Wage Effects of Labor Market Tightness

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April 2022

Abstract

I provide new microeconometric estimates of the effect of labor market tightness on wages at the firm level. Using Danish data on vacancies and unemployment at the occupational level and firm data on the occupational composition of employees, I construct firm-specific measures of labor market tightness. Using this measure, I find an elasticity of wages with respect to tightness of 0.01-0.02, 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.

*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. This paper contains revised content from my master's thesis, and is planned as the first chapter of my Ph.D. dissertation. I thank my advisors Daniel Le Maire and Søren Hove Ravn for their invaluable advice and support. I also thank Morten Ravn, Espen Moen, Rasmus Lentz, Jesper Bagger, Adrien Bilal, David Wiczer, Antoine Bertheau, Daphné Skandalis, Renato Faccini, Simone Bonin, David Pinkus, 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

The ratio of vacancies to job-seekers, usually referred to as the labor market tightness, plays a key role in the determination of wages in search and matching models with endogenous job-arrival rates. In the canonical search and matching model developed by Diamond, Mortensen, and Pissarides (Pissarides (1985, 2000)) (Henceforth, the DMP model), tightness is intimately linked with the job-finding-rate and wages. The relationship between the job-finding rate and labor market tightness is empirically well established, such as in Petrongolo and Pissarides (2001) and Hall and Schulhofer-Wohl (2018). Both find that the job-finding rate is increasing in tightness and that the relationship is well described by a constant elasticity.

The relationship between labor market tightness and wages is less studied. Work on the aggregate co-movements of wages, tightness, and productivity does exist, notably by Shimer (2005).[1] Additionally, Beaudry and DiNardo (1991) and Schmieder and von Wachter (2010) investigate the similar relationship between wages and the unemployment rate. Others, such as Jäger et al. (2020), have examined the effect of the value of non-employment, the other main driver of wages through outside options in DMP model. However, little evidence on the causal relationship between tightness and wages exists. This is possibly due a lack of disaggregated data on tightness. 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.

In this paper, I instead present evidence on the effect of tightness on wages at the firm-level using Danish data. 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 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

[1] Pissarides (2009) includes a summary of the literature on aggregate co-movements.

the analysis at the firm level blocks the feedback mechanism from the vacancy-creation curve in the DMP model. From the perspective of the firm, 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 of course relies on the assumption that firms are small compared to the labor markets they hire from. I motivate this by showing that employer concentration in each occupation is low, and using robustness checks where firms that are large employers in an occupation are excluded.

Another key assumption underlying the analysis is that the relevant labor market for each firm can be characterized by the occupational composition of its employees. This implies that the submarkets, firms hire from are distributed across occupations and not industries. Simply put, a bank and a manufacturer will hire their accountants from the same pool of candidates. This assumption is in line with evidence from Kambourov and Manovskii (2009), who show that the return to occupation tenure is substantially higher than the return to industry tenure in the U.S. This finding is backed by Zangelidis (2008) and Lagoa and Suleman (2016), using data from the UK and Portugal.

I obtain the estimates of the effect of tightness on wages using the assumption 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 captures the idea that different firms hire employees from different submarkets of the labor market and provides firm-level variation in labor market tightness.[2] The availability of firm-level variation in tightness is key to disentangling the effects from the wage-setting and vacancy creation curves.

[2]The idea of using vacancy data to calculate occupation-specific tightness measures is similar to Turrell et al. (2021), who study the productivity effects of aggregate mismatch, measured as differences in tightness across occupations and regions.

Wage rigidity might cause the effect of tightness on wages to materialize over time, as found theoretically in Hall (2005) and Pissarides (2009). I, therefore, estimate the effect of tightness on wages over different horizons. This is done using specifications that examine 1-year-differences and 5-year-differences in wages and tightness. I find wage elasticities with respect to tightness ranging from around 0.010 in the 1-year-difference specification to 0.017 in 5-year-difference specification. The positive estimates are in line with the qualitative implications of the DMP model. Furthermore, the estimates are relatively small and imply a relatively flat wage-setting curve. I also estimate specifications where I allow for on-the-job search and occupational mobility when calculating the firm-specific tightness measures. These specifications result in similar estimates, with a slightly higher elasticity of around 0.02 in the 5-year-differences specifications.

Using the reduced-form estimates obtained and the cross-sectional implications of the DMP model, I am also able to recover values for key model parameters. These differ substantially from the values used in the calibration in Shimer (2005). They imply that the slope of the wage-setting curve is much lower, and close to the calibration in Hagedorn and Manovskii (2008).

The estimates in this paper also have implications for larger macroeconomic models where the labor market is modelled as a DMP-type framework. Ravn and Sterk (2021) argue that the volatility of business cycles in these models depends on whether the earnings risk is countercyclical. Intuitively, tightness affects earnings risk through two effects with opposite direction. It affects it positively through the job finding rate since a fall in tightness makes it harder to find a job, but it affects it negatively trough 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. In a back-of-the-envelope exercise, I show that this is likely the case for Denmark.

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 main 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 does not contain any substantial innovations compared to the canonical DMP-model, but is used to highlight why conducting the empirical analysis at the firm level allows me to identify the slope of wage-setting curve.

Time is continuous. There exist a continuum of firms with measure K indexed by k and H different types of occupation 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 distribution across firms denoted by $G_h(y_{h,k})$. This implies that no complementarities between labor types are present in the firms' production function.

I only focus on the steady-state. In steady-state, the value of a filled job 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 δ 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 $\frac{df}{dV_{h,k}} > 0$. This ensures that the firm with highest constant productivity not is the only firm that creates vacancies. Combining these two equations 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 $\Pi^h_v = 0$, 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 looks almost 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 the coincide.[3]

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

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

$$rV^e_{h,k} = w_{h,k} + \delta\left(V^u_h - V^e_{h,k}\right) \tag{4}$$

and the value of unemployment for a worker of occupation h, V^u_h, is given by

$$rV^u_h = z + \theta_h q(\theta_h)\left(E_j\left(V^e_{h,j}\right) - V^u_h\right) \tag{5}$$

where z is the instantaneous utility of unemployment, which is assumed to be homogeneous across occupations. Note that $E_j\left(V^e_{h,j}\right)$ is the expected value of employment for a worker of type h, with the expectation taken over the firm dimension, i.e. $E_j\left(V^e_{h,j}\right) = \int \psi_h(j)V^e_{h,j})dj$, where $\psi_h(j)$ 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 j, and the probability of getting a job at firm j, which is determined by the share of vacancies for occupation h posted by firm j. This is the case 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 β is the relative bargaining power of workers.[4] 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 still must account for 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 very similar to the wage-setting curve in the DMP model. 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 to

[4]See Appendix A for the derivation

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 firms 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-supply 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.

While firms do not take their individual effect on tightness into account, equilibrium tightness is still determined by the sum of individual firm behaviour. Consider the weighted sum of firm-specific vacancy-creation curves in equation (3),

$$\int \psi_h(k) \frac{y_{h,k} - w_{h,k}}{r + \delta} dk = \int \psi_h(k) \frac{c_{h,k}}{q(\theta_h)} dk \tag{8}$$

where $\psi_h(k)$ here denotes the share of the total number of occupation h workers employed at firm k.[5] Inserting the wage equation, (7), allows one to rewrite the above into

$$\frac{(1-\beta)\,(y_h - z)}{r + \delta + \beta\theta_h q(\theta_h)} = \frac{c_h}{q(\theta_h)} \tag{9}$$

where $y_h = \int \psi_h(k) y_{h,k} dk$ and $c_h = \int \psi_h(k) c_{h,k} dk = E_k(c_{h,k})$ This is the equivalent to the equilibrium condition for tightness in the DMP model. Importantly, it shows that while firm-specific productivity affects wages directly, the indirect effect through tightness comes from average occupational productivity. This influences how one should control for productivity when trying to estimate the effect of tightness on wages. I elaborate this point in the description of the empirical approach in Section 3.

[5]Since I only characterize the steady-state this is equivalent to weighing by the share of vacancies posted by firm k

For simplicity, I assume that average instantaneous cost is the same across occupations, that is $E_k(c_{h,k}) = c$. This effect therefore only generates dispersion in hiring costs within an occupation. However, between-occupation differences in total hiring costs 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

$$w_{h,k} = (1-\beta)z + \beta\left(y_{h,k} + c\theta_h\right) \tag{10}$$

The direct effect of tightness on wages at the firm level is given by βc, 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 (10) 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 Appendix E, I consider how to recover parameter values for the theoretical model present in Section 2 using the estimates obtained from the reduced-form model in this section.

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

$$\ln w_{i,t} = \rho \ln \theta_{h(i,t),t} + \lambda \ln y_{k(i,t),h(i,t),t} + a\mathbf{x}_{k(i,t),t} + \epsilon_{i,t} \tag{11}$$

Here $\ln w_{i,t}$ denotes log individual wages, $\ln \theta_{h(i,t),t}$ 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 and 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. Unfortunately, individual and occupational productivity is not observed. I do, however, 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:

$$\hat{w}_{k,t} = \rho\hat{\Theta}_{k,t} + \lambda\hat{y}_{k,t} + a\hat{\mathbf{x}}_{k,t} + \hat{\epsilon}_{k,t} \tag{12}$$

where $\hat{w}_{k,t}$ denotes the change in average log wages 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, $\hat{\Theta}_{k,t}$, can be seen as a firm-specific measure of the change in labor market tightness. It captures the intuitive 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 requires the labor input of engineers, the corresponding occupation share, $s_{h,k,t}$, will be positive, and the labor market tightness for engineers will affect the firm-specific labor market tightness. This measure is a key novelty of this paper, as this what allows me to disentangle the effects of the wage-setting curve from the vacancy-creation curve, as discussed in Section 2. It is possible to construct due to the data on vacancies collected by the Danish Agency for Labour Market and Recruitment. The data is described in detail in Section 4.

The measure of change in tightness, $\hat{\Theta}_{k,t}$, is similar in form to shift-share measures described in Adão et al. (2019), and I use their framework and assumptions to establish identification and consistency. In the following I first give a very brief overview of the state of the shift-share literature. Second, I then describe the assumptions needed to ensure that constructed tightness measure captures the conditions in the labor markets that the individual firm is hiring from. Finally, I state the needed assumptions for consistency and inference when using the measure in my estimation.

Most of the literature using shift-share designs have regions as observational units, including the original implementation in Bartik (1991), while I use methodology at the firm-level in this paper. Recently, two different approaches to the shift-share design have emerged. Goldsmith-Pinkham et al. (2020) establish identification trough 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 choosing which approach to use. They argue that one should use the shares-approach if one wants to achieve identification from units having different exposure to a common shock. An example of this is Autor et al. (2013), where regions have different exposures to a Chinese import shock, due to different initial industry compositions. 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, two conditions need to hold in order to argue that $\hat{\Theta}_{k,t}$ captures the changing state of the labor market, that a specific firm is facing. First, the relevant pool of candidates from each occupation for the individual firm must be well proxied by the aggregate pool. 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 geographical size of Denmark, I assume that each occupation specific labor market covers the entire country. Additionally, the pool of candidates might vary between sectors or industries. This would, for example, be the case if an engineer that has worked in one industry has learned 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. 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 vacanices to unemployed might still not be the best measure of tightness for each occupation. A large part of the search- and matching literature has for example focused on the presence of on-the-job search. To examine whether the results are robust to the inclusion of on-the-job searchers, I include a specification where occupation-level tightness is calculated as in Bilal et al. (2019), 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 ξ_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 ξ_h using the observed number of transitions from unemployment to employment and from employment to employment for each occupation.

Until now, I have also assumed that no occupational mobility is present when calculating occupational tightness. This assumption is observably false, and 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 $\pi_{h,p,t}$ denote the probability that a worker switches from occupation p to h in time t 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

$$S_{h,t}^{om} = \sum_{p} \pi_{h,p,t-1} S_{p,t} \tag{13}$$

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 $\pi_{h,p,t}$ using the observed transition probabilities each year.[6]

[6]Appendix D.2 contains a robustness check where the transition probabilities are assumed to be static.

Even if the pool of candidates for each occupation is correctly specified, the initial occupation-share of employees must also represent the current needed occupational composition, to argue that the tightness measure captures the state of labor market that the individual firm is facing . 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 D.4, and obtain similar results to the main specification. Substitution effects from changes in tightness will also be captured by this approach. 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 also conduct the same analysis using hires to create the occupation shares. The results are shown in Appendix D.5, and they are very similar to the ones shown in the main analysis in Section 5.

Finally, a number of assumptions are needed for the shift-share-design to provide consistent estimation of ρ using OLS, and for valid inference. The most important is that the log change in occupational tightness, $\theta_{h,t}$ is as good as randomly assigned across occupations conditional on the controls.[7] Informally, this relies on achieving two things. First, I 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.[8] 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. This does not change the results as can be seen in Appendix D.1.

Second, I must properly control for productivity. As mentioned above, productivity is not observed and will be proxied by the value-added per worker at each firm. However, the

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

[8]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)

theory described in Section 2 also suggests that tightness primarily is affected by the firm's average occupational productivity, through the outside option of its employees. Firm-level average value-added per worker is, therefore, a noisy control. I therefore also estimate a version of equation (12) where I include the predicted average value-added based on the occupation shares at the firm. The predicted productivities are based on the simple regression of value-added per worker on occupation shares,

$$y_{k,t} = \sum_{h \in H} s_{h,k,t} y_{h,t} + \omega_{k,t} \tag{14}$$

I then predict firm-level log value-added per worker, $\check{y}_{k,t} = \sum_{h \in H} s_{h,k,t} \check{y}_{h,t}$, where $\check{y}_{h,t}$ denotes the coefficients from the estimation. I then include the first-difference of the prediction when estimating (12). 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 D.6.

A problem with regards 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 rejections rates, even as high as 50 pct. To handle this I estimate standard errors using the estimator developed by the authors, which is robust to this type of correlation.[9] Standard errors for the effect of productivity are clustered at the industrial level (NACE Section).

As mentioned in Section 1, the results form Hall (2005) and Pissarides (2009) highlight that wage rigidity may be important in the DMP model. I, therefore, estimate ρ using specifications that use changes over 1 year and 5 years. Otherwise, the specifications are similar to (12), in that they use the initial-period occupations-shares and the same controls.[10] The results from the shift-share design are shown in Section 5.

[9]All the assumptions needed for consistent estimation and valid inference are stated in Appendix B, along with a description of the standard error estimator.

[10]Note, that the simple extended DMP model presented in Section 2 does not feature wage-rigidity since

4 Data

In this section I present the different data sources used in the analysis and provide descriptive statistics.

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 recruitment, STAR facilitates a vacancy database, where firms can post open positions, which the recruitment centers and the unemployed have access to. Importantly, the vacancies are categorized based on occupations according to the DISCO-AMS classification, which is a variation of the International Standard Classification of Occupations (ISCO-08). I aggregate these into 2 digit ISCO-codes. The data from STAR is available for 2013-2018.

Unemployment: To calculate tightness, I also need data on unemployment across occupations. I calculate this 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 all Danes' employment status and an occupation code if employed. If an individual is currently unemployed and has held a job of 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.[11] Again, occupations are defined at the level of 2-digit ISCO-codes.

Wages and occupation shares: Since IDA is a matched employer-employee data set,

both wages and tightness are jump variables.

[11] Appendix D.3 contains a robustness check where only the last held job is used to determine occupation, which produces similar results.

I use it to calculate the firm average wages and occupation shares for each firm. Before calculating these variables I conduct the following sample selection: I need to know the occupation of employees to create the occupation-shares. I, therefore, start by dropping all employments which do not have an ISCO-classification. This results in an initial sample of 15,201,849 worker-firm-year observations. Additionally, I only keep primary employments for workers between the ages of 18 and 75 not undergoing education, who are employed in full-time jobs with positive wages and at least 30 days of employment in the given year.[12] 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.[13] Finally, I restrict the analysis to private-sector firms with at least 10 employees.[14] This results in 3,507,414 worker-firm-year observations from 2013 to 2018 across 1,040,187 workers and 16,981 firms. All wages are calculated as full-year equivalents based on the fraction of employment during the year, and these wages are then deflated using the Danish consumer price index from Statistics Denmark. I then calculate the average (log) wage and occupation shares for each firm. Using the occupation shares, I am then able to construct the firm-specific tightness measures by interacting the shares with aggregate occupational tightness, i.e. $\Theta_{k,t} = \sum_{h \in H} s_{h,k,t} \theta_{h,t}$.

Accounting data: The data on value-added is drawn from the FIRM and FIRE databases, which are also maintained by Statistics Denmark. 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. In the shift-share design, the change in value-added between two years is the only accounting data needed and I keep all firms with accounting data in both years.

Merging the wage and accounting data results in a final sample of 52,897 firm-year

[12]Days of employment in a given job is calculated using data from BFL which is maintained by Statistics Denmark and contains daily data on employments

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

[14]Firms are defined as a corporate entity corresponding to a unique firm identification number (CVR-number). These identify firms and not individual plants.

observations across 14,449 firms. Table 1 contains descriptive statistics for the firms in the sample including the firm-specific tightness. 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-index for occupations, is low during the sample period.[15]

Table 1: Descriptive Statistics for firms

		2013	**2014**	**2015**	**2016**	**2017**	**2018**
Wages	Mean	401,302	401,850	407,871	409,473	416,047	424,492
	Std. dev.	86,598	88,047	91,486	89,402	91,509	94,767
Value Added per worker	Mean	598,208	622,764	642,984	659,081	669,526	662,576
	Std. dev.	632,119	744,845	855,942	1,182,887	2,243,335	799,571
Tightness	Mean	0.13	0.14	0.17	0.19	0.18	0.09
	Std. dev.	0.09	0.10	0.11	0.13	0.11	0.09
No. of Employees	Mean	57.98	59.30	59.05	59.01	58.38	55.46
	Std. dev.	226.89	234.82	230.24	236.26	227.57	215.99
No. of occupations	Mean	5.51	5.22	5.10	5.07	5.17	5.07
	Std. dev.	3.53	3.51	3.49	3.54	3.60	3.59
Occupation HHI	Mean	0.034	0.033	0.040	0.040	0.026	0.028
	Std. dev.	0.052	0.047	0.075	0.078	0.039	0.049
No. of Firms		7,695	8,153	8,505	8,959	9,363	10,204

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. Wages and value-added are denoted in Dkk. and is CPI-deflated. The table is based on data from STAR and Statistics Denmark. The mean occupation Herfindahl index (HHI) is calculated as the average HHI across occupationz with the index in an occupation given by $\sum_i s^2_{h,k,t}$, where $s_{h,k,t}$ denotes the share of all occupation h workers employed at firm i.

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 unemployed and less likely to fill a vacancy, and this shifts the relative bargaining power. I, therefore, start the empirical analysis examining whether these connections

[15] Moderate concentration would correspond to a HHI between 0.15-0.25 (Azar et al., 2020)

between vacancies, unemployment and matches also are present in the data. Figure 1 shows the empirical Beveridge Curve in a binned scatter plot of firm-year observations. It shows a negative relationship between vacancies and unemployment as ratios of the labor force. This is in line with the DMP model where more vacancies per worker leads to more unemployed getting a job.

Figure 1: Firm-level Beveridge curve

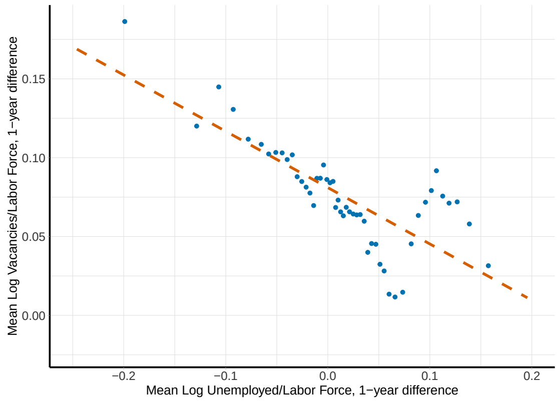
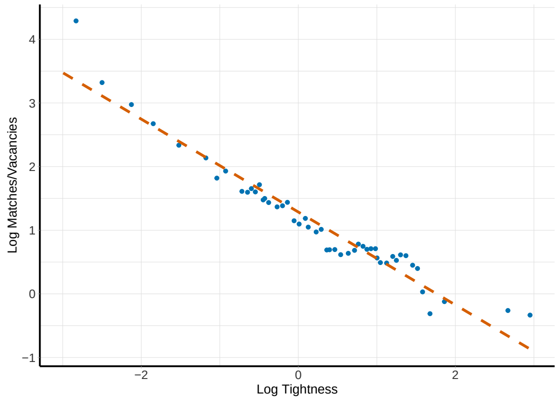


Figure 2: Occupational matches and tightness

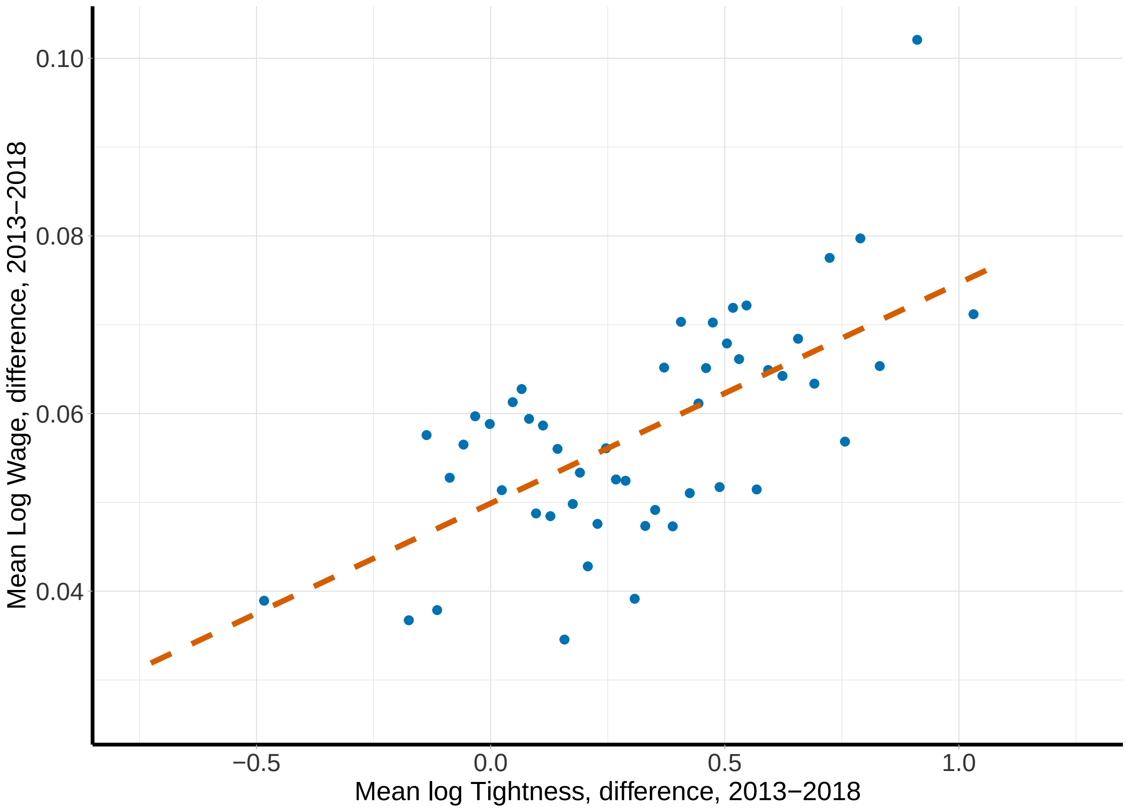


Notes: Labor Force is defined as the number of employed and unemployed within each occupation. Firm-level vacancy- and unemployment rates and tightness are calculated as weighted averages of their occupational-level counter parts, using firm-specific occupation shares as weights. Firm-Year observations are aggregated into 50 bins. Occupations are defined by a 2-digit ISCO-code. Data is from 2013 to 2018.

Figure 2 also shows the expected negative relationship between the log ratio of matches to vacancies and log tightness. Again, the intuition is straight forward. When tightness is high, there are more vacancies per unemployed job seeker, and fewer of the vacant jobs will therefore be filled. The figure indicates that the elasticity of the matching function is around -0.66, fairly similar to the -0.72 found in Shimer (2005) for U.S. aggregate data.

Figures 1 and 2, both support the qualitative implications of the DMP 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 (10) in Section 2, the DMP model implies a positive connection between wages and tightness. Figure 3 shows that the correlation between wages and tightness at the firm level. Here firm-level changes in tightness are calculated by a weighted average of log changes in occupational tightness from 2013 to 2018, with the weights given by the occupation composition at the firm in 2013. This is similar to the shift-share design described in Section 3. The figure shows a clear positive correlation between firm-level tightness changes and changes in the firm average (log) wages. This supports the predictions of the DMP model and motivates the further analysis conducted in Section 5. Appendix C also include figures of the correlation between wages and the two elements of tightness, i.e. vacancies and unemployment. These figures also show the expected positive and negative correlation, respectively.

Figure 3: Firm level correlation between wage and tightness growth



Notes: Firm-level tightness growth is calculated using aggregate occupational tightness growth from 2013 to 2018 and the occupational composition in the firm in 2013. The figure is based on data from STAR and DST. Firm-Year observations are aggregated into 50 bins. Occupations are defined by a 2-digit ISCO-code.

5 Results

In this section I first present the estimation results obtained using method described in Section 3, including key robustness checks. I then describe the main macroeconomic implications of the estimates, both with regards 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

In this section, I present the results from the estimation described in Section 3. Table 2 contains the results from the estimation using 1-year differences. For all specifications, I find a positive and statistically significant effect on wages from an increase in tightness. Specifications (1), (3) and (6) use the normal definition of tightness and find an elasticity of 0.010-0.013. This roughly corresponds to a 100 pct. increase in tightness leading to a 1 pct. 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 and using no controls tend to result in larger elasticities, but all estimates are fairly similar.

Table 2: Wage effects of labor market tightness - 1-year differences.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Differences	1-year	1-year	1-year	1-year	1-year	1-year
ρ - Tightness	0.010^{**}	0.010^{**}	0.010^{***}	0.010^{**}	0.012^{***}	0.016^{***}
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.006)
λ - Productivity	0.047^{***}	0.048^{***}	0.004^{***}	0.004^{***}	-	-
	(0.008)	(0.008)	(0.001)	(0.001)	(-)	(-)
Predicted Value-added	X	X				
Observed Value-added			X	X		
On-the-Job Search		X		X		X
Period, Industry & Region FE	X	X	X	X		
No. Obs.	35,314	35,314	35,314	35,314	35,314	35,314

*Notes: The estimation is based on equation (12). Industry is defined as NACE Section level. Predicted value-added indicates that the value-added used as control is a prediction based on occupation shares, as in equation (14). The sample period is from 2013 to 2018. Standard errors for ρ are based on the standard error estimator from Adão et al. (2019), while standard errors for γ are clustered at the industry level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

The estimates obtained when using 5-year-differences are shown in Table 3. Unsurprisingly, specifications using 5-year changes find the larger effects of around 1.5-1.9 times that of the corresponding short-run effect. This fits well with the stylized fact that wages tend to be rigid in the short-run, discussed in Section 1.

Table 3: Wage effects of labor market tightness - 5-year differences.

	(7)	(8	(9)	(10)	(11)	(12)
Differences	5-year	5-year	5-year	5-year	5-year	5-year
ρ - Tightness	0.017***	0.024***	0.013***	0.017***	0.025***	0.029***
	(0.005)	(0.006)	(0.004)	(0.006)	(0.008)	(0.0011)
λ - Productivity	0.091***	0.093***	0.020***	0.020***	-	-
	(0.014)	(0.014)	(0.003)	(0.003)	(-)	(-)
Predicted Value-added	X	X				
Observed Value-added			X	X		
On-the-Job Search		X		X		X
Industry & Region FE	X	X	X	X		
No. Obs.	5,667	5,667	5,667	5,667	5,667	5,667

*Notes: The estimation is based on equation (12). Industry is defined as NACE Section level. Predicted value-added indicates that the value-added used as control is a prediction based on occupation shares, as in equation (14). The sample period is from 2013 to 2018. Standard errors for ρ are based on the standard error estimator from Adão et al. (2019), while standard errors for γ are clustered at the industry level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Specifications (1),(2),(7) and (8) control for productivity using the predicted firm average value-added as discussed in Section 3, while specification (3), (4), (9) and (10) simply use observed firm average value-added. The estimated effects of varying labor market tightness on wages are similar in the two setups. However, the estimated effect of log mean value-added, γ, is much larger when using the predicted log mean value-added as a control. One possible explanation is that higher predicted value-added represents an actual increase in the outside option of the workers employed at a firm. Firm-specific productivity shocks will not lead to higher productivity at other firms and therefore the outside option does not improve.

Table 4 contains the estimates of the wage setting curve when allowing for occupational mobility. 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 4: Wage effects of labor market tightness - adjusting for occupational mobility.

	(13)	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**
Differences	1-year	1-year	5-year	5-year	1-year	1-year	5-year	5-year
ρ - Tightness	0.011***	0.010**	0.021***	0.023***	0.012***	0.011**	0.018***	0.019***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)	(0.006)	(0.007)
λ - Productivity	0.047***	0.048***	0.090***	0.091***	0.004***	0.004***	0.020***	0.020***
	(0.008)	(0.008)	(0.014)	(0.014)	(0.001)	(0.001)	(0.003)	(0.003)
Predicted Value-added	X	X	X	X				
Observed Value-added					X	X	X	X
On-the-Job Search		X		X		X		X
Period, Industry & Region FE	X	X			X	X		
Industry & Region FE			X	X			X	X
No. Obs.	35,314	35,314	5,667	5,667	35,314	35,314	5,667	5,667

*Notes: The estimation is based on equation (12). Industry is defined as NACE Section level. Predicted value-added indicates that the value-added used as control is a prediction based on occupation shares, as in equation (14). The sample period is from 2013 to 2018. Standard errors for ρ are based on the standard error estimator from Adão et al. (2019), while standard errors for γ are clustered at the industry level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

5.2 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, I for example difference out year, industry and region effects in all estimations. Any general equilibrium effects will therefore not be captured by my estimate. Nevertheless, it is possible to deduct meaningful implications from cross-sectional behavior. Consider the wage equation (10) from the model in Section 2. It implies that the average wage at the firm is given by

$$w_{k,t} = (1-\beta)z_t + \beta\left(\sum_h s_{h,k,t}y_{h,t} + c\sum_h s_{h,k,t}\theta_{h,t}\right) = (1-\beta)z_t + \beta\left(y_{k,t} + c\Theta_{k,t}\right) \quad (15)$$

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

$$\ddot{w}_{k,t} = \beta\left(\ddot{y}_{k,t} + c\ddot{\Theta}_{k,t}\right) \quad (16)$$

Since the estimated model from Section 3 is log-linear, the estimated effect of tightness on wages, ρ, does not directly correspond to βc in the model. However, one can recover a good approximation using the variance-weights produced by OLS, under the assumption that equation (10) is the correct model. The exact procedure is described in Appendix E. Using this method, the estimates imply that βc is around 0.032 if we normalize by mean value-added.[16] For comparison, Shimer (2005) calibrates his 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, in addition to the lack of wage rigidity. 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, β, to 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

[16] This is based on the estimates of 0.010 for ρ in Table 2. Note, that normalize by the average value-added per worker

cost to $c = 0.584$. This results in $\beta c \approx 0.03$, which is very close to the value implied by the estimates in this paper. It is, however, important to note that both Shimer (2005) and Hagedorn and Manovskii (2008) argue that a relatively flat wage setting alone isn't enough to produce realistic unemployment volatility in the canonical DMP-model.[17]

However, the relatively flat wage-setting curve estimated in this paper can lead to 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 the second effect is larger than the first. If this is the case earnings risk is counter cyclical 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 trough 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 monentary policy depends on whether the precautionary savings motive dominates the motive intertemporal substitution, and that this is the case when earnings risk is counter cyclical.

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

$$ER = \delta(1 - f(\theta))(w - z) \tag{17}$$

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

where $f(\theta)$ is the job-finding rate, and everything else is the same as in Section 2. The earnings risk will then be countercyclical if

$$\epsilon_{f,\theta} > \frac{(1-f(\theta))}{f(\theta)} \epsilon_{w,\theta} \frac{1}{1-\frac{z}{w}} \tag{18}$$

where $\epsilon_{f,\theta}$ and $\epsilon_{w,\theta}$ denotes the elasticity of the job-finding rate and wages with respect to tightness. $\epsilon_{w,\theta}$ simply correspond to the estimate of 0.01 from Table 2. If I assume that the matching function is a Cobb-Douglas function, I can recover $\epsilon_{f,\theta}$ as one minus the slope in Figure 2, resulting in $\epsilon_{f,\theta} \approx 0.44$. 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, I use the estimate of the degree of unemployment compensation from the ADAM model maintained by Statistics Denmark, $\frac{z}{w} \approx 0.5$ (Knudsen, 2019). Plugging these in to (18) results in $0.44 > 0.001$. This exercise, therefore, indicates that earnings risk is counter cyclical in a Danish context.

6 Conclusion

The effect from labor market tightness on wages through outside options play a key role in many search and matching models. In this paper, I have provided new microeconometric estimates of this effect. I first created firm-level tightness measures using data on vacancies and unemployment across occupations and the occupational composition of workers at each firm. Using these firm-level tightness measures I found that an increase in firm-specific labor market tightness leads to higher wages, with an elasticity of 0.01-0.02. These results are robust to allowing the tightness measure to include on-the-job search and occupational mobility.

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 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 counter-cyclical 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.

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A Derivation of wage equations

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

$$V^e_{h,k} - V^u_h = \beta \left(\Pi^e_{h,k} - \Pi^v_{h,k} + V^e_{h,k} - V^u_h \right) \tag{19}$$

where β is the relative bargaining power of workers. Plugging in (1), (4) and the free-entry condition results in

$$w_{h,k} = rV^u_h + \beta \left(y_{h,k} - rV^u_h \right) \tag{20}$$

Taking the expectation of (19) with respect to firm heterogeneity, and then inserting it and (5) into (20) results in wage equation (6), shown in Section 2,

$$w_{h,k} = (1-\beta)z + \beta y_{h,k} + \beta \theta_h q(\theta_h) E_k(\Pi^e_{h,k}) \tag{21}$$

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 in the changes in tightness in the same occupation. 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

$$s_{j,l} = \begin{cases} s_{h,k,t} & \text{if } j = (k,t) \text{ and } l = (h,t) \\ 0 & \text{if } j = (k,t), l = (h,t') \text{ and } t' \neq t \end{cases} \tag{22}$$

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

$$\mathfrak{F} = \{\hat{w}_j, s_{j,l}, \omega_j, \hat{\mathbf{x}}_j, \hat{y}_l, \hat{\epsilon}_j\}_{l=1,j=1}^{L,J} \tag{23}$$

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

Assumption B.1 *Equation (12) holds, i.e. the functional form is correctly specified.*

Assumption B.2 *The tightness measures θ_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 $\hat{\mathbf{x}}^k_{h,t}$*

$$\mathbb{E}[\theta_l | \hat{y}_l, \hat{\mathbf{x}}_j] = a\hat{y}_l + b\mathbf{x}_j \tag{24}$$

Assumption B.4

$$\left(\sum_{h=1}^{H} n_h^2\right)^{\frac{1}{2}} \sum_{n=1}^{N} \mathbb{E}[\omega_{h,t}^2] \rightarrow 0 \quad \textit{for} \quad H \times T \rightarrow \infty \tag{25}$$

Assumption B.5 $\max_l \frac{n_l}{\sum_{l' \in S} n'_l} \rightarrow 0$, *i.e. the relative size of each occupation-year decreases to 0 as the number of occupation-years increases to ∞*

Assumption B.6 $\max_c \frac{n_c^2}{\sum_{j \in C} n_c^2} \rightarrow 0$, *i.e. the asymptotic contribution to the variance from each cluster becomes negligible as the number of cluster, C, increases to ∞*

These assumption ensure consistency for OLS and valid standard errors for the estimator from Adão et al. (2019). In this specific setting the standard error estimator takes the following form: Let $Z_{k,t}$ denote the entire vector of controls for firm k at time t, i.e. $\hat{\Theta}_{k,t}$ and $\hat{\mathbf{x}}_{k,t}$, and $\mathbf{Z}$ the matrix containing the KT vectors of $Z_{k,t}$. Let $\mathbf{\Psi}$ denote the $KT \times H$ matrix of occupation shares, and let $\hat{\Theta}$ denote the KT vector containing all firm level tightness measures $\Theta_{k,t}$. Let $\ddot{\Theta}$ denote the part of $\hat{\Theta}$ that is orthogonal to the controls $\mathbf{Z}$, i.e. $\ddot{\Theta} = \hat{\Theta} - \mathbf{Z}(\mathbf{Z}^\top \mathbf{Z})^{-1}\mathbf{Z}^\top \hat{\Theta}$. Finally $\ddot{\Theta}$ is projected onto occupation-space, by regressing it on $\mathbf{\Psi}$, i.e. $\check{\theta} = (\mathbf{\Psi}^\top \mathbf{\Psi})\, \mathbf{\Psi}^\top \ddot{\Theta}$. Adão et al. (2019) then propose the following variance estimator that is valid under assumptions B.1 - B.6:

$$\hat{V}_{AKM}(\hat{\beta}) = \frac{\sum_{c=1}^{C} \sum_{l,l'} \left(\mathbb{I}\left(c(l) = c(l') = c\right) \check{\theta}_l \sum_j \left(s_{j,l}\hat{\epsilon}_j\right) \check{\theta}_{l'} \sum_j \left(s_{j,l'}\hat{\epsilon}_j\right)\right)}{\left(\sum_{j=1}^{J} \ddot{\Theta}_j^2\right)^2} \tag{26}$$

This variance estimator allows for arbitrary correlation structure caused by shares in the residuals, and for tightness measures to be correlated over time. In practice I estimate the standard error using the code provided by the authors.

C Correlation between the vacancy rate, the unemployment rate, and wages at the firm level

Figure 4 and 5 show the correlation between wages and the components of labor market tightness, i.e., the vacancy rate and unemployment rate. These are calculated using the same procedure 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, as it becomes harder to fill vacancies. On the other hand, the unemployment rate is negatively correlated with wages, as it is easier to fill a vacancy if many unemployed potential employees are available.

Figure 4: Firm level correlation between wages and vacancies

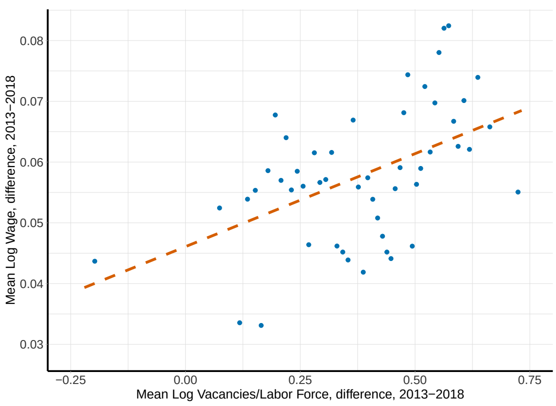
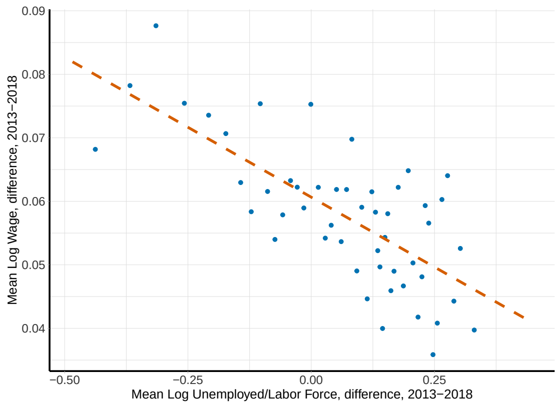


Figure 5: Firm level correlation between wages and unemployment



Notes: Firm-level vacancy and unemployment rate changes are calculated using aggregate occupational vacancy and unemployment rate changes from 2013 to 2018 and the occupational composition in the firm in 2013. The figure is based on data from STAR and DST. Firm-Year observations are aggregated into 50 bins.

D Additional Robustness checks

D.1 Removing firms with monopsony power

As mentioned in Section 3 the validity of the results depend 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 ρ using samples where only firms that employ less than 5 pct. and 0.5 pct. of the total workers in an occupation. The results are shown in Table 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 5: Wage effects of labor market tightness - Firms with small total occupation shares.

	(21)	**(22)**	**(23)**	**(24)**
Differences	1-year	1-year	5-year	5-year
Max occupation share	5 pct.	0.5 pct.	5 pct.	0.5 pct.
ρ - Tightness	0.010^{**}	0.009^{**}	0.017^{***}	0.016^{***}
	(0.004)	(0.004)	(0.005)	(0.005)
λ - Productivity	0.047^{***}	0.051^{***}	0.093^{***}	0.092^{***}
	(0.008)	(0.009)	(0.013)	(0.015)
Predicted Value-added	X	X	X	X
Period, Industry & Region FE	X	X		
Industry & Region FE			X	X
No. Obs.	35,219	32,974	5,646	5,212

*Notes: The estimation is based on equation (12). Industry is defined as NACE Section level. Predicted value-added indicates that the value-added used as control is a prediction based on occupation shares, as in equation (14). Max occupation share indicates the exclusion criteria for firm with a large share of total employment in an occupation. The sample period is from 2013 to 2018 Standard errors for ρ are based on the standard error estimator from Adão et al. (2019), while standard errors for γ are clustered at the industry level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

D.2 Occupational mobility with static transition probabilities

Table 4 in Section 5 show the estimates when allowing for occupational mobility, using a dynamic transition probabilities calculated each period. As a robustness check, I also estimate a specification using static transition probabilities calculated over the entire sample period. The results are seen in Table 6. Many estimates are identical to ones found in Table 4. The estimates found using the long-difference are a bit higher, but none of the estimates are qualitatively different.

Table 6: Wage effects of labor market tightness - adjusting for occupational mobility - static transition probabilities.

	(25)	**(26)**	**(27)**	**(28)**	**(29)**	**(30)**	**(31)**	**(32)**
Differences	1-year	1-year	5-year	5-year	1-year	1-year	5-year	5-year
ρ - Tightness	0.011^{**}	0.011^{**}	0.023^{***}	0.028^{***}	0.012^{***}	0.011^{**}	0.018^{***}	0.021^{***}
	(0.005)	(0.005)	(0.006)	(0.007)	(0.004)	(0.005)	(0.006)	(0.007)
λ - Productivity	0.048^{***}	0.048^{***}	0.092^{***}	0.093^{***}	0.004^{***}	0.004^{***}	0.020^{***}	0.020^{***}
	(0.008)	(0.008)	(0.014)	(0.014)	(0.001)	(0.001)	(0.003)	(0.003)
Predicted Value-added	X	X	X	X				
Observed Value-added					X	X	X	X
On-the-Job Search		X		X		X		X
Period, Industry & Region FE	X	X			X	X		
Industry & Region FE			X	X			X	X
No. Obs.	35,314	35,314	5,667	5,667	35,314	35,314	5,667	5,667

Notes: The estimation is based on equation (12). Industry is defined as NACE Section level. Predicted value-added indicates that the value-added used as control is a prediction based on occupation shares, as in equation (14). The sample period is from 2013 to 2018. Standard errors for ρ are based on the standard error estimator from Adão et al. (2019), while standard errors for γ are clustered at the industry level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.3 Occupation based on last job only

Table 7 contains estimates obtained when unemployed are allocated to an occupation based only on their last job, instead of all jobs. Overall, the estimates are similar to the ones found in Table 2.

Table 7: Wage effects of labor market tightness - Only use last job when calculating unemployment shares.

	(33)	(34)	(35)	(36)
Differences	1-year	1-year	5-year	5-year
ρ - Tightness	0.010**	0.010***	0.016***	0.013***
	(0.004)	(0.004)	(0.005)	(0.005)
λ - Productivity	0.047***	0.004***	0.091***	0.020***
	(0.008)	(0.001)	(0.014)	(0.003)
Predicted Value-added	X		X	
Observed Value-added		X		X
Period, Industry & Region FE	X	X		
Industry & Region FE			X	X
No. Obs.	35,314	35,314	5,667	5,667

*Notes: The estimation is based on equation (12). Industry is defined as NACE Section level. Predicted value-added indicates that the value-added used as control is a prediction based on occupation shares, as in equation (14). Max occupation share indicates the exclusion criteria for firm with a large share of total employment in an occupation. The sample period is from 2013 to 2018 Standard errors for ρ are based on the standard error estimator from Adão et al. (2019), while standard errors for γ are clustered at the industry level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

D.4 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 and the initial occupation shares used for 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 8. The IV estimation leads to estimates very similar to the main reduced-form approach. The short-run effects are almost identical, and the long-run effects increase marginally. This is consistent with the occupation composition being more rigid in the short-run. However, none of the estimates changes the conclusions based on Table 2.

Table 8: Wage effects of labor market tightness - IV-Approach.

	(37)	**(38)**	**(39)**	**(40)**	**(41)**	**(42)**	**(43)**	**(44)**
Differences	1-year	1-year	5-year	5-year	1-year	1-year	5-year	5-year
ρ - Tightness	0.010**	0.011**	0.018***	0.027***	0.011***	0.011**	0.014***	0.020***
	(0.004)	(0.005)	(0.005)	(0.007)	(0.004)	(0.005)	(0.005)	(0.007)
λ - Productivity	0.045***	0.044***	0.086***	0.081***	0.004***	0.004***	0.020***	0.020***
	(0.008)	(0.008)	(0.014)	(0.014)	(0.001)	(0.001)	(0.003)	(0.003)
Predicted Value-added	X	X	X	X				
Observed Value-added					X	X	X	X
On-the-Job Search		X		X		X		X
Period, Industry & Region FE	X	X			X	X		
Industry & Region FE			X	X			X	X
No. Obs.	35,314	35,314	5,667	5,667	35,314	35,314	5,667	5,667

*Notes: The estimation is based on equation (12). Industry is defined as NACE Section level. Predicted value-added indicates that the value-added used as control is a prediction based on occupation shares, as in equation (14). Max occupation share indicates the exclusion criteria for firm with a large share of total employment in an occupation. The sample period is from 2013 to 2018 Standard errors for ρ are based on the standard error estimator from Adão et al. (2019), while standard errors for γ are clustered at the industry level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

D.5 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, it is possible that each firm exposure to changes in occupational tightness is driven by occupation they hire from and not the occupational composition of workers already employed. As robustness check I estimate equation (12) again, but where I now construct the tightness measures using the lagged occupational shares for new hires instead of for all employees. Note, that I predict productivity using all employees. The results are shown in Table 9. The results are very similar to those shown in Table 2 from the main regression. This is consistent with the flow of hires having a occupational composition similar to that of the stock of employees.

Table 9: Wage effects of labor market tightness - Using occupational shares of hires

	(45)	**(46)**	**(47)**	**(48)**	**(49)**	**(50)**	**(51)**	**(52)**
Differences	1-year	1-year	5-year	5-year	1-year	1-year	5-year	5-year
ρ - Tightness	0.011***	0.013***	0.013***	0.022***	0.012***	0.013***	0.009***	0.014***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)
λ - Productivity	0.046***	0.046***	0.093***	0.094***	0.003*	0.003*	0.021***	0.021***
	(0.006)	(0.007)	(0.015)	(0.015)	(0.002)	(0.002)	(0.004)	(0.004)
Predicted Value-added	X	X	X	X				
Observed Value-added					X	X	X	X
On-the-Job Search		X		X		X		X
Period, Industry & Region FE	X	X			X	X		
Industry & Region FE			X	X			X	X
No. Obs.	31,018	31,018	4,952	4,952	31,018	31,018	4,952	4,952

*Notes: The estimation is based on equation (12), except that tightness now 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, $\hat{\Theta}_{k,t}$. Industry is defined as NACE Section level. Predicted value-added indicates that the value-added used as control is a prediction based on occupation shares, as in equation (14). Max occupation share indicates the exclusion criteria for firm with a large share of total employment in an occupation. The sample period is from 2013 to 2018 Standard errors for ρ are based on the standard error estimator from Adão et al. (2019), while standard errors for γ are clustered at the industry level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

D.6 Productivity based 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. This includes observed revenue per worker and predicted revenue per worker, where the latter is constructed in the same way as predicted value-added per worker as described in Section 3. The results are shown in Table 10. 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. The estimated coefficient for the productivity is also very similar for the observed revenue measure. However, the coefficient for productivity found using the predicted measure is very close to zero and highly insignificant. This is in contrast to the estimate found when using value-added based measure.

Table 10: Wage effects of labor market tightness - revenue based productivity measures.

	(53)	**(54)**	**(55)**	**(56)**	**(57)**	**(58)**	**(59)**	**(60)**
Differences	1-year	1-year	5-year	5-year	1-year	1-year	5-year	5-year
ρ - Tightness	0.010***	0.010**	0.014***	0.019***	0.010***	0.010**	0.012***	0.016**
	(0.004)	(0.005)	(0.004)	(0.007)	(0.004)	(0.005)	(0.004)	(0.006)
λ - Productivity	0.000	0.000	-0.002	-0.002	0.008***	0.008***	0.025***	0.025***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)
Predicted revenue per worker	X	X	X	X				
Observed revenue per worker					X	X	X	X
On-the-Job Search		X		X		X		X
Period, Industry & Region FE	X	X			X	X		
Industry & Region FE			X	X			X	X
No. Obs.	35,277	35,277	5,650	5,650	35,277	35,277	5,650	5,650

*Notes: The estimation is based on equation (12). Industry is defined as NACE Section level. Predicted revenue indicates that the revenue per worker used as control is a prediction based on occupation shares, as in equation (14). The sample period is from 2013 to 2018. Standard errors for ρ are based on the standard error estimator from Adão et al. (2019), while standard errors for γ are clustered at the industry level. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

E Recovering parameters from linear DMP model

The reduced-form estimating equation (12), 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

$$\rho_{k,t} = \frac{\beta c \Theta_{k,t}}{w_{k,t}} \tag{27}$$

where all variables are denoted in levels and

$$\Theta_{k,t} = \sum_{h \in H} s_{h,k,t} \theta_{h,t} \tag{28}$$

. If elasticities are in fact firm and time specific, the estimand ρ given by the OLS estimator will then be a variance-weighted average of the firm-time specific elasticities. Let ϑ be the 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:

$$\rho = \sum_t \sum_k \frac{var(\ddot{\vartheta}_{k,t})}{\sum_t \sum_k var(\ddot{\vartheta}_{k,t})} \rho_{k,t} = \sum_t \sum_k \alpha^{\vartheta}_{k,t} \rho_{k,t} \tag{29}$$

Given that the assumptions in Appendix B hold, OLS consistently estimates ρ, with the following estimate.

$$\hat{\rho} = \sum_t \sum_k \frac{\ddot{\vartheta}^2_{k,t}}{\sum_t \sum_k \ddot{\vartheta}^2_{k,t}} \rho_{k,t} = \sum_t \sum_k \hat{\alpha}^{\vartheta}_{k,t} \rho_{k,t} \tag{30}$$

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

$$\hat{\rho} = \sum_t \sum_k \hat{\alpha}^{\vartheta}_{k,t} \frac{\beta c \Theta_{k,t}}{w_{k,t}} \Leftrightarrow \beta c = \frac{\hat{\rho}}{\sum_t \sum_k \hat{\alpha}^{\vartheta}_{k,t} \frac{\Theta_{k,t}}{w_{k,t}}} \tag{31}$$

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