate is around 14 pct as seen in Table I.

[Table III about here.]

## 5.3 Macroeconomic Implications

The previous section established that labor market tightness affects firms' wage-setting behavior. Overall, the results are in line with the implications of the DMP-type model presented in Section 2. Firms that hire workers from occupations with higher tightness do indeed pay higher wages, ceteris paribus.

Rather than focusing on the firm level most of the literature on the effect of labor market tightness has focused on the aggregate equilibrium effects, such as Shimer (2005). Furthermore, the DMP model has become increasingly adopted in full-scale macroeconomic models such as in Christiano et al. (2016) and Ravn and Sterk (2021). How do the microeconometric estimates in the paper apply to the aggregate effects investigated in the literature? As noted in Nakamura and Steinsson (2018), it is often hard to directly transfer microeconometric results to aggregate effects, as the microeconometric methods often rely on differencing out aggregate effects. In this paper, for example, I difference out year, industry, and region effects in all estimations. Any general equilibrium effects will therefore not be captured by my estimate. However, cross-sectional behavior can have meaningful implications for the mechanism that also governs the general equilibrium effects in a model. Consider the wage equation (8) from the model in Section 2. It implies that the average wage at the firm is given by

$$w_{k,t} = (1-\beta)z_t + \beta\left(\sum_h s_{h,k,t}y_{h,t} + c\sum_h s_{h,k,t}\theta_{h,t}\right) = (1-\beta)z_t + \beta\left(y_{k,t} + c\Theta_{k,t}\right) \quad (12)$$

Some of the variation in the variables can be attributed to aggregate effects. Let $\ddot{x}_{k,t}$ denote the firm-level variable with aggregate effects projected out. The above then implies that

$$\ddot{w}_{k,t} = \beta\left(\ddot{y}_{k,t} + c\ddot{\Theta}_{k,t}\right) \quad (13)$$

Since the estimated model, i.e. equation (10) from Section 3, is in logs, the estimated effect of tightness on wages, $\rho$, is an elasticity and does not directly correspond to $\beta c$ in the model. However, a good approximation can be recovered using the variance weights produced by OLS, under the assumption that equation (8) is the correct model. The exact procedure is described in Appendix F, but intuitively the elasticity is converted to a linear effect by multiplying it with a weighted ratio of wages over tightness. Using this method, the estimates imply that $\beta c$ is around 0.055 if we normalize by mean value added per worker.[12] For comparison, Shimer (2005) calibrates the DMP model with the parameters $\beta = 0.72$ and $c = 0.213$, which result in $\beta c = 0.153$. This higher value is part of the reason why Shimer (2005) finds that the DMP model predicts much higher wage volatility relative to tightness volatility than found empirically. Hagedorn and Manovskii (2008) demonstrate that a different calibration leads to the moments generated by the model being much closer to their empirical counterparts. Their calibration strategy relies on matching bargaining power, $\beta$, using an estimated wage elasticity with respect to productivity. They calibrate the bargaining power to $\beta = 0.052$, much lower than Shimer (2005), where bargaining power is calibrated based on the efficiency condition from Hosios (1990). Additionally, they calibrate the vacancy cost to $c = 0.584$. This results in $\beta c \approx 0.03$, which is close to the value implied by the estimates in this paper. Hall and Milgrom (2008) show that switching the surplus sharing rule inspired by Nash Bargaining, with an alternating-offer scheme, where the threat point is a counter-offer instead of a break-down of negotiations, can also limit the influence of unemployment on bargained wages. The results presented in this paper do not allow me to determine whether one of the reasons for a flat wage-setting curve is more likely. It is, also, important to note that both Shimer (2005) and Hagedorn and Manovskii (2008) argue that a relatively flat wage-setting curve alone is not enough to produce realistic unemployment volatility in the canonical DMP-model.[13]

However, the relatively flat wage-setting curve estimated in this paper can lead to

[12]This is based on the estimates of 0.014 for $\rho$ in Table II.

[13]The calibration in Hagedorn and Manovskii (2008) also introduces a high value of unemployment to get larger volatility.

even higher unemployment volatility in larger macroeconomic models with a search-and-matching labor market such as in Ravn and Sterk (2021). The authors show that incorporating a search-and-matching labor market into a Heterogeneous Agents New Keynesian model (HANK) model results in a model with many realistic implications if earnings risk is countercyclical. Here, earnings risk is defined as the gap in earnings between employed and unemployed times the probability of staying unemployed given a separation. While the earnings gap is increasing in tightness, the probability of staying unemployed is decreasing in tightness. For a given matching function, a flatter wage-setting curve makes it more likely that the second effect is larger than the first. If this is the case, earnings risk is countercyclical since it is decreasing in tightness. In the model presented in Ravn and Sterk (2021), a fall in tightness will therefore increase earnings risk. This will trigger a precautionary savings motive, which will reduce demand. In turn, firms will post fewer vacancies, causing tightness to drop even more, leading to a contractionary spiral. A flatter wage-setting curve can therefore increase volatility in tightness and unemployment both through the traditional feedback mechanism found in the canonical DMP-model and through its effect on precautionary savings. Challe (2020) also shows in a similar model that the optimal monetary policy depends on whether the precautionary savings motive dominates the intertemporal substitution motive, and that this is the case when the earnings risk is countercyclical.

I assess whether earnings risk is countercyclical, using the following back-of-the-envelope calculation: Let the earnings risk be given by

$$ER = \delta(1 - f(\theta))(w - z) \tag{14}$$

where $f(\theta)$ is the job-finding rate, and everything else is the same as in Section 2, i.e. earnings risk is the probability of losing your job and not finding a new job multiplied by the drop in income when unemployed. The earnings risk will then be countercyclical if

$$\epsilon_{f,\theta} > \frac{(1 - f(\theta))}{f(\theta)} \epsilon_{w,\theta} \frac{1}{1 - \frac{z}{w}} \tag{15}$$

where $\epsilon_{f,\theta}$ and $\epsilon_{w,\theta}$ denote the elasticity of the job-finding rate and wages with respect to tightness. $\epsilon_{w,\theta}$ simply corresponds to the estimate of 0.014 from Table II, and I use the estimate $\epsilon_{f,\theta} = 0.28$ from Shimer (2005). Using the unemployment duration from Bagger and Lentz (2019) based on Danish data, I get a quarterly job-finding rate of $f(\theta) = \frac{1}{1.054} \approx 0.95$. Finally, the maximum degree of unemployment compensation in Denmark is 90 pct., $\frac{z}{w} = 0.9$.[14] Inserting these in to (15) results in $0.28 > 0.007$. This exercise, therefore, indicates that earnings risk is countercyclical in a Danish context. In a setting such as the one presented Ravn and Sterk (2021), the feedback between earnings risk and precautionary savings would therefore lead to a contractionary spiral.

# 6 Conclusion

The effect from labor market tightness on wages through outside options plays a key role in many search-and-matching models. However, we lack evidence of this effect. In this paper, I have provided new microeconometric estimates of this effect from tightness to wages. I first created firm-level tightness measures using Danish data on vacancies and unemployment across occupations and the occupational composition of workers in each firm. These measures capture the tightness in the occupation that each individual firm is hiring from. I argue that if each firm takes occupational tightness as given, then I can block the feedback between the wage-setting and vacancy-creation curves if I estimate the effect from tightness on wages at the firm level. Using these firm-level tightness measures in a shift-share design, I found that an increase in firm-specific labor market tightness leads to higher wages, with an elasticity of around 0.015. These results are robust to a range of extensions, including allowing the tightness measure to include on-the-job search

[14] Unemployment compensation is capped, so for many, the degree of compensation will be smaller.

and occupational mobility. I also find that firm-level EE separations are increasing in tightness, with an estimated semi-elasticity of 0.7 - 1.7 pct. points

The estimates support the qualitative implications of the DMP model. The estimates also imply values for key parameters controlling the slope of the wage-setting curve in the DMP model that are in line with the calibration used in Hagedorn and Manovskii (2008). Additionally, the relatively flat wage-setting curve implied by the estimates makes it likely that earnings risk is countercyclical in the type of model developed by Ravn and Sterk (2021). Further possible avenues of research include the degree to which high labor market tightness leads to substitution between workers of different occupations and capital, and whether tightness drives occupational mobility.

# References

**Abowd, John M., Francis Kramarz, and David N. Margolis**, "High Wage Workers and High Wage Firms," *Econometrica*, 1999, *67* (2), 251–333.

**Adão, Rodrigo, Michal Kolesár, and Eduardo Morales**, "Shift-Share Designs: Theory and Inference," *The Quarterly Journal of Economics*, November 2019, *134* (4), 1949–2010.

**Azar, José, Ioana Marinescu, Marshall Steinbaum, and Bledi Taska**, "Concentration in US labor markets: Evidence from online vacancy data," *Labour Economics*, October 2020, *66*, 101886.

**Bagger, Jesper and Rasmus Lentz**, "An Empirical Model of Wage Dispersion with Sorting," *The Review of Economic Studies*, January 2019, *86* (1), 153–190.

**Bartik, Timothy**, "Who Benefits from State and Local Economic Development Policies?," *W.E. Upjohn Institute*, January 1991.

**Beaudry, Paul and John DiNardo**, "The Effect of Implicit Contracts on the Movement of Wages Over the Business Cycle: Evidence from Micro Data," *Journal of Political Economy*, 1991, *99* (4), 665–688.

**Bilal, Adrien, Niklas Engbom, Simon Mongey, and Giovanni L. Violante**, "Firm and Worker Dynamics in a Frictional Labor Market," *Econometrica*, 2022, *90* (4), 1425–1462.

**Bilbiie, Florin**, "Monetary Policy and Heterogeneity: An Analytical Framework," Technical Report, University of Lausanne 2021.

**Borusyak, Kirill, Peter Hull, and Xavier Jaravel**, "Quasi-Experimental Shift-Share Research Designs," *The Review of Economic Studies*, January 2022, *89* (1), 181–213.

**Challe, Edouard**, "Uninsured Unemployment Risk and Optimal Monetary Policy in a Zero-Liquidity Economy," *American Economic Journal: Macroeconomics*, April 2020, *12* (2), 241–283.

**Christiano, Lawrence J., Martin S. Eichenbaum, and Mathias Trabandt**, "Unemployment and Business Cycles," *Econometrica*, 2016, *84* (4), 1523–1569.

**DA**, "Dansk Arbejdsgiverforening: Mindstebetaling er det mest udbredte lønsystem på DA/LO-området.," 2018. URL: https://www.da.dk/politik-og-analyser/overenskomst-og-arbejdsret/2018/mindstebetaling-er-det-mest-udbredte-loensystem-paa-dalo-omraadet. Website link (accessed December, 19 2022).

**Domash, Alex and Lawrence H. Summers**, "How Tight are U.S. Labor Markets?," Working Paper 29739, National Bureau of Economic Research February 2022. Series: Working Paper Series.

**Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift**, "Bartik Instruments: What, When, Why, and How," *American Economic Review*, August 2020, *110* (8), 2586–2624.

**Hagedorn, Marcus and Iourii Manovskii**, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited," *The American Economic Review*, 2008, *98* (4), 1692–1706.

**Hall, Robert E.**, "Employment Fluctuations with Equilibrium Wage Stickiness," *The American Economic Review*, 2005, *95* (1), 50–65.

_ **and Paul R. Milgrom**, "The Limited Influence of Unemployment on the Wage Bargain," *American Economic Review*, September 2008, *98* (4), 1653–1674.

**Hosios, Arthur J.**, "On the Efficiency of Matching and Related Models of Search and Unemployment," *The Review of Economic Studies*, 1990, *57* (2), 279–298.

**Jäger, Simon, Benjamin Schoefer, Samuel Young, and Josef Zweimüller**, "Wages and the Value of Nonemployment," *The Quarterly Journal of Economics*, November 2020, *135* (4), 1905–1963.

**Kambourov, Gueorgui and Iourii Manovskii**, "Occupational Mobility and Wage Inequality," *The Review of Economic Studies*, 2009, *76* (2), 731–759.

**Kreiner, Claus Thustrup and Michael Svarer**, "Danish Flexicurity: Rights and Duties," *Journal of Economic Perspectives*, November 2022, *36* (4), 81–102.

**Lagoa, Sérgio and Fátima Suleman**, "Industry- and occupation-specific human capital: evidence from displaced workers," *International Journal of Manpower*, 2016, *37* (1), 44–68.

**Lise, Jeremy and Jean-Marc Robin**, "The Macrodynamics of Sorting between Workers and Firms," *American Economic Review*, April 2017, *107* (4), 1104–1135.

**Mercan, Yusuf and Benjamin Schoefer**, "Jobs and Matches: Quits, Replacement Hiring, and Vacancy Chains," *American Economic Review: Insights*, March 2020, *2* (1), 101–124.

**Mincer, Jacob A.**, *Schooling, Experience, and Earnings*, NBER, 1974.

**Moscarini, Giuseppe and Fabien Postel-Vinay**, "The Relative Power of Employment-to-Employment Reallocation and Unemployment Exits in Predicting Wage Growth," *American Economic Review*, May 2017, *107* (5), 364–368.

_ **and** _ , "On the Job Search and Business Cycles," *IZA Discussion Papers*, September 2018. Number: 11853 Publisher: Institute of Labor Economics (IZA).

**Nakamura, Emi and Jón Steinsson**, "Identification in Macroeconomics," *Journal of Economic Perspectives*, August 2018, *32* (3), 59–86.

**Pissarides, Christopher A.**, "Short-Run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages," *The American Economic Review*, 1985, *75* (4), 676–690.

—, *Equilibrium Unemployment Theory*, MIT Press, 2000.

—, "The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer?," *Econometrica*, 2009, *77* (5), 1339–1369.

**Ravn, Morten O and Vincent Sterk**, "Macroeconomic Fluctuations with HANK & SAM: an Analytical Approach," *Journal of the European Economic Association*, April 2021, *19* (2), 1162–1202.

**Schubert, Gregor, Anna Stansbury, and Bledi Taska**, "Employer Concentration and Outside Options," SSRN Scholarly Paper ID 3599454, Social Science Research Network, Rochester, NY January 2021.

**Shimer, Robert**, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, March 2005, *95* (1), 25–49.

**Solon, Gary, Robert Barsky, and Jonathan A. Parker**, "Measuring the Cyclicality of Real Wages: How Important is Composition Bias," *The Quarterly Journal of Economics*, 1994, *109* (1), 1–25.

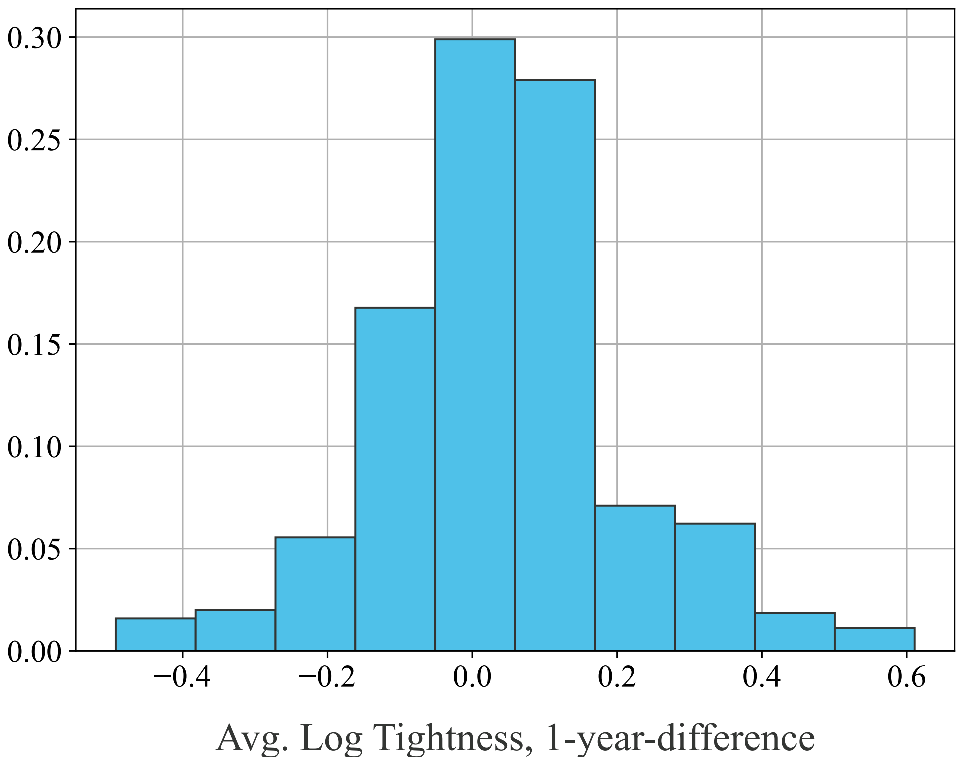
**Turrell, Arthur, Bradley Speigner, David Copple, Jyldyz Djumalieva, and James Thurgood**, "Is the UK's productivity puzzle mostly driven by occupational mismatch? An analysis using big data on job vacancies," *Labour Economics*, August 2021, *71*, 102013.

**Zangelidis, Alexandros**, "Occupational and Industry Specificity of Human Capital in the British Labour Market," *Scottish Journal of Political Economy*, September 2008, *55* (4), 420–443.

# List of Figures

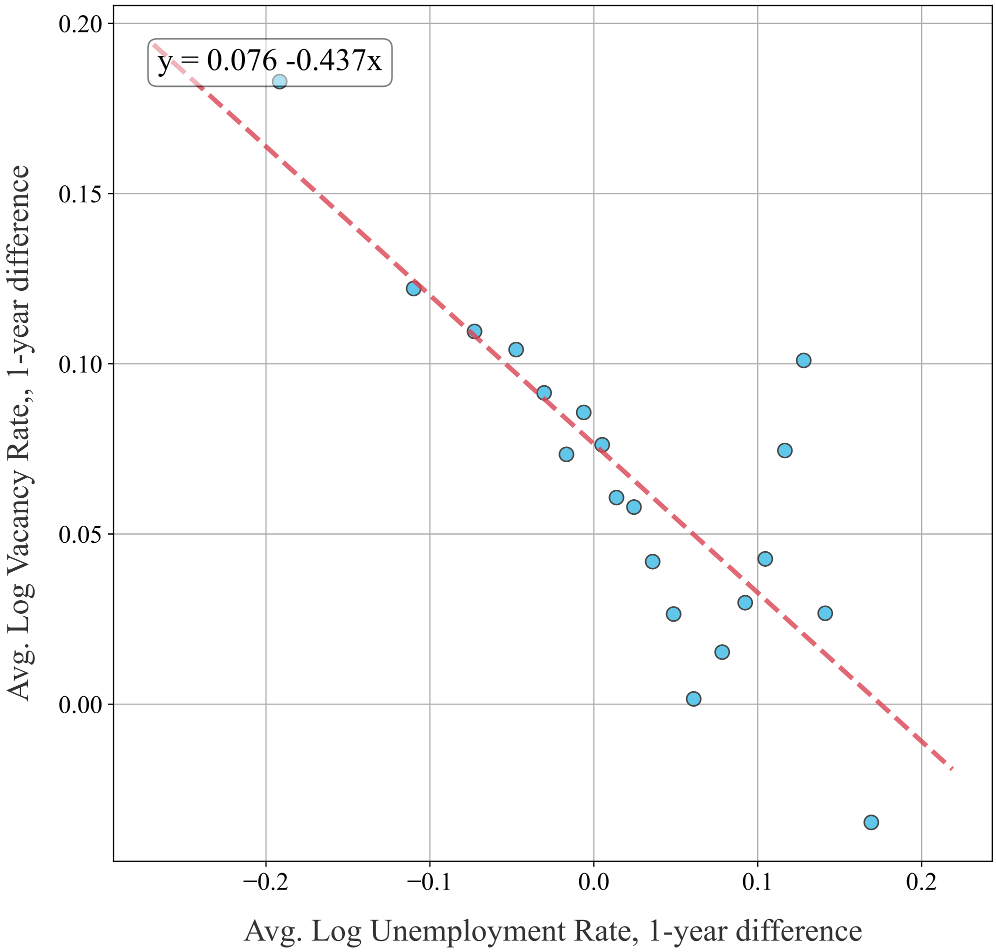
# Figures

Figure I: Distribution of 1-year Differences in Firm-level Log Tightness




*Notes: The change in tightness is calculated as weighted averages of the occupational-level counterparts, using firm-specific occupation shares as weights. The top and bottom 0.1 pct. of shocks are winsorized in the figure for anonymity. Occupations are defined by a 2-digit ISCO-code.*

Figure II: Firm-level Beveridge Curve

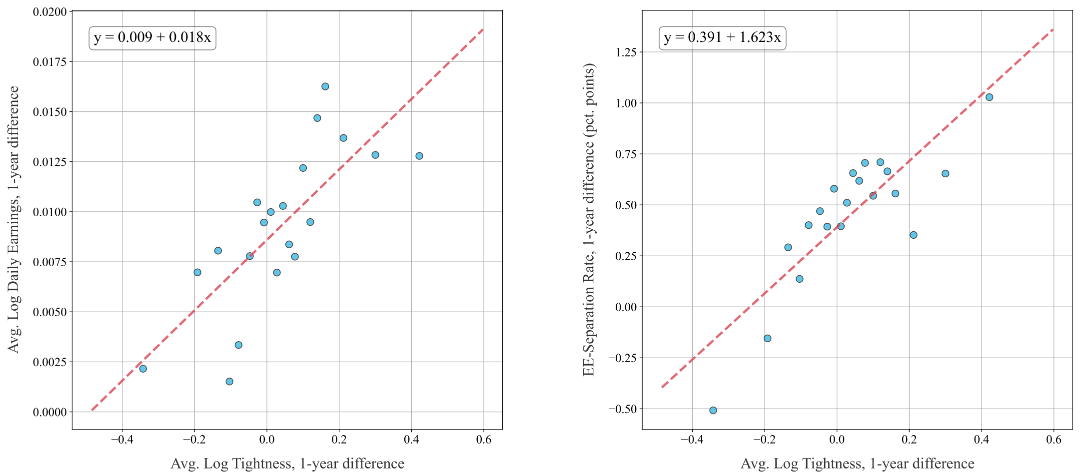



*Notes: Changes in the firm-level vacancy and unemployment rates are calculated as weighted averages of the occupational-level counterparts, using firm-specific occupation shares as weights. The occupational labor force is calculated as the sum of employed and unemployed belonging to a given occupation. Firm-year observations are aggregated into 20 bins. Occupations are defined by a 2-digit ISCO-code. The top and bottom 0.1 pct. of all variables are winsorized in the figure for anonymity.*

Figure III: Firm-level Effects of Labor Market Tightness

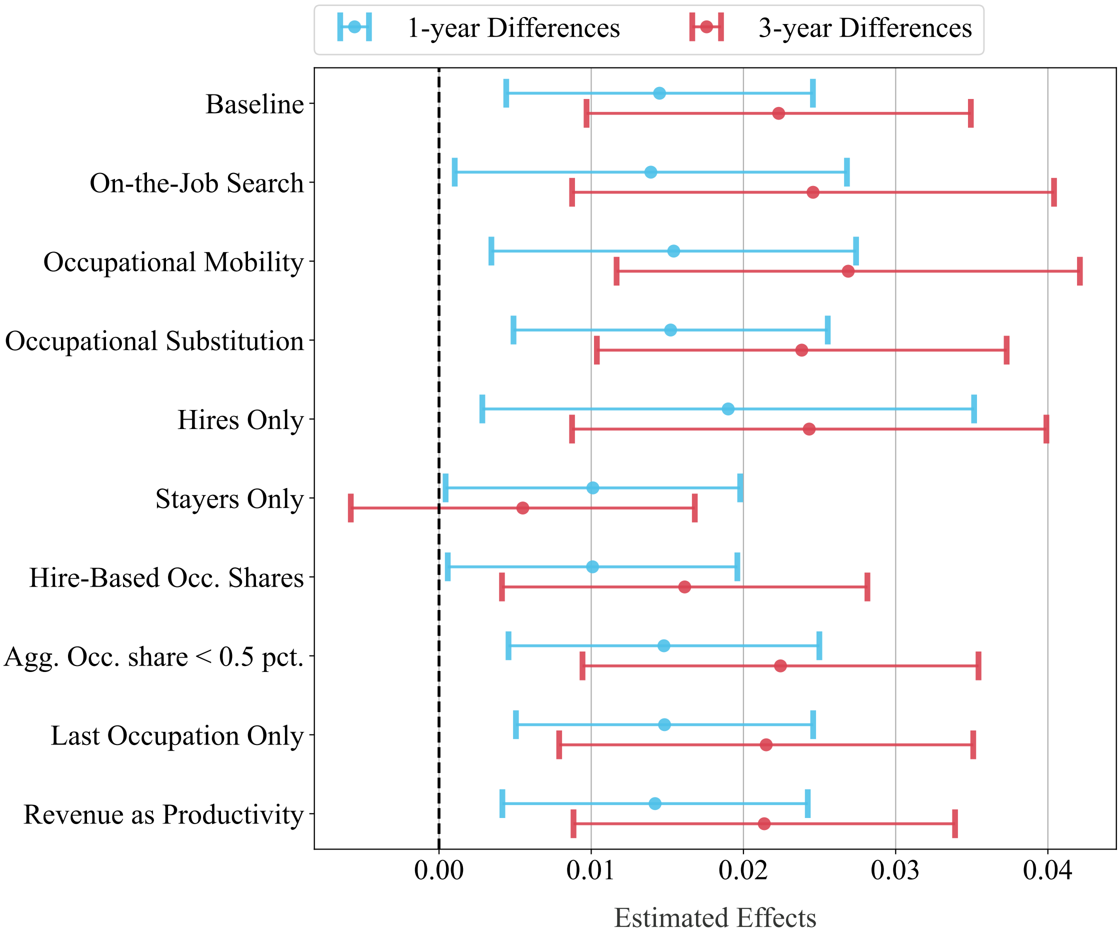
(a) Firm-level correlation between wage and tightness growth

(b) Firm-level correlation between EE-separation rate and tightness growth




*Notes: Changes in the firm-level tightness is calculated as the weighted average of the occupational-level counterparts, using firm-specific occupation shares as weights. Firm-year observations are aggregated into 20 bins. Occupations are defined by a 2-digit ISCO-code. The top and bottom 0.1 pct. of all variables are winsorized in the figures for anonymity.*

Figure IV: Wage Effects of Labor Market Tightness: Robustness Checks




*Notes: The estimation is based on equation (10). All specifications use the difference in log value added per worker, and period, industry, and region fixed effects as controls, except for "Revenue as Productivity", where the difference in log revenue per worker is used instead of value added. Industry is defined as NACE Section level. Error bars indicate 95 pct. confidence intervals. Standard errors are based on the standard error estimator from Adão et al. (2019).*

# List of Tables

# Tables

Table I: Descriptive statistics for firms

| | | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|
| **Avg. Yearly Earnings** | Mean | 50,827 | 51,053 | 52,029 | 52,627 | 53,275 | 54,238 | 54,464 |
| | Std. dev. | 11,609 | 11,833 | 12,168 | 12,107 | 12,436 | 12,893 | 13,188 |
| **EE-Separation Rate, pct.** | Mean | 12.54 | 13.35 | 13.86 | 14.27 | 14.53 | 14.40 | 13.94 |
| | Std. dev. | 9.20 | 9.66 | 9.85 | 10.03 | 10.06 | 10.03 | 10.05 |
| **Value Added per Worker** | Mean | 75,122 | 74,294 | 76,795 | 79,228 | 80,078 | 82,869 | 79,512 |
| | Std. dev. | 388,409 | 88,069 | 100,047 | 134,239 | 270,795 | 313,870 | 137,284 |
| **Tightness** | Mean | 0.12 | 0.14 | 0.17 | 0.19 | 0.19 | 0.18 | 0.16 |
| | Std. dev. | 0.10 | 0.10 | 0.11 | 0.14 | 0.11 | 0.10 | 0.09 |
| **Tightness 1-year change** | Mean | 0.10 | 0.18 | 0.12 | -0.01 | -0.01 | -0.10 | - |
| | Std. dev. | 0.16 | 0.12 | 0.12 | 0.10 | 0.15 | 0.17 | - |
| **No. of employees** | Mean | 36.47 | 37.97 | 38.62 | 39.63 | 38.85 | 37.23 | 37.44 |
| | Std. dev. | 174.32 | 183.81 | 182.23 | 191.03 | 182.41 | 174.23 | 170.26 |
| **No. of occupations** | Mean | 4.19 | 3.98 | 3.94 | 3.98 | 4.01 | 3.91 | 3.92 |
| | Std. dev. | 3.10 | 3.06 | 3.05 | 3.12 | 3.17 | 3.15 | 3.12 |
| **Occupation HHI** | Mean | 0.03 | 0.02 | 0.03 | 0.03 | 0.02 | 0.02 | 0.02 |
| | Std. dev. | 0.04 | 0.04 | 0.06 | 0.04 | 0.03 | 0.03 | 0.04 |
| **No. of firms** | | 15,568 | 15,997 | 16,064 | 16,179 | 17,149 | 18,870 | 19,135 |

*Note: The firm-specific tightness measure is calculated using the aggregate occupational tightness level and firm-specific occupation shares. Occupations are defined by a 2-digit ISCO-code. Average yearly earnings and value-added are CPI-deflated and shown in EUR (1 EUR = 7.44 DKK). The table is based on data from STAR and Statistics Denmark. The mean occupation Herfindahl index (HHI) is calculated as the average HHI across occupations with the index in an occupation given by* $\sum_k s^2_{h,k,t}$*, where* $s_{h,k,t}$ *denotes the share of all occupation h workers employed at firm k.*

Table II: Wage Effects of Labor Market Tightness.

| | Avg. Log Daily Earnings | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-year differences | | | | 3-year differences | | | |
| Log Tightness | 0.014*** | 0.018*** | 0.014** | 0.020*** | 0.022*** | 0.017*** | 0.025*** | 0.024*** |
| | (0.005) | (0.005) | (0.007) | (0.007) | (0.006) | (0.005) | (0.008) | (0.008) |
| No. obs. | 81,522 | 81,522 | 81,522 | 81,522 | 22,921 | 22,921 | 22,921 | 22,921 |
| On-the-job search | | | X | X | | | X | X |
| Controls | X | | X | | X | | X | |

*Notes: The estimation is based on equation (10). Controls include the difference in log value added per worker, and period, industry, and region fixed effects. Industry is defined as NACE Section level. Standard errors are based on the standard error estimator from Adão et al. (2019). Significance:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table III: Effect of Labor Market Tightness on EE-separation rate.

| | EE-Separation Rate, pct. points | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-year differences | | | | 3-year differences | | | |
| Log Tightness | 0.709*** | 1.624*** | 0.834*** | 1.724*** | 0.876*** | 1.853*** | 1.091*** | 2.364*** |
| | (0.244) | (0.350) | (0.299) | (0.611) | (0.267) | (0.205) | (0.349) | (0.475) |
| No. obs. | 81,522 | 81,522 | 81,522 | 81,522 | 22,921 | 22,921 | 22,921 | 22,921 |
| On-the-job search | | | X | X | | | X | X |
| Controls | X | | X | | X | | X | |

*Notes: The estimation is based on equation (10), except that the difference in the firm-level EE-separation rate is the outcome of interest, instead of the average log daily earnings. Controls include the difference in log value added per worker, and period, industry, and region fixed effects. Industry is defined as NACE Section level. Standard errors are based on the standard error estimator from Adão et al. (2019). Significance:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

# A Derivation of Wage Equations

When a match is made, the surplus is distributed using generalized Nash Bargaining,

$$V^e_{h,k} - V^u_h = \beta\left(\Pi^e_{h,k} - \Pi^v_{h,k} + V^e_{h,k} - V^u_h\right) \tag{16}$$

where $\beta$ is the relative bargaining power of workers. Inserting (1), (4) and the free-entry condition results in

$$w_{h,k} = rV^u_h + \beta\left(y_{h,k} - rV^u_h\right) \tag{17}$$

Taking the expectation of (16) with respect to firm heterogeneity, and then inserting it and (5) into (17) results in wage equation (6), shown in Section 2,

$$w_{h,k} = (1-\beta)z + \beta y_{h,k} + \beta\theta_h q(\theta_h) E_j(\Pi^e_{h,j}) \tag{18}$$

# B Assumptions Needed for Shift-Share Design

This appendix describes the assumptions needed for consistency and inference using the shift-share design. I also describe the standard error estimator used, which is developed by Adão et al. (2019). All assumptions are based on their paper.

As recommended by the authors, I allow for correlation across time for each shock, in this case, changes in tightness in the same occupation in different years. Let $c(l) = c(h,t)$ denote the cluster for each occupation across time, such that $c(l) = c(h,t) = c(h',t') = c(l')$ if $h = h'$. To improve readability, I follow Adão et al. (2019) and define the new indices $j = (k,t)$ and $l = (h,t)$ such that $\theta_l = \theta_{h,t}$, $y_j = y_{k,t}$, etc. and $L = H \times T$ and $J = K \times T$. Additionally, let

$$s_{j,l} = \begin{cases} s_{h,k,t} & \text{if } j = (k,t) \text{ and } l = (h,t) \\ 0 & \text{if } j = (k,t), l = (h,t') \text{ and } t' \neq t \end{cases} \tag{19}$$

Let $\mathfrak{F}$ denote the collection of all variables except occupation-specific tightness shocks, i.e.

$$\mathfrak{F} = \{\hat{w}_j, s_{j,l}, \hat{\mathbf{x}}_j, \hat{y}_l, \hat{\epsilon}_j\}_{l=1,j=1}^{L,J} \tag{20}$$

The following assumptions are needed for identification, consistent estimation, and valid inference for $\rho$ using OLS:

**Assumption B.1** *Equation (10) holds, i.e. the functional form is correctly specified.*

**Assumption B.2** *The tightness measures $\theta_l$ and $\theta_{l'}$ are independent conditional on $\mathfrak{F}$ if $c(l) = c(h,t) \neq c(h',t') = c(l')$*

**Assumption B.3** *The conditional expectation of $\hat{\theta}_l$ is linear in $\hat{y}_l$ and $\hat{\mathbf{x}}_{h,t}^k$*

$$\mathbb{E}[\theta_l|\hat{y}_l, \hat{\mathbf{x}}_j] = a\hat{y}_l + b\mathbf{x}_j \tag{21}$$

**Assumption B.4** $\max_l \frac{n_l}{\sum_{l' \in S} n'_l} \rightarrow 0$, *i.e. the relative size of each occupation-year decreases to 0 as the number of occupation-years increases to* $\infty$

**Assumption B.5** $\max_c \frac{n_c^2}{\sum_{j \in C} n_c^2} \rightarrow 0$, *i.e. the asymptotic contribution to the variance from each cluster becomes negligible as the number of clusters, $C$, increases to* $\infty$

These assumptions ensure consistency for OLS and valid standard errors for the estimator from Adão et al. (2019).

# C Data Sources

Table C.1 contains information on the individual data sources used in this paper.

Table C.1: Summary of the Data Sources

| Data set | Source | Year | Main Variables |
|---|---|---|---|
| IDA persondata (IDAN) | DST | 2010-2019 | Employer, Wages, Occupation |
| IDA persondata (IDAP) | DST | 2010-2019 | Workforce characteristics |
| Detaljeret lønmodtagerdata fra e-Indkomst (BFL) | DST | 2010-2020 | Employment Spell Information |
| Generel firmastatistik (FIRM) | DST | 2013-2019 | Value added, Revenue, Industry |
| Befolkningen (BEF) | DST | 2013-2019 | Age |
| Occupation-level vacancy data | STAR | 2013-2019 | Vacancies |

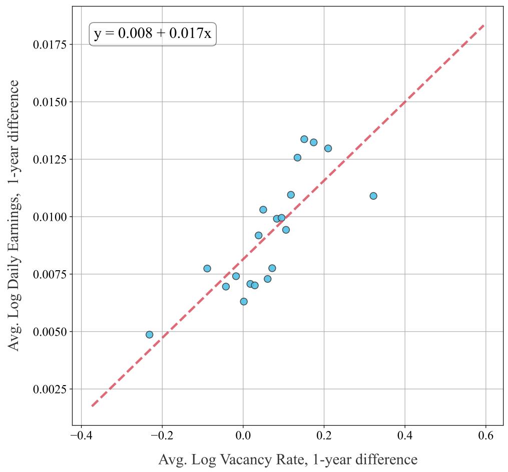
Note: The table reports the data sets used. The data sets come from the national statistical agency (DST, *Danmarks Statistik*) and from the government agency responsible for promoting efficient employment policies (STAR, *Styrelsen for Arbejdsmarked og Rekruttering*). Official documentation can be found at:
*https://www.dst.dk/extranet/forskningvariabellister/Oversigt%20over%20registre.html*

# D Correlation Between the Vacancy Rate, the Unemployment Rate, and Wages at the Firm Level

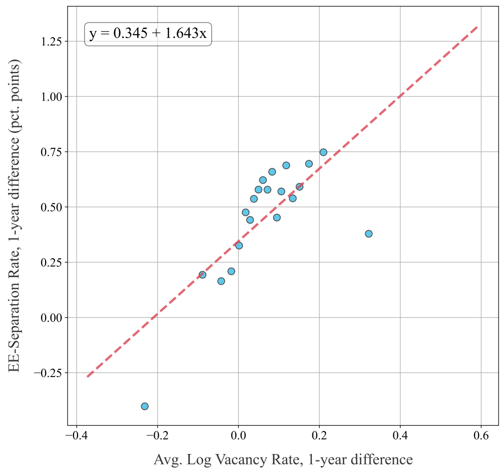
Figure D.1a, D.1b, D.1c and D.1d show the correlation between firm-level average log daily earnings and EE-separation rates and the components of labor market tightness, i.e. the vacancy rate and unemployment rate. These are calculated using the same procedure that is used for tightness. Both figures show the correlation implied by the DMP model. A higher vacancy rate in the labor market relevant for the firm is correlated with higher wages and EE-separation rates, as it becomes harder to fill vacancies and easier to find another job. On the other hand, the unemployment rate is negatively correlated with wages and EE-separation rates, as it is easier to fill a vacancy if many unemployed potential employees are available, and harder to find another job.

Figure D.1: Firm-level Effects of Vacancies and Unemployment

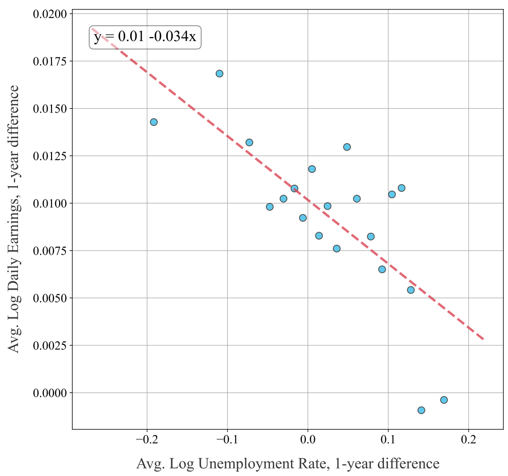
(a) Firm-level correlation between wages and vacancies



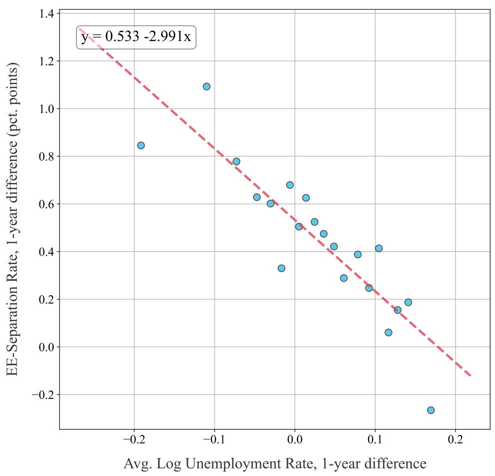

(b) Firm-level correlation between EE-separations and vacancies




(c) Firm-level correlation between wages and unemployment




(d) Firm-level correlation between EE-separations and unemployment




*Notes: Changes in the firm-level vacancy and unemployment rates are calculated as weighted averages of the occupational- level counterparts, using firm-specific occupation shares as weights. The occupational labor force is calculated as the sum of employed and unemployed belonging to a given occupation. Firm-year observations are aggregated into 20 bins. The top and bottom 0.1 pct. of all variables are winsorized in the figures for anonymity.*

# E Additional Robustness Checks

## E.1 Occupational Mobility

Table E.1 contains the estimates of the wage-setting curve when allowing for occupational mobility, using the method described in Section 5. From the table, it is clear that the findings are robust to allowing for occupational mobility. Most estimates are unaffected, and none lie outside the range of estimates already found in the previous specifications.

Table E.1: Wage Effects of Labor Market Tightness - Allowing for Occupational Mobility.

| | Avg. Log Daily Earnings | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-year differences | | | | 3-year differences | | | |
| Log Tightness | 0.015** | 0.021*** | 0.014** | 0.021*** | 0.027*** | 0.022*** | 0.026*** | 0.026*** |
| | (0.006) | (0.006) | (0.007) | (0.007) | (0.008) | (0.007) | (0.008) | (0.009) |
| No. obs. | 81,522 | 81,522 | 81,522 | 81,522 | 22,921 | 22,921 | 22,921 | 22,921 |
| On-the-job search | | | X | X | | | X | X |
| Controls | X | | X | | X | | X | |

*Notes: The estimation is based on equation (10), where the tightness measures used allows for occupational mobility as described in equation (11). Controls include the difference in log value added per worker, and period, industry, and region fixed effects. Industry is defined as NACE Section level. Standard errors are based on the standard error estimator from Adão et al. (2019). Significance:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## E.2 Occupational Substitution: IV Approach

The estimations in Section 5 use the shift-share measure of firm-specific tightness in a reduced-form setting. Specifically, the estimation does not account for differences in the current occupation shares and the initial occupation shares used in the estimation. If firms can easily substitute between occupations when hiring, this limits the interpretation of the estimated coefficients. They can however still be interpreted as the increase in wages at a firm, when tightness increases for the initial occupation bundle, and the firm is allowed to substitute between occupations. For many purposes this will also be the relevant effect, i.e. to answer the question: Do firms increase wages when tightness increases for their employees? However, to get the effect for fixed shares I can simply use the tightness measure as an instrument for a new tightness measure calculated using both current and lagged occupation shares, i.e. $\sum_{h \in H} s_{h,k,t+\Delta t}\theta_{h,t+\Delta t} - \sum_{h \in H} s_{h,k,t}\theta_{h,t}$. The resulting estimates are shown in Table E.2. The IV estimation leads to estimates very similar to the main reduced-form approach in Table II.

Table E.2: Wage Effects of Labor Market Tightness - Occupational Substitution: IV-Approach.

| | Avg. Log Daily Earnings | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-year differences | | | | 3-year differences | | | |
| Log Tightness | 0.015*** | 0.018*** | 0.015** | 0.021*** | 0.024*** | 0.017*** | 0.027*** | 0.024*** |
| | (0.005) | (0.005) | (0.007) | (0.007) | (0.007) | (0.005) | (0.009) | (0.008) |
| No. obs. | 81,522 | 81,522 | 81,522 | 81,522 | 22,921 | 22,921 | 22,921 | 22,921 |
| On-the-job search | | | X | X | | | X | X |
| Controls | X | | X | | X | | X | |

*Notes: The estimation is based on equation (10), except that tightness is given by* $\sum_{h \in H} s_{h,k,t}\theta_{h,t} - \sum_{h \in H} s_{h,k,t-1}\theta_{h,t-1}$ *which is then instrumented by my main tightness measure,* $\hat{\Theta}_{k,t}$*. Controls include the difference in log value added per worker, and period, industry, and region fixed effects. Industry is defined as NACE Section level. Standard errors are based on the standard error estimator from Adão et al. (2019). Significance:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## E.3 Hires and Stayers

In the results presented in Section 5, I do not differentiate between the response of new hires and employees who stay at the firm. However, it is often argued, such as in Pissarides (2009), that it is the wage of new hires that drives fluctuations over the business cycle. In Table E.3 I, therefore, examine the effect of tightness on earnings for hires and stayers separately. From the table, we see that the estimated effects indeed are stronger for new hires and that many of the estimates for stayers are statistically insignificant. This indicates that the estimated effects in Table II, are, at least to some degree, driven by the earnings of new hires.

Table E.3: Wage Effects of Labor Market Tightness - Wages of Hires and Stayers.

| | Avg. Log Daily Earnings | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Hires | | | | | | | |
| | 1-year differences | | | | 3-year differences | | | |
| Log Tightness | 0.019** | 0.021*** | 0.018* | 0.025** | 0.024*** | 0.016*** | 0.029*** | 0.023** |
| | (0.008) | (0.007) | (0.010) | (0.011) | (0.008) | (0.006) | (0.010) | (0.010) |
| No. obs. | 61,691 | 61,691 | 61,691 | 61,691 | 17,293 | 17,293 | 17,293 | 17,293 |
| | Stayers | | | | | | | |
| | 1-year differences | | | | 3-year differences | | | |
| Log Tightness | 0.010** | 0.013** | 0.011* | 0.014* | 0.006 | 0.009 | 0.006 | 0.007 |
| | (0.005) | (0.006) | (0.006) | (0.007) | (0.006) | (0.006) | (0.008) | (0.010) |
| No. obs. | 81,385 | 81,385 | 81,385 | 81,385 | 21,476 | 21,476 | 21,476 | 21,476 |
| On-the-job search | | | X | X | | | X | X |
| Controls | X | | X | | X | | X | |

*Notes: The estimation is based on equation (10). When estimating the effect for each group, the sample is restricted to firms that have at least one hire or stayer. Controls include the difference in log value added per worker, and period, industry, and region fixed effects. Industry is defined as NACE Section level. Standard errors are based on the standard error estimator from Adão et al. (2019). Significance:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## E.4 Shares Based on Hires

The results in Section 5 are based on the firm-specific tightness measure constructed using the occupation composition of employees at each firm. However, each firm's exposure to changes in occupational tightness may be driven by the occupations they hire from and not the occupational composition of workers already employed. As a robustness check, I estimate equation (10) again, but now construct the tightness measures using the occupational shares for new hires instead of for all employees. The results are shown in Table E.4. The results are roughly similar to those shown in Table II from the main regression, though somewhat smaller. This is consistent with the flow of hires having an occupational composition roughly similar to that of the stock of employees.

Table E.4: Wage Effects of Labor Market Tightness - Using Occupational Shares of Hires

| | Avg. Log Daily Earnings | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-year differences | | | | 3-year differences | | | |
| Log Tightness | 0.010** | 0.015*** | 0.009 | 0.015** | 0.016*** | 0.015*** | 0.017** | 0.019** |
| | (0.005) | (0.005) | (0.006) | (0.007) | (0.006) | (0.005) | (0.008) | (0.008) |
| No. obs. | 61,691 | 61,691 | 61,691 | 61,691 | 17,293 | 17,293 | 17,293 | 17,293 |
| On-the-job search | | | X | X | | | X | X |
| Controls | X | | X | | X | | X | |

*Notes: The estimation is based on equation (10), but instead of the composition of hires instead of employees has been used to construct the tightness measure,* $\hat{\Theta}_{k,t}$*. The sample is therefore also restricted to firms with at least 1 new hire in a firm-year. Controls include the difference in log value added per worker, and period, industry, and region fixed effects. Industry is defined as NACE Section level. Standard errors are based on the standard error estimator from Adão et al. (2019). Significance:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## E.5 Removing Firms with Monopsony Power

As mentioned in Section 3, the validity of the results depends on the assumption that each firm has a negligible impact on the labor markets it is hiring from. I test the results' sensitivity to this assumption by conducting the same estimations on samples where firms that employ non-negligible shares of the total number of workers in an occupation have been excluded. Specifically, I estimate $\rho$ using samples where only firms that employ less than 5 percent and 0.5 percent. of the total workers in an occupation. The results are shown in Table E.5. From the table, it is clear that the estimates obtained are not sensitive to excluding firms that might be large enough to influence market conditions.

Table E.5: Wage Effects of Labor Market Tightness - Firms with Small Total Occupation Shares.

| | Avg. Log Daily Earnings | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Max Agg. Occupation Share: 5 pct. | | | | | | | |
| | 1-year differences | | | | 3-year differences | | | |
| Log Tightness | 0.014*** | 0.018*** | 0.014** | 0.019*** | 0.022*** | 0.017*** | 0.025*** | 0.024*** |
| | (0.005) | (0.005) | (0.007) | (0.007) | (0.006) | (0.005) | (0.008) | (0.008) |
| No. obs. | 81,448 | 81,448 | 81,448 | 81,448 | 22,893 | 22,893 | 22,893 | 22,893 |
| | Max Agg. Occupation Share: 0.5 pct. | | | | | | | |
| | 1-year differences | | | | 3-year differences | | | |
| Log Tightness | 0.015*** | 0.018*** | 0.014** | 0.020*** | 0.022*** | 0.017*** | 0.025*** | 0.023*** |
| | (0.005) | (0.005) | (0.007) | (0.007) | (0.007) | (0.005) | (0.008) | (0.008) |
| No. obs. | 79,206 | 79,206 | 79,206 | 79,206 | 22,169 | 22,169 | 22,169 | 22,169 |
| On-the-job search | | | X | X | | | X | X |
| Controls | X | | X | | X | | X | |

*Notes: The estimation is based on equation (10). Controls include the difference in log value added per worker, and period, industry, and region fixed effects. Industry is defined as NACE Section level. Max Aggregate Occupation Share indicates the exclusion criteria for a firm with a large share of total employment in an occupation. Standard errors are based on the standard error estimator from Adão et al. (2019). Significance:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## E.6 Occupation Based on Latest Job Only

Table E.6 contains estimates obtained when unemployed are allocated to an occupation based only on their last job, instead of all jobs. Overall, the results are similar to the ones found in Table II.

Table E.6: Firm Effects of Labor Market Tightness - Only Use Latest Job when Calculating The Number of Job-Seekers.

| | Avg. Log Daily Earnings | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-year differences | | | | 3-year differences | | | |
| Log Tightness | 0.015*** | 0.017*** | 0.014** | 0.019*** | 0.021*** | 0.016*** | 0.025*** | 0.023*** |
| | (0.005) | (0.005) | (0.006) | (0.007) | (0.007) | (0.006) | (0.008) | (0.009) |
| No. obs. | 81,522 | 81,522 | 81,522 | 81,522 | 22,169 | 22,169 | 22,169 | 22,169 |
| On-the-job search | | | X | X | | | X | X |
| Controls | X | | X | | X | | X | |

*Notes: The estimation is based on equation (10). Controls include the difference in log value added per worker, and period, industry, and region fixed effects. Industry is defined as NACE Section level. Standard errors are based on the standard error estimator from Adão et al. (2019). Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

## E.7 Productivity Based on Revenue per Worker

All the results presented have used a measure of productivity based on value added per worker. As a robustness check, I also present estimates where I control for productivity using measures based on revenue per worker. The results are shown in Table E.7. The estimates of the effect from tightness on wages are very similar to the ones obtained using value added per worker. All estimates lie within the range of estimates found in the main analysis.

Table E.7: Wage Effects of Labor Market Tightness - Revenue-based Productivity Measures.

| | Avg. Log Daily Earnings | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-year differences | | | | 3-year differences | | | |
| Log Tightness | 0.014*** | 0.018*** | 0.014** | 0.019*** | 0.021*** | 0.017*** | 0.023*** | 0.024*** |
| | (0.005) | (0.005) | (0.007) | (0.007) | (0.006) | (0.005) | (0.008) | (0.008) |
| No. obs. | 81,499 | 81,499 | 81,499 | 81,499 | 22,915 | 22,915 | 22,915 | 22,915 |
| On-the-job search | | | X | X | | | X | X |
| Controls | X | | X | | X | | X | |

*Notes: The estimation is based on equation (10). Controls include the difference in log revenue per worker, and period, industry, and region fixed effects. Industry is defined as NACE Section level. Standard errors are based on the standard error estimator from Adão et al. (2019). Significance:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

## E.8 Geographic differences in tightness

All the results presented so far have assumed that occupational tightness is homogenous across geographical areas. However, the demand and supply of different skills might differ geographically. In Section 3, I argue that the relatively small size of Denmark can mitigate this concern. I now also present a robustness check where I allow for geographical differences in the number of searchers and allow for geographical mobility. To this end, I calculate the number of searchers within each of the five administrative regions of Denmark, $S_{h,r,t}$, which can either be only unemployed or also include on-the-job searchers. Similarly to when allowing for occupational mobility, I can then construct tightness measures allowing geographical heterogeneity and mobility

$$S^{ogm}_{h,r,t} = \sum_{p} \sum_{l} \pi_{h,p,r,l} S_{p,l,t} \tag{22}$$

where $S_{p,l,t}$ is the number of job-seekers in occupation $p$ and region $l$ and $\pi_{h,p,r,l}$ is probability that a worker switches from occupation $p$ and region $l$ to occupation $h$ and region $r$. The mobility-adjusted number of job-seekers is then used to calculate the tightness and estimate the slope of the wage-setting curve analogously to the specification not allowing for occupational mobility. I calculate a proxy for $\pi_{h,p,r,l}$ using the observed transition probabilities. The resulting estimates are shown in Table E.8. The estimates are very similar to those obtained using the specification that only allows for occupational mobility in Table E.1.

Table E.8: Wage Effects of Labor Market Tightness - Allowing for geographical heterogeneity and mobility .

| | Avg. Log Daily Earnings | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1-year differences | | | | 3-year differences | | | |
| Log Tightness | 0.016*** | 0.021*** | 0.014*** | 0.021*** | 0.027*** | 0.023*** | 0.026*** | 0.027*** |
| | (0.000) | (0.002) | (0.000) | (0.002) | (0.000) | (0.001) | (0.000) | (0.001) |
| No. obs. | 81,522 | 81,522 | 81,522 | 81,522 | 22,921 | 22,921 | 22,921 | 22,921 |
| On-the-job search | | | X | X | | | X | X |
| Controls | X | | X | | X | | X | |

*Notes: The estimation is based on equation (10), where the tightness measures used allow for occupational and regional mobility as described in equation (22). Controls include the difference in log value added per worker, and period, industry, and region fixed effects. Industry is defined as NACE Section level. Standard errors are based on the standard error estimator from Adão et al. (2019). Significance:* * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

# F Recovering Parameters from Linear DMP model

The reduced-form estimation equation (10) posits a model where the effect of tightness on wages is given by a constant elasticity. This is standard when doing reduced-form wage regressions. However, the wage equation from the DMP model actually posits a relationship that is linear in levels. It is therefore the case that $\rho \neq \beta c$. If we assume that the DMP model is true, the elasticity of wages with respect to tightness at firm $k$ will be given by

$$\rho_{k,t} = \frac{\beta c \Theta_{k,t}}{w_{k,t}} \tag{23}$$

where all variables are denoted in levels and

$$\Theta_{k,t} = \sum_{h \in H} s_{h,k,t} \theta_{h,t} \tag{24}$$

If elasticities are in fact firm and time specific, the estimand $\rho$ given by the OLS estimator will then be a variance-weighted average of the firm-time specific elasticities. Let $\vartheta$ be the $KT \times 1$ vector of firm-specific tightness measures, used in the regression, i.e. weighted averages of tightness log-diffs, and let $Z$ be the $KT \times M$ matrix of all $M$ other controls, including productivity. Finally, let $\ddot{\vartheta}$ be the $n \times 1$ vector of tightness measures orthogonal to the controls,

$$\ddot{\vartheta} = \left(I - Z\left(Z^{\top} Z\right)^{-1} Z^{\top}\right) \vartheta$$

The estimand is then given by a variance-weighted average of the firm-time-specific elasticities:

$$\rho = \sum_t \sum_k \frac{var(\ddot{\vartheta}_{k,t})}{\sum_t \sum_k var(\ddot{\vartheta}_{k,t})} \rho_{k,t} = \sum_t \sum_k \alpha^{\vartheta}_{k,t} \rho_{k,t} \tag{25}$$

Given that the assumptions in Appendix B hold, OLS consistently estimates $\rho$, with the following estimate:

$$\hat{\rho} = \sum_t \sum_k \frac{\ddot{\vartheta}^2_{k,t}}{\sum_t \sum_k \ddot{\vartheta}^2_{k,t}} \rho_{k,t} = \sum_t \sum_k \hat{\alpha}^{\vartheta}_{k,t} \rho_{k,t} \tag{26}$$

The estimate $\hat{\rho}$ and estimated variance weights $\hat{\alpha}^{\vartheta}_{k,t}$ therefore pins down $\beta c$

$$\hat{\rho} = \sum_t \sum_k \hat{\alpha}^{\vartheta}_{k,t} \frac{\beta c \Theta_{k,t}}{w_{k,t}} \Leftrightarrow \beta c = \frac{\hat{\rho}}{\sum_t \sum_k \hat{\alpha}^{\vartheta}_{k,t} \frac{\Theta_{k,t}}{w_{k,t}}} \tag{27}$$

This is simply the mathematical conversion from an elasticity to a linear effect, where the conversion ”units”, $\frac{f(x)}{x}$, are given by a variance-weighted average.