Endogenous Separations, Wage Rigidities and Unemployment Volatility[*]

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Abstract

We show that in microdata, as well as in a search and matching model with flexible wages for new hires, wage rigidities of incumbent workers have substantial effects on separations and unemployment volatility. Allowing for an empirically relevant degree of wage rigidities for incumbent workers drives unemployment volatility, as well as the volatility of vacancies and tightness to that in the data. Thus, the degree of wage rigidity for newly hired workers is not a sufficient statistic for determining the effect of wage rigidities on macroeconomic outcomes. This finding affects the interpretation of a large empirical literature on wage rigidities.

Keywords: Search and matching, Unemployment volatility puzzle, Wage rigidities, Job Destruction

JEL classification: J63, J64, E30.

1 Introduction

In a recent very influential paper, Pissarides (2009) showed that in the baseline search and matching model job creation, and hence unemployment volatility, is only affected by wage setting in new matches. This is important, since it points to the degree of wage rigidity of new hires as the key statistic determining labor-market dynamics as opposed to wage rigidities in general.[1] Naturally, this insight spurred a growing empirical literature studying wage setting for new hires (see e.g. Carneiro, Guimarães and Portugal, 2012, Gertler, Trigari and Huckfeldt, 2016, Haefke, Sonntag and van Rens, 2013 and Martins, Thomas and Solon, 2012).

Pissarides (2009) analyzes the case with exogenous separations, a route supported by the influential finding of Shimer (2007, 2012) that separations contribute very little to unemployment fluctuations. However, recent work by Barnichon (2012) show that this result hinges crucially on the assumption that the job finding and the job separation rates are two independent determinants of unemployment. Relaxing this assumption increases the role of separations in unemployment volatility substantially to about 40 percent of unemployment's variance; see also Fujita and Ramey (2009), Elsby, Michaels, and Solon (2009) for additional evidence of the importance of the separations margin in understanding unemployment volatility. In light of this finding, we take a step back in this paper and study the role of wage rigidities for incumbent workers in a search and matching model with endogenous separations as in e.g. Pissarides (1994), where wages of new hires are fully flexible. We begin by showing that wage rigidities of incumbent workers are important for separations and hence employment volatility in a simple partial equilibrium setup. Intuitively, a positive shock to productivity increases all wages that can be adjusted, but with wage frictions some wages in existing matches are unchanged leading to a decrease in separations. Then, since the incumbent wage affects job separations, employment is affected. Thus, to only focus on wage setting for new hires is not enough in this framework in order to fully capture the link between wage-setting rigidities and unemployment volatility.

To provide evidence on the link between separations and incumbent wages, we rely on linked Swedish employer-employee microdata. We show theoretically that if incumbent workers' wages are flexible there should be no relationship between the firm wage and separations conditional on the marginal revenue product of the firm and the workers' outside option. In contrast, the data give stark evidence for a strong positive conditional relationship as expected when incumbent worker wages are rigid. This finding is thus in line with the literature studying the cyclicality of wages documenting wage rigidities in incumbents' wages; see Pissarides (2009) for an overview of this large literature. In a similar vein, Schmeider and Von Wachter (2010) provide evidence that workers with higher wages

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[1] Specifically, wage rigidities for new hires are then what is needed in order to mitigate the unemployment volatility puzzle present in this model (see Shimer, 2005, and Hall, 2005).

due to past favorable labor market conditions face higher risk of job loss in U.S. data. Earlier work by Card (1990) also points to that preset wages have an allocative effect.

Since general equilibrium feedback effects may overturn partial equilibrium intuition, we proceed by introducing endogenous separations in combination with rigid wages for incumbent workers in a DSGE model. In this setup, we find that an empirically relevant degree of wage rigidities for incumbent workers has large quantitative effects on unemployment volatility even when wages for new hires are fully flexible, producing a standard deviation of unemployment that matches the standard deviation in the data. Importantly, the model also matches the quantitative microdata evidence on the conditional firm-level wage elasticity of separations without this moment being targeted in the model calibration. In contrast, if we turn off the wage rigidity - making all wages flexible - unemployment volatility drops significantly indicating that wage rigidities for incumbent workers provide a substantial propagation force. Thus, as a corollary to these findings, the degree of wage rigidity for newly hired workers is not a sufficient statistic for determining the effect of wage rigidities on macroeconomic outcomes. Instead, wage frictions for incumbent workers turn out to have large effects on employment volatility, despite wages for new hires being flexible. This finding, in turn, affects the interpretation of a large empirical literature on wage rigidities; see Pissarides (2009) for a summary.

Three related papers are Bils, Chang, and Kim (2016), Schoefer (2015) and Fujita and Ramey (2012). Bils, Chang, and Kim (2016) argue that endogenous effort can break the neutrality result of wages for existing workers. Even though wages for new hires are flexible, future effort choices are affected by wage frictions, in turn affecting job creation and employment. However, to achieve a significant difference vis-à-vis a model with fully flexible wages, equilibrium effort needs to depend not only on the individual worker's wage, but also on the wage of all workers in the firm, which in turn equalizes the effort level across all workers in the firm. In Schoefer (2015), there is a financial friction in the form of a requirement on firms to use internal funds when hiring workers. Wage rigidities then make firm internal funds vary substantially with shocks, in turn leading to a large volatility in hiring and employment. In both papers, any effects of wage frictions on unemployment volatility work through the hiring margin, though. Fujita and Ramey (2012) analyses a model with endogenous separations and on-the-job search with flexible wages for all workers. Their calibrated model generates countercyclical separations and an unemployment volatility that is more in line with the data than that generated by the classical search and matching model, albeit still on the low side. We show that introducing wage frictions for incumbent wages brings the model much closer in matching the data moments, especially for unemployment, vacancies and tightness. Also, with flexible wages for all workers the model predicts a zero conditional firm-level wage elasticity of separations, which is, again, clearly rejected by the microdata.

This paper is outlined as follows. In Section 2 we present the basic mechanism we have in mind, in Section 3 we present microdata evidence supporting that incumbent wage stickiness affect separations, in Section 4 we outline the framework for the quantitative evaluation and in Section 5 we present the calibration and the quantitative results. Finally, Section 6 concludes.

2 The Mechanism

To set ideas, it is helpful to first focus on a stylized model of the labor market with search and matching frictions captured by a constant returns matching function and where wages are determined by the Nash-Bargaining solution. Moreover, separations are endogenous and the firm can close jobs at no cost as along the lines of Mortensen and Pissarides (1994). Thus, an idiosyncratic productivity shock a_{jt} is drawn in each firm j at each period t, following the cdf G. The firm decides on a cutoff level of idiosyncratic productivity, denoted R_{jt}, where the firm is indifferent between terminating the match and keeping the worker. Firm marginal revenue product, given the idiosyncratic productivity shock, is

$$p_{jt} z_t a_{jt} \tag{1}$$

where p_{jt} is the price of the firm's output and z_t an aggregate productivity shock.

2.1 Flexible Wages

We denote the surplus of the firm (worker) when wages change by J_{jt} (H_{jt}). Letting $w_{jt}(a_{jt})$ denote the rebargained wage, the expected firm value is

$$J_{jt}(a_{jt}) = p_{jt} z_t a_{jt} - w_{jt}(a_{jt}) + \beta \rho \int_0^1 \max\{J_{jt+1}(r), 0\} dG(r) \tag{2}$$

where β is the discount factor and ρ is the fixed probability that the match survives into the next period, capturing an exogenous component of separations (i.e. voluntary quits). When the firm has the right to manage, the firm choose separations (i.e. the cutoff productivities R_{jt}) so that $J_{jt}(R_{jt}) = 0$.

Similarly, the surplus for the worker when wages change is

$$H_{jt}(a_{jt}) = w_{jt}(a_{jt}) - b + \beta \left[\rho \int_{r \geq R_{jt+1}}^1 H_{jt+1}(r) \, dG(r) - s_t H_{t+1}^e \right], \tag{3}$$

where b is the flow payoff of the worker when unemployed, s the probability of finding a job and H_t^e the average value of being employed across all firms in the economy.

Wages are determined in bargaining and are given by the Nash Bargaining Solution (NBS)

$$\max_{w_{jt}(a_{jt})} \left(H_{jt}\left(a_{jt}\right)\right)^{\varphi} \left(J_{jt}\left(a_{jt}\right)\right)^{1-\varphi}. \tag{4}$$

Note that, removing the firm's right to manage and instead assuming that separations are also bargained over, the separation cutoff is determined so that the total surplus $S_{jt} = J_{jt} + H_{jt}$ is zero, i.e. $S_{jt}\left(R_{jt}\right) = 0$. Since $J_{jt} = (1 - \varphi) S_{jt}$, the solution is the same as under right to manage; see also Fujita and Ramey (2012). Moreover, wages do not affect separations in equilibrium, since wages just redistribute surplus between the firm and the worker. We have

$$R_{jt} = \frac{b - \left[\beta\rho \int_0^1 \max\{S_{jt+1}\left(r\right), 0\}dG\left(r\right) - \beta s_t \varphi S_{t+1}^e\right]}{p_{jt}z_t}, \tag{5}$$

which does not depend on wages, but only on (the current and future through S_{jt+1} and S_{t+1}^e) outside option of the worker and the marginal revenue product of the firm.

2.2 Wage Frictions

We denote the surplus of the firm (worker) when wages change by J_{jt} (H_{jt}). Letting $w_{jt}\left(a_{jt}\right)$ denote the rebargained wage, the expected firm value is

$$\begin{aligned}
J_{jt}\left(a_{jt}\right) &= p_{jt}z_t a_{jt} - w_{jt}\left(a_{jt}\right) + \alpha\beta\rho \int_0^1 \max\{J_{jt+1}\left(r\right), 0\}dG\left(r\right) \\
&+ (1 - \alpha)\beta\rho \int_0^1 \max\{\hat{J}_{jt+1}\left(r, w_{jt}\left(a_{jt}\right)\right), 0\}dG\left(r\right),
\end{aligned} \tag{6}$$

where α is the probability that wages are adjusted and $\hat{J}_{jt+1}\left(r, \hat{w}_{jt}\right)$ the surplus of the firm when wages are fixed at $\hat{w}_{jt}$. Also, for firms where the wage is fixed at $\hat{w}_{jt}$, noting that $\hat{w}_{jt}$ is a state variable,

$$\begin{aligned}
\hat{J}_{jt}\left(a_{jt}, \hat{w}_{jt}\right) &= p_{jt}z_t a_{jt} - \hat{w}_{jt} + \alpha\beta\rho \int_0^1 \max\{J_{jt+1}\left(r\right), 0\}dG\left(r\right) \\
&+ (1 - \alpha)\beta\rho \int_0^1 \max\{\hat{J}_{jt+1}\left(r, \hat{w}_{jt}\right), 0\}dG\left(r\right).
\end{aligned} \tag{7}$$

Firms choose separations (i.e. the cutoff productivities R_{jt} and $\hat{R}_{jt}\left(\hat{w}_{jt}\right)$) so that

$$J_{jt}\left(R_{jt}\right) = 0 \tag{8}$$

$$\hat{J}_{jt}\left(\hat{R}_{jt}\left(\hat{w}_{jt}\right), \hat{w}_{jt}\right) = 0. \tag{9}$$

Similarly, the surplus for the worker when wages change is

$$H_{jt}\left(a_{jt}\right) = w_{jt}\left(a_{jt}\right) - b + \alpha\beta\left[\rho\int_{r\geq R_{jt+1}}^{1} H_{jt+1}\left(r\right)dG\left(r\right) - s_t H_{t+1}^e\right] \quad (10)$$

$$+ \left(1-\alpha\right)\beta\left[\rho\int_{r\geq \hat{R}_{jt+1}\left(w_{jt}\left(a_{jt}\right)\right)}^{1} \hat{H}_{jt+1}\left(r, w_{jt}\left(a_{jt}\right)\right)dG\left(r\right) - s_t H_{t+1}^e\right],$$

When wages are not rebargained, $\hat{H}_{jt}\left(a_{jt}, \hat{w}_{jt}\right)$ is defined along the lines of (10) with $\hat{w}_{jt}$ replacing $w_{jt}\left(a_{jt}\right)$. In case wages are renegotiated, they are again given by the NBS (4).

If wages are sticky, the wage will have allocative effects through separations, in contrast to when wages are flexible as in (5). For workers that don't rebargain their wage, the separation cutoff $\hat{R}_{jt}$ is determined so that $\hat{J}_{jt}\left(\hat{R}_{jt}\left(\hat{w}_{jt}\right), \hat{w}_{jt}\right) = 0$, which implies that

$$\hat{R}_{jt}\left(\hat{w}_{jt}\right) = \frac{\hat{w}_{jt} - \alpha\beta\rho\int_0^1 \max\{J_{jt+1}\left(r\right), 0\}dG\left(r\right) - \left(1-\alpha\right)\beta\rho\int_0^1 \max\{\hat{J}_{jt+1}\left(r, \hat{w}_{jt}\right), 0\}dG\left(r\right)}{p_{jt}z_t}. \quad (11)$$

Assuming that $\frac{d\hat{J}_{jt+1}\left(r, \hat{w}_{jt}\right)}{d\hat{w}_{jt}} < 0$, we get $d\hat{R}_{jt}/d\hat{w}_{jt} > 0$ and thus that separations increase in the wage. Notice that this derivative is conditional on holding the marginal revenue product of the firm as well as the outside option of the worker constant.

While the model above only has single worker firms, it can be recast in a model where firms are large, given that firms have a constant returns technology. For incumbent workers, some wages are renegotiated and some are not and separations are given by (8) and (9), respectively. For new hires, on the other hand, all wages are negotiated at entry and the separation decision is given by (8). Thus, rigid wages affect separations for incumbent workers.

3 Are Separations Driven by Sticky Incumbent Wages?

To test which model of wage setting is best aligned with microdata, we rely on equations (5) and (11) and impose a log-linear technology (Cobb-Douglas) to account for the fact that most firms have many employees. We also assume that the variation in the outside option is common across workers in the same sector and time period and can thus be captured by the interaction of time and sector dummies, denoted λ_{st}.[2] We then estimate the following regression using IV-techniques

$$\ln sep_{jt} = \alpha_j + \beta_w \ln w_{jt} + \beta_{mrp} \ln mrp_{jt} + \lambda_{st} + \epsilon_{jt}, \quad (12)$$

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[2]See Carlsson, Messina and Nordström Skans, 2016, for direct evidence on the importance of sectoral variation in outside options for wage setting. We will also experiment with the triple interaction of time, sector and county below, taking into account the possibility that the reservation wage within a sector and time period may also vary across regions.

where sep_{jt} is the number of separations, mrp_{jt} is the nominal firm marginal revenue product of labor, w_{jt} is the nominal firm wage and α_j captures all firm-level constants. Here mrp_{jt} is defined as $p_{jt}y_{jt}/n_{jt}$, where $p_{jt}y_{jt}$ is nominal value added and n_{jt} employment. Moreover, w_{jt} is defined as $wagebill_{jt}/n_{jt}$.[3] The parameter of interest is then β_w, i.e. the conditional firm-level wage elasticity of separations, which in the IV strategy outlined below will be identified using covariation in incumbents' wages over time. From the simple model outlined above we expect that $\beta_w > 0$ when controlling for marginal revenue product and outside options under the null of sticky incumbent wages. Before proceeding there are however some identification- and technical issues associated with estimating equation (12) which we need to discuss.

First, the firm fixed effect will remove all differences between firms on average and the sector by time fixed effects will remove all common variation in the data due to e.g. aggregate or sectoral shocks. Thus, the identification of β_w will come from purely idiosyncratic firm-level variation, which is what we need for our empirical test of the model predictions. Note also that including the interaction of time and sector dummies will handle the deflation of the variables and we therefore rely on nominal measures of the firm-level marginal revenue product and the wage in the specification (12).

Second, to handle simultaneity and potential measurement errors we need instruments correlated with $\ln mrp_{jt}$ and $\ln w_{jt}$ - to provide independent variation vis-à-vis the outside option of the workers - captured by time by sector dummies, but uncorrelated with any idiosyncratic shocks simultaneously driving $\ln sep_{jt}$. Naturally, these restrictions leave a very small set of potential instruments. However, as shown by Fujita and Ramey (2012) and echoed in our own findings reported below, matching a model with endogenous separations to the data requires idiosyncratic shocks that are, for all practical purposes, to be regarded as i.i.d. on the annual frequency (see Section 5 below for a discussion). This result opens up for plausibly using lagged information when constructing instruments. Importantly, even with non-persistent idiosyncratic shocks, wage stickiness, as included in the model, still gives rise to a positive correlation of wages over time through (sometimes) unchanged wages for incumbent workers. We can use this for identification. Similarly, although not explicitly modeled, the presence of price stickiness in the data (as reported by Carlsson and Nordström Skans, 2012) generates a positive correlation of the marginal revenue product over time, which also can be used for identification.[4] Moreover, from the model above, idiosyncratic technology shocks that drive down separations would also drive up the wage. Thus, autocorrelation in the idiosyncratic technology shocks and the use of instruments based on lagged information would bias us towards finding a negative sign on the key parameter of interest in this exercise, β_w. In this sense, the positive estimate of β_w presented below is

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[3]Future values affect today's separations and we have common autocorrelated shocks in the model outlined below. Note, however, that this common variation in future values will be captured by the time dummies.

[4]In Appendix A, we present results from the first-stage regressions with signs that are in line with these predictions.

to be regarded as a lower bound. In Appendix A we show that this result is robust, with only mildly increasing point estimates of β_w when using higher order lags of the instruments, which should further alleviate any potential bias from autocorrelated idiosyncratic shocks.

Third, the model predicts that there should only be an effect of incumbent workers wages on separations in the case incumbents wages are sticky. Note that if incumbent workers wages are sticky, it is possible to think of stories where new-hires wages could also be affected by the lagged wage of incumbents through new hires wages beeing tied to incumbent workers wages in a rigid wage structure within the firm. Although the degree of flexibility of new hires wages is the subject of intense debate (see e.g. Carneiro, Guimarães and Portugal, 2012, Gertler, Trigari and Huckfeldt, 2016, Haefke, Sonntag and van Rens, 2013, Martins, Thomas and Solon, 2012 and Pissarides, 2009), from the model outlined above it is clear that this indirect effect would impose a negative force on β_w since higher incumbent wages, ceteris paribus, also lower the incentive to create new jobs and thus mitigate the incentives to substitute away from incumbent workers. This again would be a reason for viewing the positive estimate for β_w as a lower bound.

Fourth, to compute separations we rely on the Register Based Labor Markets Statistics (RAMS) collected by the Swedish Tax Authority for tax reasons and containing individual worker information on annual total labor income by employment spell (measured as start and end month) by each firm (see Section 3.1 below for a more detailed discussion of the data). The RAMS data set does not contain any information on the intensive labor-input margin in this data. Conceptually, we want to think of workers with at least some degree of attachment to the firm when studying wage effects on the firm-level separations margin, but it is not obvious where to draw the line. Below, we discuss in detail what we do to mitigate this problem by using a cut-off for the individual monthly wage (calculated by dividing annual labor income by the employment spell length in months), but regardless of what exactly we do, we should acknowledge that there will be measurement errors in the separations variable. The existence of measurement errors in the left hand side variable in the regression is not a serious issue per se since it only affects the precision of the estimates. However, using the wage measure from the RAMS data to compute a firm-level wage as the average monthly wage across all workers within the firm is more problematic. First, lacking data on the intensive labor-input margin makes the metric for this measure unclear. Also, separations from weakly attached workers with a low measured monthly wage causes the RAMS measure of the firm-level wage to rise mechanically. Moreover, via the flow equation of employment, i.e. $n_{jt} = n_{jt-1} + hires_{jt} - sep_{jt}$, we arrive at a version of the classic division-bias problem. The dynamic nature of the same flow equation also renders the use of a lag of the RAMS measure of the firm-level wage as an instrument for the current value of the same measure questionable. Fortunately, we have access to a completely separate measure of firm-level

wages from the database Företagens Ekonomi (FEK), which is based on a firm-level survey maintained by Statistics Sweden. From this source we can compute a firm-level wage as the wage sum paid by the firm divided by the number of *full time equivalent* employes. First, this gives us a wage metric that handles the intensive margin to be used as the dependent variable. Second, this measure will not be subject to the problematic dependencies between the measures of separations and firm-level wages discussed above. We will also use this data source when computing our measure of the firm-level marginal revenue product used both as an independent variable and as an instrument when lagged.

Fifth, there may be true systematic sorting of workers into separations that may give rise to a non-zero β_w even under flexible wages for incumbents. If the separation probability of a worker is related to the wage ranking of the workers within the firm, the firm-level wage would move when workers separate. This issue prevents us from using the lagged firm-level wage from the FEK data as an instrument. Instead, to handle such sorting effects on the estimate of β_w we construct an instrument for the firm-level wage that controls for the composition of workers within the firm. Specifically, we estimate the following regression on RAMS data in a first step

$$\ln w_{ijt} = \gamma_{ij} + \ln w_{jt}^{cc} + \xi_{ijt}, \tag{13}$$

where $\ln w_{ijt}$ is the wage for a worker i in firm j in time t, γ_{ij} is a match-specific effect, $\ln w_{jt}^{cc}$ is firm specific time fixed effects. The estimate $\ln \hat{w}_{jt}^{cc}$ is then a measure of the firm-level wage controlling for the composition of the workers in the firm.[5] We will use the lag of this measure as an instrument and thus rely on covariation in the incumbent workers' wages over time via wage stickiness for identification of β_w while controlling for any sorting effects on the same parameter.[6,7]

Finally, many firms are small and to conserve on the data and not throw out all zero observations on separations we will use the approximation $sep_{jt}/\overline{sep}_j$, where $\overline{sep}_j$ denotes the firm average of separations, instead of $\ln sep_{jt}$, as the dependent variable in the specification (12).[8] In the Appendix A we evaluate this approximation and show that it performs well on an overlapping sample.

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[5] The composition cleaned firm-level wage, $\ln \hat{w}_{jt}^{cc}$, is identified up to firm-specific constant, which in turn, is estimated in the second step where the (lag of the) measure is used as an instrument. Also, $\ln \hat{w}_{jt}^{cc}$ is an estimated measure, but since it will be used as an instrument (and not a regressor) this will not affect the inference; see Wooldridge (2002).

[6] Note that the IV-procedure would break down already in the first stage if there is no wage stickiness for incumbent workers in the data.

[7] Removing the match-specific fixed effects is an alternative way to address the problematic dependencies between the measures of separations and firm-level wages discussed above. But since it is still less clear how to think of the wage metric in the composition cleaned firm-level wage derived from the RAMS data, we use it to form an instrument and use the firm-level wage from the FEK data, where the wage metric is clear (full time wage), as the explanatory variable.

[8] Note that in (12), $\beta_w = d \ln sep_{jt}/d \ln w_{jt} = (dsep_{jt}/sep_{jt})/(dw_{jt}/w_{jt}) \simeq (dsep_{jt}/\overline{sep}_j)/(dw_{jt}/w_{jt})$, where the latter expression is estimated when the approximation is used.

3.1 Microdata

As discussed above, the firm-level microdata we use to estimate equation (12) are drawn from two sources. First, we use annual information from the survey/register FEK database maintained by Statistics Sweden, on value added, labor costs, the number of employees (in terms of full-time equivalents) and a five-digit (NACE) sector code for all employing non-financial Swedish firms in the private sector from 1997 to 2011, which is the last year we have access to. We then compute mrp_{jt} as nominal value added ($p_{jt}y_{jt}$) divided by the number of full-time equivalent workers (l_{jt}). To obtain a measure of the firm wage we divide total firm-level nominal labor costs ($wagebill_{jt}$) by the number of full-time equivalent workers.[9] Thus the FEK data gives us a proper measure of the average firm-level, full-time wage since the labor input measure accounts for both the extensive and intensive labor-input margin.

Second, to compute separations we use the RAMS database. This database is also maintained by Statistics Sweden and contains information about labor earnings for all employment spells in the Swedish private sector as well as a plant and a firm identifier. The plant and firm identifiers enable us to match the individual employment spells to the employing firm in the FEK database. Importantly, the RAMS database is based on a completely separate data source than the FEK database, so there is no scope for overlapping measurement errors in the two databases. Specifically, the raw data for the RAMS database is collected from employers by the Swedish Tax Authority in order to calculate taxes. Data include information on annual earnings, as well as the first and last remunerated month in the year. Using this information, we can construct a firm measure of separations. Here, separations are defined in the same way as they enter into the flow equation of employment, i.e. $n_{jt} = n_{jt-1} + hires_{jt} - sep_{jt}$. The baseline definition of separations we employ is based on the primary employment of full-time workers. The RAMS data lacks information on actual hours, so to restrict attention to workers that are reasonably close to full time workers we only consider a person to be a full-time employee if the (monthly) wage exceeds 75 percent of the mean (monthly) wage of janitors employed by municipalities. Also, since we are aiming to identify full-time workers we only count an individual as employed by at most one firm each year by only keeping the employment with the highest wage in November (which is the reference month used by Statistics Sweden). In other words, with this definition we focus on individual's primary employment.[10] Self-employed workers are not counted as employed in any of the definitions of separations used in the paper.

Third, using the same RAMS data on individual's primary employment, we compute the compo-

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[9]Swedish collective agreements, covering about 90 percent of the work force, are bargained at the sectoral level, but a substantial part of wage bargaining is done by local parties at the firm level, see Nordström Skans, Edin, and Holmlund (2009).

[10]Nordström Skans, Edin, and Holmlund (2009) and Carlsson, Messina, and Nordström Skans (2016) use a similar approach to identify full-time workers' primary employment.

sition cleaned firm-level wage $\ln w_{jt}^{cc}$ by estimating equation (13).

Fourth, note that the RAMS database contains geographical information on the plant where the worker is employed. Using this information we can also experiment by including controls for regional variation in the workers' outside option. Thus, we can include the triple interaction of time, two-digit (NACE) sector and county (NUTS3) as a control for the workers' outside option.

Putting everything together, we end up with a sample of $175,459$ firms and $1,147,875$ firm/year observations for which we can compile all the information we need for estimating the baseline IV-specification.

Finally, two additional complications arise from the fact that many firms are small and there are many instances of zero separations (about 41 percent of the data). To handle very large swings in separations and to acknowledge that $\ln w_{jt}^{cc}$ is estimated as an average across workers within a firm/year, we first require that the firms have at least 10 full-time employees for a firm/year observation to be included (according to the strict definition used to compute separations in the RAMS data), leaving a sample of $52,653$ firms and $316,903$ firm/year observations. Secondly, to conserve on the data and not throw out all zero observations on separations we use the approximation $sep_{jt}/\overline{sep}_j$, as discussed above, instead of $\ln sep_{jt}$, as the dependent variable in the regression (12). However, even with this approximation we need to drop firms with a zero firm average of separations. Thus, all in all, the baseline estimation sample amounts to $49,824$ firms and $313,383$ firm/year observations. For this sample, we control for outside options by using 814 sector by time dummies (when using sector by time by county dummies to control for outside options, we use $12,741$ dummies).[11] Note that the sample size information in the tables below is adjusted for removing singletons in the estimation.

3.2 Microdata Results

As can be seen in the first column of Table 1, IV estimation yields a statistically significant estimate of the conditional firm-level wage elasticity of separations, β_w, equal to 6.029 (firm-level clustered s.e. 0.309), thus rejecting the null of flexible incumbent wages with a sign consistent with the presence of wage frictions in the data. Moreover, the negative sign of the coefficient for the estimated conditional firm-level marginal revenue product elasticity of separations, β_{mrp} (-2.261, s.e. 0.173), is also in line with what is expected from the model. As reported in Appendix A, the instruments are highly relevant with F-statistics of 589 and 437, in respective first-stage regression.[12]

From column (2) we see that allowing for geographical variation, over and above sector time variation, in the workers' outside option does not change the results quantitatively. Specifically,

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[11]Estimation is performed using the reghdfe routine for Stata; see Correia (2014).

[12]Also, a formal under-identification test confirms that the IV specification is well identified (Kleibergen and Paap (2006) rk LM statistic: $\chi^2(1) = 465$, p-val $= 0.000$)

Table 1: Micro-Data Results

	(1)	(2)	(3)
β_{mrp}	-2.261	-2.331	-2.483
	$(0.173)^{**}$	$(0.206)^{**}$	$(0.314)^{**}$
β_w	6.029	5.773	6.553
	$(0.309)^{**}$	$(0.331)^{**}$	$(0.460)^{**}$
Dummies:			
Firm	YES	YES	YES
Sector by Time	YES	YES	YES
Sector by County by Time	NO	YES	NO
2008-2011 Included	YES	YES	NO
Observations	$306,205$	$261,452$	$207,230$
Firms	$42,656$	$38,525$	$35,024$

* (**) Denotes significance on the 5 (1) percent level from zero. Standard errors clustered on the firm level reported inside parenthesis. Sector denotes two-digit NACE codes. All regressions include firm-level fixed effects. Sample sizes are adjusted for singletons dropped in the estimation.

including the triple interaction of sector (NACE two-digit) by time by county yields similar results as to relying on only the interaction of sector (NACE two-digit) by time. Note that the number of observations falls a bit when also allowing for geographical variation in the reservation wage since we loose firms with multi-county activity in this version of the regression.

In column (3) we show that dropping years affected by the financial crisis (2008-2011) yields very similar results, quantitatively.

In Appendix A we also show that the results are also robust to: (i) employing a loose measure of firm-level separations in the regression, relying on all employment spells of all workers regardless of their degree of firm attachment when calculating separations, (ii) looking at larger firms (iii) focusing on the manufacturing sector only, and (iv) lagging the instrument set further backwards in time. Overall, the point estimates of the conditional firm-level wage elasticity of separations are all statistically significant and lie between 5.067 and 8.333 across all the exercises in the paper, implying a back of the envelope 95-percent confidence interval of 4.542 and 9.846. Thus, all in all, we conclude from this exercise that the microdata strongly and robustly rejects a flexible incumbent wage model, and instead favours the hypothesis that incumbent wages do affect separations and that wages thereby are being allocative. This finding is also in line with the literature studying the cyclicality of wages documenting wage rigidities in incumbents' wages; see Pissarides (2009) for an overview of this large literature. In a similar vein, Schmeider and Von Wachter (2010) provide evidence that workers with higher wages due to past favorable labor market conditions face higher risk of job loss in U.S. data. Earlier work by Card (1990) also provide evidence of that preset wages have an allocative effect.

Note that there is a large literature, surveyed in Manning (2011), that seeks to infer the elasticity of labor supply by looking at how sensitive firm recruitment is to wages. Since recruitment is equal to the negative of separations for a firm with constant employment, this is in a number of studies indirectly measured by the separation elasticity with respect to wages. Since this strand of the literature tries to estimate the labor supply elasticity, i.e., movements along the labor supply curve, the relationship between wages and separations is found to be negative. Note that the exercise in this paper is very different. We seek to identify a mechanism that acts via firms labor demand by estimating the effect of variations in incumbents' wages on separations, conditional on the marginal revenue product of the firm and the workers' outside option. Naturally, the effect of wages on separations working through the firm's labor demand is positive.

4 A Model for Quantitative Evaluation

The next step in our analysis attempts to realistically evaluate the macroeconomic quantitative importance of the mechanism outlined above by embedding it in a standard Mortensen and Pissarides (1994) model. Since we are not interested in studying nominal variables per se, we treat prices as flexible and normalize the price p_{jt} in (6) to unity in every period. This provides a framework for the quantitative evaluation that shares many elements of standard real models.

In the model, firms use labor to produce output and post vacancies on a search and matching labor market. Wages are bargained between workers and firms in a setting with stochastic impediments to rebargaining, akin to Calvo (1983). New hires, however, always bargain their wage. On-the-job search is endogenous along the lines of Pissarides (1994).[13] Unemployed workers receive unemployment benefits paid by the government that are financed via lump-sum taxes.

4.1 Firms

Firms each employ one worker to produce a homogenous good with a constant returns technology that is sold at unit price to retailers. Firm revenue is $z_t a_t$, where z_t is an aggregate productivity shock and a_t an idiosyncratic productivity shock. Note that for notational convenience we suppress the j index used in Section 2 on idiosyncratic productivity. The idiosyncratic shock is assumed to follow the cdf G with upper and lower bounds, a_{ub} and a_{lb}, respectively. As in the example in section 2, if idiosyncratic productivity is sufficiently low, the firm will cease operations and lay off the worker.

---

[13]The key contribution of endogenous on-the-job search is to generate a Beveridge curve with a negative slope. Removing this feature of the model does not affect the overall findings of this paper.

4.2 Search and Matching and the Hiring Decision

Letting u_t denote unemployment, ν_t vacancies and ϕ_t the number of matched workers searching, the total number of searching workers is $u_t + \phi_t$. Match formation is governed by the Cobb-Douglas matching function

$$m\left(u_t + \phi_t, v_t\right) = \sigma_\mu \left(u_t + \phi_t\right)^{\sigma_a} \nu_t^{1-\sigma_a}. \tag{14}$$

Labor-market tightness is given by

$$\theta_t = \frac{\nu_t}{u_t + \phi_t}. \tag{15}$$

Vacancies are determined as usual by the equalization of the vacancy cost, denoted c, of an employee and the expected value of the worker to the firm. As in Pissarides (1994), when workers enter a firm, they enter at the highest idiosyncratic productivity a_{ub}. Job creation is then given by

$$c = \beta E_t q\left(\theta_t\right) J_{t+1}\left(a_{ub}\right), \tag{16}$$

where β is the discount factor, $q\left(\theta_t\right)$ the probability of filling a vacancy and J_t the value of a firm. A detailed description of employment flows, which are somewhat involved, can be found in the Appendix B.1.

4.3 Value Functions

Let H^s and H^{ns} denote worker surplus when the worker searches and does not search on the job, respectively. We assume that workers face a cost σ of searching on the job. With probability λ, workers' idiosyncratic productivity changes and is again drawn from the distribution G and with probability $(1 - \lambda)$ that the probability is unchanged. Note that the wage will depend on idiosyncratic productivity a_t. Let $w^s\left(a_t\right)$ ($w^{ns}\left(a_t\right)$) denote the worker wages when searching (not searching). The expected net surplus for an employed worker in a firm that resets the wage this period is

$$
\begin{aligned}
H_t^i\left(a_t\right) = {} & w_t^i\left(a_t\right) - b - \mathbb{I}_t\sigma + \beta E_t \alpha \rho^i \left(\lambda \int_0^1 H_{t+1}\left(r\right) dG\left(r\right) + (1 - \lambda) H_{t+1}\left(a_t\right)\right) \\
& + \beta E_t \left(1 - \alpha\right) \rho^i \left(\lambda \int_0^1 \hat{H}_{t+1}\left(r, w_t^i\left(a_t\right)\right) dG\left(r\right) + (1 - \lambda) \hat{H}_{t+1}\left(a_t, w_t^i\left(a_t\right)\right)\right) \\
& + \beta E_t \left(g^i - f\left(\theta_t\right)\right) H_{t+1}\left(a_{ub}\right),
\end{aligned} \tag{17}
$$

where $\mathbb{I}_t$ is an indicator function that is equal to one of the worker searches on the job and zero otherwise, again surpressing the aggregate state variable z_t. Moreover, b is the flow payoff of the

worker when unemployed, $g^{ns} = 0$ and $g^s = f(\theta_t)$, $\rho^{ns} = (1-s)$ and $\rho^s = (1 - f(\theta_t))(1-s)$,

$$
H_t(a_t) = \begin{cases} \max\left(H_t^{ns}(a_t), H_t^s(a_t)\right) & \text{if } a_t > R_t^{ns} \text{ and } a_t > R_t^s \\ H_t^{ns}(a_t) & \text{if } a_t > R_t^{ns} \text{ and } a_t \leq R_t^s \\ H_t^s(a_t) & \text{if } a_t \leq R_t^{ns} \text{ and } a_t > R_t^s \\ 0 & \text{otherwise,} \end{cases} \tag{18}
$$

and

$$
\hat{H}_t(a_t, \hat{w}_t) = \begin{cases} \max\left(\hat{H}_t^{ns}(a_t, \hat{w}_t), \hat{H}_t^s(a_t, \hat{w}_t)\right) & \text{if } a_t > \hat{R}_t^{ns}(\hat{w}_t) \text{ and } a_t > \hat{R}_t^s(\hat{w}_t) \\ \hat{H}_t^{ns}(a_t, \hat{w}_t) & \text{if } a_t > \hat{R}_t^{ns}(\hat{w}_t) \text{ and } a_t \leq \hat{R}_t^s(\hat{w}_t) \\ \hat{H}_t^s(a_t, \hat{w}_t) & \text{if } a_t \leq \hat{R}_t^{ns}(\hat{w}_t) \text{ and } a_t > \hat{R}_t^s(\hat{w}_t) \\ 0 & \text{otherwise.} \end{cases} \tag{19}
$$

In case wages are not reset but remain at the level $\hat{w}_t$ from the previous period, the wage $\hat{w}_t$ is a state variable and the surplus is

$$
\begin{aligned} \hat{H}_t^i(a_t, \hat{w}_t) &= \hat{w}_t - b - \mathbb{I}_t\sigma + \beta E_t \alpha \rho^i \left(\lambda \int_0^1 H_{t+1}(r)\, dG(r) + (1-\lambda) H_{t+1}(a_t)\right) \\ &\quad + \beta E_t (1-\alpha)\rho^i \left(\lambda \int_0^1 \hat{H}_{t+1}(r, \hat{w}_t)\, dG(r) + (1-\lambda)\hat{H}_{t+1}(a_t, \hat{w}_t)\right) \\ &\quad + E_t\left(g^i - f(\theta_t)\right) H_{t+1}(a_{ub}). \end{aligned} \tag{20}
$$

For firms that change wages, the surplus is, when there is no on-the-job search

$$
\begin{aligned} J_t^i(a_t) &= z_t a_t - w_t^i(a_t) + \beta E_t \rho^i \alpha \left(\lambda \int_0^1 J_{t+1}(r)\, dG(r) + (1-\lambda) J_{t+1}(a_t)\right) \\ &\quad + \beta E_t (1-\alpha)\rho^i \left(\lambda \int_0^1 \hat{J}_{t+1}\left(r, w_t^i(a_t)\right) dG(r) + (1-\lambda)\hat{J}_{t+1}\left(a_t, w_t^i(a_t)\right)\right), \end{aligned} \tag{21}
$$

where

$$
J_t(a_t) = \begin{cases} \max\left(J_t^{ns}(a_t), 0\right) & \text{if } a_t > R_t^S \\ \max\left(J_t^s(a_t), 0\right) & \text{if } a_t \leq R_t^S \end{cases} \tag{22}
$$

and

$$
\hat{J}_t(a_t, \hat{w}_t) = \begin{cases} \max\left(\hat{J}_t^{ns}(a_t, \hat{w}_t), 0\right) & \text{if } a_t > \hat{R}_t^S(\hat{w}_t) \\ \max\left(\hat{J}_t^s(a_t, \hat{w}_t), 0\right) & \text{if } a_t \leq \hat{R}_t^S(\hat{w}_t) \end{cases}. \tag{23}
$$

In case wages are not reset but remain at the level $\hat{w}_t$ from the previous period, the values are

$$
\begin{aligned} \hat{J}_t^i(a_t, \hat{w}_t) &= z_t a_t - \hat{w}_t + \beta E_t \rho^i \alpha \left(\lambda \int_0^1 J_{t+1}(r)\, dG(r) + (1-\lambda) J_{t+1}(a_t)\right) \\ &\quad + \beta E_t (1-\alpha)\rho^i \left(\lambda \int_0^1 \hat{J}_{t+1}(r, \hat{w}_t)\, dG(r) + (1-\lambda)\hat{J}_{t+1}(a_t, \hat{w}_t)\right). \end{aligned} \tag{24}
$$

4.4 Endogenous Separations and On-the-Job Search

As in Mortensen and Pissarides (1994) and Den Haan, Ramey, and Watson (2000), firms have the right to manage. A firm lays off workers if idiosyncratic productivity is at most equal to a cutoff level R^i and $\hat{R}^i$ for $i \in \{ns, s\}$. The separation cutoffs are

$$J_t^i \left(R^i \right) = 0 \text{ and } \hat{J}_t^i \left(\hat{R}^i \left(\hat{w}_t \right), \hat{w}_t \right) = 0 \text{ for } i \in \{ns, s\}. \tag{25}$$

In order to get a Beveridge curve that is in line with empirical evidence, we add on the job search.[14] Similarly, the decisions for workers when to search on the job depend on the level of the idiosyncratic productivity shock. A worker searches on the job when idiosyncratic productivity is at most equal to a cutoff level R^S and $\hat{R}^S$. The on-the-job search cutoffs are

$$H_t^s \left(R_t^S \right) = H_t^{ns} \left(R_t^S \right) \text{ and } \hat{H}_t^s \left(\hat{R}_t^S \left(\hat{w}_t \right), \hat{w}_t \right) = \hat{H}_t^{ns} \left(\hat{R}_t^S \left(\hat{w}_t \right), \hat{w}_t \right). \tag{26}$$

Note that the introduction of on the job search potentially blurs the channel between wages and separations. The simple model above predicts an unambiguous positive sign for the conditional firm-level wage elasticity of separations, β_w, under the null of wage rigidity for incumbent workers. When allowing for on the job search the sign for β_w will depend on whether the flow of separations is dominated by layoffs or by non-random quits to other jobs (i.e. job switches driven by wage differences). Specifically, a high firm-level wage, ceteris paribus, makes it less likely that you will accept a competing job-offer driving β_w towards a negative sign. We see however in the microdata that the layoff channel dominates.[15] Below, we also confirm that this is the case in the calibrated model when calculating the implied conditional firm-level wage elasticity of separations; for details see Section 5.3 below.

4.5 Wage Bargaining

The nominal wage, when wages are rebargained, is chosen such that it solves the Nash product

$$\max_{w_t^i(a_t)} \left(H_t^i \left(a_t \right) \right)^{\varphi} \left(J_t^i \left(a_t \right) \right)^{1-\varphi}, \tag{27}$$

where $i \in \{ns, s\}$ and φ denote the bargaining power of the family.

---

[14] A model with only endogenous separations tends to yield a positive correlation between unemployment and vacancies; see Fujita and Ramey (2012).

[15] Survey evidence in line with this finding suggests that a sizeable share of job quits are due to reasons unrelated to the wage. Specifically, in a survey "Svenskarnas vilja att byta jobb" from 2017 commissioned by TRR Trygghetsrådet and performed by Norstat on a random representative sample of Swedes between the ages $16 - 64$, answered by $1,010$ individuals (when first screening out students, retirees and self employed), only 18 percent of those that changed job the last five years (47 percent of all respondents) states that this was due to beeing discontent with the wage. Another 20 percent stated that they got an offer they couldn't refuse which may or may not include an offer of a higher wage.

4.6 The Resource and Government Budget Constraints

Let $n_t(a)$ denote employment in firms with idiosyncratic productivity a. The aggregate resource constraint can be written as

$$c_t + c\nu_t = \int_0^1 n_t(a) z_t a \, da. \tag{28}$$

The government uses lump-sum taxes to finance unemployment benefits. Thus, $\tau_t = (1 - n_t) b_r$.

5 Quantitative Evaluation

In the quantitative evaluation we have evaluated the performance of the full model both in a Swedish, as well as in a U.S. context. Although the Swedish labor market is considerably more rigid, with e.g. quarterly flows on par with U.S. monthly flows, the two economies are similar in terms of standard dimensions for evaluating the performance of search and matching models. Moreover, since the full model yields very similar quantitative results in these dimension, regardless of which of the two countries' data moments to match the model to, we present the U.S. results in the main text and defer the Swedish results to the Appendix B.3.

5.1 Calibration

The baseline calibration of the structural parameters is presented in Table 2 and is based on standard values for a monthly parametrization. We set β to 0.9966, which generates a real interest rate of around

Table 2: Baseline Calibration of the Model.

	Calibrated Monthly Parameters	
β	*Time preference*	0.9966
φ	*Family bargaining power*	0.5
σ_a	*Matching function*	0.5
α	*Calvo prob. of wage adjustment*	0.138
b	*Payoff when unemployed*	0.75
	Moment-Matched Monthly Parameters	
σ_μ	*Matching function productivity*	0.523
c	*Vacancy cost*	0.559
σ_G	*Idiosyncratic productivity distr. variance*	0.095
σ	*Search cost*	0.046
λ	*Prob. of new idiosyncratic draw*	0.740
s	*Exogenous separation rate*	0.0196

4 percent. We take a standard approach in the calibration of the worker outside option b and set it to 0.75, which is in the span of the estimate in Gertler, Sala, and Trigari (2008) and the calculations in

Hall and Milgrom (2008).[16,17,18] For job separations, we follow Fujita and Ramey (2012) and set total monthly separations to 0.1, implying a monthly rate of 0.02. We set the bargaining power $\varphi = 0.5$, implying symmetrical bargaining in the baseline calibration. We choose σ_a to yield a matching function elasticity of 0.5 to ensure that the (basic) Hosios condition is satisfied, following Pissarides (2009). As is commonly assumed, see e.g. Den Haan, Ramey, and Watson (2000) and Christiano, Trabandt, and Walentin (2010), we assume that the idiosyncratic productivity shock follows a log-normal distribution with mean zero and standard deviation parameter σ_G. We approximate the idiosyncratic distribution by a grid with 40 gridpoints with lower (upper) bound of 0.6 (1.1).

The Calvo parameter is set to 0.138, following Christiano, Eichenbaum, and Evans (2005). Their baseline quarterly estimate of the probability of a wage change is 0.36, implying a duration of wage contracts of slightly below three quarters. Given the U.S. microdata evidence presented in Barattieri, Basu, and Gottschalk (2014) of an overall probability of wage change in between 21.1 to 26.6 this parameter is calibrated conservatively and in the upper range of the empirically relevant region.[19]

We follow Hagedorn and Manovskii (2008) closely when calibrating the aggregate productivity process. We approximate, through a 5-state Markov chain, the continuous-valued $AR(1)$ process $\log z_t = \rho_z \log z_{t-1} + \varepsilon_t^z$ where $\rho_z \in (0,1)$ and $\varepsilon_t^z \sim N(0, \sigma_z^2)$. Following Hagedorn and Manovskii (2008) we use an autocorrelation of 0.765 and an unconditional standard deviation of 0.013 for the HP-filtered productivity process with a smoothing parameter of $1,600$. At a monthly frequency, this requires setting $\rho_z = 0.960$ and $\sigma_z^2 = 0.0085$.

We then choose the parameters σ_μ, c, σ_G, σ, λ and s so that the model matches a mean labor market tightness of 0.72 as in Pissarides (2009), a mean separation rate of 0.02, a mean job-to-job finding rate of 0.032 as in Moscarini and Thomsson (2007), a mean job finding probability of 0.34, separation persistence of 0.631 and separation standard deviation of 0.058 as closely as possible.[20] The results are presented in Table 3.[21] Comparing data moments (first column) with simulated moments from the model (second column), under the calibration in Table 2, shows that the model fits the data moments closely, overall. The only dimension where the model misses somewhat is that the

---

[16] Here, b is the payoff when unemployed, thus including e.g. the value of leisure.

[17] According to evidence cited in Hall and Milgrom (2008) the after-tax replacement rate is 36 percent. Since not all unemployed workers receive benefits, they set the rate to 25 percent. By adding the value of leisure and the difference in consumption between employed and unemployed, they find a value of 0.71 for the payoff when unemployed. The OECD statistics points towards a somewhat higher number for the after-tax replacement rate, though. We therefore find a slightly higher calibration of the worker outside option reasonable.

[18] The calibration of b is subject of intense debate, see e.g. Hagedorn and Manovskii (2008) and Chodorow-Reich and Karabarbounis (2016). Here, the calibration is close to the middle of the interval of 0.47 to 0.96 presented by the latter.

[19] An even stickier calibration could be motivated from the probability of a within-job wage change reported to be in between 16.3 and 21.6 percent per quarter in Barattieri, Basu, and Gottschalk (2014).

[20] The last five targeted moments are taken from Fujita and Ramey (2012).

[21] The number of months in the simulation is set so that it corresponds to the number of quarters in the quarterly data of Fujita and Ramey (2012) (where the period is 1976:I-2005:IV). When choosing the parameters σ_μ, c, σ_G, σ, λ and s, we simulate 100 data sets, aggregate to quarterly data and then compute the average labor market tightness, the separation

Table 3: Comparison of Matched Moments

Monthly Moments	Data, US	Model, US
Mean v_t/u_t	0.720	0.732
Mean Separation rate	0.020	0.021
Mean Job-to-job transition rate	0.032	0.033
Mean Job finding rate	0.340	0.304
Std. Separation rate	0.058	0.060
Persistence Separation rate	0.631	0.489

Note: Data moments are from Fujita and Ramey (2012) where the sample period for data is 1976:Q1-2005:Q4.

the persistence of separations is a bit too low. This latter moment is tricky to match exactly in this class of models. For example, Fujita and Ramey (2012) also has problems in this dimension, but missing the target on the other side. The parameter λ that determines the degree of persistence in the idiosyncratic productivity process is 0.740. This implies a yearly probability of remaining in the same productivity state close to zero, which is very similar to the implied probability based on the estimation results presented in Fujita and Ramey (2012). Importantly, there is thus a substantial leeway before the persistence in the idiosyncratic technology shock would give rise to any substantial bias in the IV-estimation procedure relying on annual data discussed above.

5.2 Solution Algorithm

We use nonlinear solution techniques along the lines of Hagedorn and Manovskii (2008) to solve the model. As with a standard search and matching model, the system can be solved recursively, i.e. first solving for labor market tightness, wages and values and then for employment flows. Since the system (16), (17), (20), (21), (24) and (27) above does not depend directly on unemployment, we can solve without computing employment and unemployment. Wages that change today depend on the state variables, z_t and a_t. Similarly, a wage that is reset at some point $t-k$ in the past depend on the state variables, z_{t-k} and a_{t-k}. The state for worker and firm surpluses when wages are rigid then depends on the current states, z_t and a_t, and the states when the wage was last reset. Letting Z denote the state space for z_t and A the state space for a_t, the state space for J^i and H^i is $Z \times A$ and the state space for $\hat{J}^i$ and $\hat{H}^i$ is $Z \times A \times Z \times A$.

Given the redefinition of the state space above, we guess a solution for firm and worker surpluses, wages and labor market tightness and compute new revised values using value function iteration until convergence. The model is then simulated to generate the synthetic variables required to compute the moments that we match in the calibration.

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rate, the job-to-job finding rate, the job finding rate, separation persistence and separation standard deviation.

5.3 Validation

As a first exercise on the calibrated model we compare the implied non targeted conditional firm-level wage elasticity of separations, β_w, to that of the microdata. For this we calculate the wage elasticity of separations by use of the change in separations from moving in the grid of past wages averaging over Calvo draws, thus holding the idiosyncratic- and the aggregate technology constant in the computation.[22] Then the elasticity computed at each grid point is weighted by its employment share in each time period. Finally, to average out different draws of the aggregate technology shock process, we take the average of the elasticity over 100 simulations.

The model under the Swedish calibration, described in detail in the Appendix B.3, gives a conditional firm-level wage elasticity of separations of 8.22, which is within the range of the microdata estimates. Remembering that there are reasons to believe that the point estimates are downward biased, as discussed in Section 3, there is thus a very high degree of agreement between the micro results and the model implications in this dimension. Calibrating the model in a U.S. context, as described above, yields a very similar conditional firm-level wage elasticity of separations of 7.18.

5.4 Quantitative Results

For comparison with the non-targeted moments, we use quarterly data from Fujita and Ramey (2012) that cover the period 1976:Q1-2005:Q4. The implied data moments are presented in the top rows of the top and the bottom panel of Table 4.

The simulated standard deviation for the unemployment rate, the job finding rate, total separation rate, vacancies and the vacancy unemployment ratio are presented in the top panel of Table 4.

Comparing the two top rows we see that wage rigidities for incumbent workers generate a standard deviation of unemployment in the model that is close to the level of the observed standard deviation in the data, 0.089 vs. 0.096. Importantly, the model also performs well in terms of matching the volatility of the vacancy rate, which has proven notoriously difficult in the search-matching literature - a notable exception is Hagedorn and Manovskii (2008). The reason is that the surplus of the firm from vacancy creation becomes much more sensitive to shocks when incumbent wages are rigid. Given the results for unemployment and vacancy volatility, it is not surprising that the model also performs well in terms of the volatility of tightness (v_t/u_t) vis-à-vis the data. However, we do see that the

---

[22]To see why this calculation corresponds to the IV results from the microdata and not the reduced-form estimates from directly including the instrument in the equation, note that we have two cases in the model. First, when the Calvo draw implies that the wage is fixed the lagged wage for incumbent workers perfectly explains the current wage, implying a first-stage coefficient of unity and we thus identify the second-stage IV coefficient in this case. Secondly, when the Calvo draw implies that wages are rebargained for incumbent workers the wage does not affect separations in the model and we thus identify the second-stage IV coefficient also in this case regardless of the first-stage coefficient (which is close to zero given a low autocorrelation in the idiosyncratic technology shock). The calculation then weights the two cases with the Calvo probability.

Table 4: Comparison of Monthly Moments

	u_t	Job find. rate	Sep. rate	v_t	v_t/u_t
	Standard Deviation				
Data	0.096	0.077	0.058	0.126	0.218
Model	0.089	0.029	0.060	0.186	0.225
Flex Wage - Turning off Wage Rigidities	0.022	0.025	0.000	0.034	0.051
Flex Wage - Recalibrated	0.073	0.027	0.058	0.022	0.084
	Correlation with Labor Productivity				
Data	−0.460	0.369	−0.535	0.564	0.527
Model	−0.616	0.944	−0.271	0.509	0.672
Flex Wage - Turning off Wage Rigidities	−0.854	0.958	−0.006	0.944	0.999
Flex Wage - Recalibrated	−0.896	0.951	−0.930	0.579	0.940

Note: Data moments are from Fujita and Ramey (2012) where the sample period for data is 1976:Q1-2005:Q4.

volatility of the job-finding rate is slightly less than half of that of the data. This is also a problematic moment to match in the search-matching literature, as noted by Fujita and Ramey (2012), and adding wage frictions of incumbent workers does not help in resolving this puzzle.

In the third row we turn off the wage rigidity in the model and let all wages be flexible. This leads to complete deterioration of the models ability to match any of the moments. Essentially, the model turns to a model of exogenous separations when turning off the wage rigidities, since only negative shocks large enough to eradicate the surplus of a match lead to a separation. Since these large shocks are rare, separations become almost constant. Thus the empirically relevant degree of wage rigidities carries substantial propagation force.

Note that Fujita and Ramey (2012) reports that a model with endogenous separations and fully flexible wages for all workers takes the volatility about halfway towards realistic values. In the fourth row we recalibrate the model with flexible wages to match the moments discussed above. Since the model and calibration then becomes very similar to the model of Fujita and Ramey (2012) this exercise qualitatively replicates their results. From the fourth row we see that this helps the model in matching unemployment volatility as well as the volatility of the separation rate, as in Fujita and Ramey (2012), but not the other moments in the table. The improved fit for unemployment and separation rate is essentially achieved by trading propagation in the model for increased idiosyncratic shock variance. But as discussed above, the microdata strongly and robustly rejects a flexible-wage formulation of the incumbent workers in the model.

The results presented above show that a model with flexible wages for new hires, but with realistic amount of wage rigidities for incumbent workers, can actually generate unemployment volatility in the search and matching framework in line with the data. Thus, this extension of the model with a realistic standard value of the worker outside option of 0.75 is an alternative to the Hagedorn and Manovskii

(2008) approach, where the value of unemployment is calibrated very closely to firm productivity and worker bargaining power is set close to zero, which achieves the same goal.

Next we study the business-cycle correlations of the model, the bottom panel of Table 4 reports correlations between labor productivity and variables discussed above. The model with wage frictions for incumbent workers matches this correlation well for unemployment, vacancies and tightness. In contrast, the recalibrated flexible wage model only matches the correlation between labor productivity and vacancies well. For separations, the model with wage frictions reproduces the countercyclicality of separations pointed out by Fujita and Ramey (2012), although the correlation is somewhat on the low side. For the model with wage frictions turned off, but with the same parameter calibration as for the model with wage frictions, the correlation is about zero. Thus, reducing wage frictions lowers separation volatility and its comovement with productivity as expected. When the flexible wage model is recalibrated though, implying a much higher idiosyncratic shock variance, the correlation is close to minus unity. For the job finding rate, the correlation is substantially higher than in the data for all models. All in all, the model with wage frictions matches the correlation with labor productivity better than the flexible wage case.

Turning to the elasticity of wages with respect to aggregate productivity, the implications from the model with wage rigidities for incumbent workers are close to empirical estimates. Combining the U.S. evidence reported by Haefke, Sonntag, and van Rens (2013) and Hagedorn and Manovskii (2008), the overall wage elasticity across all workers with respect to aggregate productivity is reported to lie between 0.24 and 0.45 across specifications and data sets. The former paper also report a wage elasticity from new hires with respect to aggregate productivity in between 0.79 and 0.83. The corresponding elasticities predicted by the model is 0.47 and 0.83, respectively, which is well in line with the empirical evidence. Unsurprisingly, removing the wage frictions of incumbent workers increases both the overall and the new hires wage elasticity with respect to aggregate productivity to close to unity (0.94 in both cases).[23]

As a final exercise to evaluate the performance of the calibrated model with wage frictions for incumbent workers, we have calculated the unemployment volatility decomposition of Barnichon (2012).[24] We find that separations account for 34.4 percent of the unemployment volatility. This should be compared to the results reported in Barnichon (2012) where separations account for about 40 percent of unemployment volatility. Thus, the model results presented above are not driven by an empirically unrealistically high role of separations.

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[23]To lower these elasticities under flexible wages the bargaining power of the workers needs to be close to zero as in Hagedorn and Manovskii (2008).

[24]Here, we adjust the framework of Barnichon (2012) to allow for the slightly different matching function in the model outlined above; see equation (14).

6 Concluding Discussion

In this paper we return to the question of whether or not wage rigidities for incumbent workers affect macroeconomic outcomes. By extending Pissarides (2009) and allowing for endogenous separations in line with Pissarides (1994), wage rigidities in existing matches are no longer neutral with respect to employment volatility. To provide evidence on how incumbent worker wage setting should be modeled, we rely on linked Swedish employer-employee microdata. In a simple model, we show that when incumbent workers' wages are flexible there should be no relationship between the firm wage and separations controlling for the firms marginal revenue product and the workers outside option. In contrast, the data give stark evidence of a strong positive relationship as expected under incumbent worker wage frictions. Finally, we show that the intuition, based on a simple partial equilibrium setup, also holds in a DSGE model allowing for general equilibrium feedback effects. Overall, we find that an empirically relevant degree of wage rigidities for incumbent workers has large quantitative effects on unemployment volatility even when wages for new hires are fully flexible. Specifically, we show that introducing wage frictions for incumbent wages brings the model moments close to those in the data moments, especially for unemployment, vacancies and tightness. Importantly, the model also matches the quantitative microdata evidence on the conditional firm-level wage elasticity of separations without this moment being targeted in the model calibration.

Thus, all in all, it seems that the degree of wage rigidity for newly hired workers is not a sufficient statistic for determining the effect of wage rigidities on macroeconomic outcomes. Instead, wage frictions for incumbent workers turn out to have large effects on unemployment volatility, despite wages for new hires being flexible. This finding, in turn, affects the interpretation of a large empirical literature on wage rigidities.

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A   Appendix: Robustness of Empirical Results

This appendix addresses the robustness of the micro-econometric evidence. In Table 5 we present the first-stage results corresponding to the baseline results presented in column (1) of Table 1. As

Table 5: First Stage Results for Baseline Specification

	(1)	(2)
Dependent Variable	$\ln mrp_{jt}$	$\ln w_{jt}$
$\ln mrp_{jt-1}$	0.206	0.051
	(0.007)**	(0.006)**
$\ln \hat{w}^{cc}_{jt-1}$	0.081	0.191
	(0.012)**	(0.008)**
Dummies:		
Firm	YES	YES
Sector by Time	YES	YES
F Stat($\ln mrp_{jt-1} = \ln \hat{w}_{jt-1} = 0$)	589**	437**
Observations	$306,205$	$306,205$
Firms	$42,656$	$42,656$

* (**) Denotes significance on the 5 (1) percent level from zero. Standard errors clustered on the firm level reported inside parenthesis. Sector denotes two-digit NACE codes. Sample sizes are adjusted for singletons dropped in the estimation.

can be seen in both columns, the instruments are strongly relevant with F statistics of 589 and 437, respectively. Also, a formal under-identification test confirms that the baseline IV specification is well identified (Kleibergen and Paap (2006) rk LM statistic: $\chi^2(1) = 465$, p-val = 0.000). Moreover, as expected under wage and price stickiness there is a strong positive relationship for each respective "own lag".

In Table 6 we perform various robustness exercises on our baseline results replicated in column (1) for convenience. In column (2) of Table 6 we first focus only on the manufacturing sector. As can be seen in the table, this does not change the results qualitatively. In column (3) we increase the employment requirement to 20 full-time employees and find qualitatively the same results as in the base-line specification in column (2). In column (4) of Table 6, we use a much looser definition of employment when computing separations, using all employment spells of all workers regardless of their degree of firm attachment. This means that a worker is counted as employed regardless of the (monthly) wage or the timing or length of the spell within a year. Again, the results are qualitatively unchanged. In the final column of Table 6 we lag the instrument one additional time period. As can be seen in column (5) this increase the parameter estimate on the wage slightly, as expected from the discussion in the main text, but does not change the results qualitatively.

Table 6: Robustness

	(1)	(2)	(3)	(4)	(5)
β_{mrp}	-2.261	-2.359	-2.329	-1.806	-2.603
	$(0.173)^{**}$	$(0.279)^{**}$	$(0.329)^{**}$	$(0.151)^{**}$	$(0.422)^{**}$
β_w	6.029	8.159	8.333	5.067	7.827
	$(0.309)^{**}$	$(0.830)^{**}$	$(0.772)^{**}$	$(0.268)^{**}$	$(0.541)^{**}$
Dummies:					
Firm	YES	YES	YES	YES	YES
Sector by Time	YES	YES	YES	YES	YES
Manufacturing Only	NO	YES	NO	NO	NO
$\geq$ # Full Time Employees	10	10	20	10	10
Separations Definition	BASELINE	BASELINE	BASELINE	LOOSE	BASELINE
Instrument lag order	1	1	1	1	2
Observations	$306,205$	$78,730$	$149,988$	$307,132$	$267,187$
Firms	$42,656$	$10,039$	$20,867$	$43,034$	$38,487$

* (**) Denotes significance on the 5 (1) percent level from zero. Standard errors clustered on the firm level reported inside parenthesis. Sector denotes two-digit NACE codes. Sample sizes are adjusted for singletons dropped in the estimation.

In Table 7 we evaluate the use of the approximation $sep_{jt}/\overline{sep}_j$, where $\overline{sep}_j$ denotes the firm average of separations, instead of $\ln sep_{jt}$ in the regressions above. To this end we estimate the baseline specification on an overlapping sample where all zero separation observations have been removed. As can be seen in the table, the approximation works well with only a mild downward bias from using the approximation for separations we employ in the regressions as compared to using the log of separations.

B   Appendix: Derivations

B.1   Employment Flows

Let $e_{t-1}(a, \hat{w})$ denote employment for workers with idiosyncratic productivity at most a with wage $\hat{w}$ in period $t-1$. Total employment for workers with idiosyncratic productivity at most a in period $t-1$ is then

$$e_{t-1}^{agg}(a) = e_{t-1}^c(a) + \sum_{\hat{w}} e_{t-1}^{nc}(a, \hat{w}). \tag{B.1}$$

Employment evolution for workers with idiosyncratic productivity at most a that change wages is, when $a \in [R_{t-1}, R_{t-1}^S]$

$$\begin{aligned}
e_t^c(a) &= \alpha\rho\left[\lambda\left(G(a) - G(R_t)\right)\left(e_{t-1}^{agg}(a_{ub}) - e_{t-1}^{agg}(R_{t-1}^S) + (1 - f(\theta_t))e_{t-1}^{agg}(R_{t-1}^S)\right)\right. \\
&\quad \left. + (1 - \lambda)(1 - f(\theta_t))\left(e_{t-1}^{agg}(a) - e_{t-1}^{agg}(R_t)\right)\right],
\end{aligned} \tag{B.2}$$

Table 7: Comparisson between Normalized and Log Separations

	(1) IV	(2) IV
β_{mrp}	-2.119	-2.408
	$(0.182)^{**}$	$(0.222)^{**}$
β_{w}	5.681	6.854
	$(0.327)^{**}$	$(0.399)^{**}$
Dummies:		
Firm	YES	YES
Sector by Time	YES	YES
Dependent Variable	Normalized	Log
Observations	$270,266$	$270,266$
Firms	$40,388$	$40,388$

* (**) Denotes significance on the 5 (1) percent level from zero. Standard errors clustered on the firm level reported inside parenthesis. Sector denotes two-digit NACE codes. Sample sizes are adjusted for singletons dropped in the estimation.

when $a \in [R_{t-1}^S, a_{ub})$

$$
\begin{aligned}
e_t^c(a) = {} & \alpha\rho \left[\lambda \left(G(a) - G(R_t) \right) \left(e_{t-1}^{agg}(a_{ub}) - e_{t-1}^{agg}(R_{t-1}^s) + (1 - f(\theta_t)) e_{t-1}^{agg}(R_{t-1}^S) \right) \right. \\
& \left. + (1 - \lambda) \left(e_{t-1}^{agg}(a) - e_{t-1}^{agg}(R_{t-1}^S) + (1 - f(\theta_t)) \left(e_{t-1}^{agg}(R_{t-1}^S) - e_{t-1}^{agg}(R_t) \right) \right) \right]
\end{aligned}
\tag{B.3}
$$

and when $a = a_{ub}$

$$
\begin{aligned}
e_t^c(a) = {} & \alpha\rho \left[\lambda \left(G(a) - G(R_t) \right) \left(e_{t-1}^{agg}(a_{ub}) - e_{t-1}^{agg}(R_{t-1}^s) + (1 - f(\theta_t)) e_{t-1}^{agg}(R_{t-1}^S) \right) \right. \\
& \left. + (1 - \lambda) \left(e_{t-1}^{agg}(a) - e_{t-1}^{agg}(R_{t-1}^S) + (1 - f(\theta_t)) \left(e_{t-1}^{agg}(R_{t-1}^S) - e_{t-1}^{agg}(R_t) \right) \right) \right] \\
& + f(\theta_t) \left(u_{t-1} + \phi_{t-1} \right),
\end{aligned}
\tag{B.4}
$$

where ϕ_{t-1} are workers searching on the job. When $R_{t-1} > R_{t-1}^S$ we have, for $a \in [R_{t-1}, a_{ub})$

$$
e_t^c(a) = \alpha\rho \left[\lambda \left(G(a) - G(R_t) \right) e_{t-1}^{agg}(a_{ub}) + (1 - \lambda) \left(e_{t-1}^{agg}(a) - e_{t-1}^{agg}(R_t) \right) \right]
\tag{B.5}
$$

and for $a = a_{ub}$

$$
\begin{aligned}
e_t^c(a) = {} & \alpha\rho \left[\lambda \left(G(a) - G(R_t) \right) e_{t-1}^{agg}(a_{ub}) + (1 - \lambda) \left(e_{t-1}^{agg}(a) - e_{t-1}^{agg}(R_t) \right) \right] \\
& + f(\theta_t) \left(u_{t-1} + \phi_{t-1} \right).
\end{aligned}
\tag{B.6}
$$

Then we have, slightly abusing notation by letting $e_t^c(a-1)$ denote employment at the grid point

below a,

$$n_t(a) = e_t^c(a) - e_t^c(a-1) + \sum_{\hat{w}} \left[e_t^{nc}(a, \hat{w}) - e_t^{nc}(a-1, \hat{w}) \right].$$

Employment for workers who do not change wages can be computed as follows. First, suppose $\hat{R}_{t-1}^S(\hat{w}) > \hat{R}_{t-1}(\hat{w})$. For wage state $\hat{w}$, when OJS is chosen, i.e., for $a \in [\hat{R}_{t-1}(\hat{w}), \hat{R}_{t-1}^S(\hat{w})]$, employment evolves according to

$$
\begin{aligned}
e_t^{nc}(a, \hat{w}) = {} & (1-\alpha)\rho \Big[\lambda \left(G(a) - G\left(\hat{R}_t(\hat{w})\right) \right) \\
& \times \left(e_{t-1}^{nc}(a_{ub}, \hat{w}) - e_{t-1}^{nc}\left(\hat{R}_{t-1}^S(\hat{w}), \hat{w}\right) + (1 - f(\theta_t)) e_{t-1}^{nc}\left(\hat{R}_{t-1}^S(\hat{w}), \hat{w}\right) \right) \quad \text{(B.7)} \\
& + (1-\lambda)(1 - f(\theta_t)) \left(e_{t-1}^{nc}(a, \hat{w}) - e_{t-1}^{nc}\left(\hat{R}_t(\hat{w}), \hat{w}\right) \right) \Big]
\end{aligned}
$$

and, when OJS is not chosen, i.e., for $a \in [\hat{R}_{t-1}^S(\hat{w}), a_{ub}]$,

$$
\begin{aligned}
e_t^{nc}(a, \hat{w}) = {} & (1-\alpha)\rho \Big[\lambda \left(G(a) - G\left(\hat{R}_t(\hat{w})\right) \right) \left\{ e_{t-1}^{nc}(a_{ub}, \hat{w}) - e_{t-1}^{nc}\left(\hat{R}_{t-1}^S(\hat{w}), \hat{w}\right) \right. & \text{(B.8)} \\
& \left. + (1 - f(\theta_t)) e_{t-1}^{nc}\left(\hat{R}_{t-1}^S(\hat{w}), \hat{w}\right) \right\} + (1-\lambda) \left\{ e_{t-1}^{nc}(a, \hat{w}) - e_{t-1}^{nc}\left(\hat{R}_{t-1}^S(\hat{w}), \hat{w}\right) \right. \\
& \left. + (1 - f(\theta_t)) \left(e_{t-1}^{nc}\left(\hat{R}_{t-1}^S(\hat{w}), \hat{w}\right) - e_{t-1}^{nc}\left(\hat{R}_t, \hat{w}\right) \right) \right\} \Big].
\end{aligned}
$$

Now, suppose $\hat{R}_{t-1}^S(\hat{w}) \leq \hat{R}_{t-1}(\hat{w})$. Then, for $a \in [\hat{R}_{t-1}^S(\hat{w}), \hat{R}_{t-1}(\hat{w})]$ we have $e_t^{nc}(a, \hat{w}) = 0$ and for $a \in [\hat{R}_t(\hat{w}), a_{ub}]$ we have, modifying the expression above,[25]

$$
\begin{aligned}
e_t^{nc}(a, \hat{w}) = {} & (1-\alpha)\rho \Big[\lambda \left(G(a) - G\left(\hat{R}_t(\hat{w})\right) \right) e_{t-1}^{nc}(a_{ub}, \hat{w}) \\
& + (1-\lambda) \left(e_{t-1}^{nc}(a, \hat{w}) - e_{t-1}^{nc}\left(\hat{R}_t(\hat{w}), \hat{w}\right) \right) \Big]. & \text{(B.9)}
\end{aligned}
$$

Finally, the unemployment to employment transitions are

$$UE_t = A\theta_{t-1}^{1-\alpha} u_{t-1} \qquad \text{(B.10)}$$

---

[25] Note that workers with idiosyncratic productivity realization at or below $\hat{R}_{t-1}^S(\hat{w})$ search on the job and lose their job only in the current period.

and separations evolve according to, letting $\mathbb{I}_t = 1$ if $\hat{R}_{t-1}^S(\hat{w}) > \hat{R}_{t-1}(\hat{w})$ and $\mathbb{I}_t = 0$ otherwise,

$$
\begin{aligned}
EU_t &= (1-\rho)\left(e_{t-1}^c(a_{ub}) + \sum_{\hat{w}} e_{t-1}(a_{ub}, \hat{w})\right) + \\
&\quad + \alpha\rho\left[\lambda G(R_t)\left(e_{t-1}^{agg}(a_{ub}) - e_t^{agg}(R_{t-1}^S) + (1-f(\theta_t))\, e_{t-1}^{agg}(R_{t-1}^S)\right)\right. \\
&\quad \left. + (1-\lambda)(1-f(\theta_t))\, e_{t-1}^{agg}(R_t)\right] \\
&\quad + (1-\alpha)\sum_{\hat{w}} \rho\left[\lambda G\left(\hat{R}_t(\hat{w})\right)\left(e_t(a_{ub}, \hat{w}) - \mathbb{I}_t f(\theta_t)\, e_t\left(\hat{R}_{t-1}^S(\hat{w}), \hat{w}\right)\right)\right. \\
&\quad \left. + (1-\lambda)(\mathbb{I}_t(1-f(\theta_t)) + (1-\mathbb{I}_t))\, a_{ubt}\left(\hat{R}_t(\hat{w}), \hat{w}\right)\right].
\end{aligned}
\tag{B.11}
$$

B.2   The Algorithm

Since the system (16), (17), (20), (21), (24) and (27) above does not depend directly on unemployment, we can solve without using unemployment as a state variable. Now, for clarity, we do not surpress the dependence of wages, surpluses and labor market tightness on aggregate productivity. Then, since the values of newly created firms and newly hired workers depend on current and future productivities only (through future surpluses, tightness and H^e), the current wage depends only on the current productivities and tightness depends only on aggregate productivity. Hence, w_t^i is a function of z_t and a_t only. Then, for firm-worker pairs that did not reset their wage today, the wage depends on the productivity when the wage was last reset, say $\hat{z}$ and $\hat{a}$. We then write $\hat{w}(\hat{z}, \hat{a})$. Then worker surpluses are

$$
\begin{aligned}
H^i(z_t, a_t) &= w^i(z_t, a_t) - b - \mathbb{I}_t\sigma + \beta E_t \alpha\rho^i\left(\lambda\int_0^1 H(z_{t+1}, r)\, dG(r) + (1-\lambda) H(z_{t+1}, a_t)\right) \\
&\quad + \beta E_t(1-\alpha)\rho^i\left(\lambda\int_0^1 \hat{H}(z_{t+1}, r, w_t^i(z_t, a_t))\, dG(r)\right. \\
&\quad \left. + (1-\lambda)\hat{H}(z_{t+1}, a_t, w_t^i(z_t, a_t))\right) + \beta E_t\left(g^i - f(\theta(z_t))\right) H(z_{t+1}, a_{ub}).
\end{aligned}
\tag{B.12}
$$

In case wages are not reset but remain at the level $\hat{w}_t$ from the previous period, the wage $\hat{w}_t$ is a state variable and the values are

$$
\begin{aligned}
\hat{H}^i(z_t, a_t, \hat{w}(\hat{z}, \hat{a})) &= \hat{w}(\hat{z}, \hat{a}) - b - \mathbb{I}_t\sigma + \beta E_t\alpha\rho^i\left(\lambda\int_0^1 H(z_{t+1}, r)\, dG(r) + (1-\lambda) H(z_{t+1}, a_t)\right) \\
&\quad + \beta E_t(1-\alpha)\rho^i\left(\lambda\int_0^1 \hat{H}(z_{t+1}, r, \hat{w}(\hat{z}, \hat{a}))\, dG(r)\right. \\
&\quad \left. + (1-\lambda)\hat{H}(z_{t+1}, a_t, \hat{w}(\hat{z}, \hat{a}))\right) + E_t\left(g^i - f(\theta(z_t))\right) H(z_{t+1}, a_{ub}).
\end{aligned}
\tag{B.13}
$$

We can proceed similarly for the remaining value equations so that surpluses when wages are reset depend on current productivity only and surpluses when wages are not rebargained depend on productivity at the last rebargain together with the current productivity.

We solve by fixing a solution for the wage, surpluses and tightness and then use value function iteration to find revised surpluses, wages and tightness. Given convergence of the value function iteration, we can then proceed to compute employment, unemployment, vacancies and separations.

B.3   Appendix: Swedish Calibration

In the Swedish calibration the parameters β, φ, σ_a and b are set to the same values as in the U.S. calibration, see Table 8 in the main text. Following the estimates from Swedish data presented in Adlolfsson, Laseen, Linde, and Villani (2008), we set the Calvo probability of wage adjustment to 0.091 on a monthly basis. The parameters σ_μ, c, σ_G, σ, λ and s are set matching the same moments as for the US calibration; see Table 9 for details.

Table 8: Calibration of the Swedish Model.

	Calibration Monthly Parameters	
β	*Time preference*	0.9966
φ	*Family bargaining power*	0.5
σ_a	*Matching function*	0.5
α	*Calvo prob. of wage adjustment*	0.091
b	*Payoff when unemployed*	0.75
	Moment-Matched Monthly Parameters	
σ_μ	*Matching function productivity*	0.317
c	*Vacancy cost*	1.384
σ_G	*Idiosyncratic productivity distr. variance*	0.313
σ	*Search cost*	0.057
λ	*Prob. of new idiosyncratic draw*	0.537
s	*Exogenous separation rate*	0.005

Table 9 gives the moments in data and in the model that results when calibrating the parameters σ_μ, c, σ_G, σ, λ and s.

Although the Swedish labor markets flows are clearly lower than in the U.S., the fit between the simulated moments and the data moments is high, and in fact slightly better than for the U.S. calibration. In Table 10, the moments for unemployment, the job finding rate, the separation rate, vacancies and the vacancy/unemployment rate are illustrated. Again the model performs very well when it comes to the volatility of unemployment, vacancies and tightness. Although, as for the U.S. the model volatility of the job-finding rate is substantially lower than in the data. With respect to the business-cycle correlations, the performance is slightly below that of the U.S. calibration, but the overall conclusions is unaffected.

Table 9: Comparison of Matched Moments Sweden

Monthly Moments	Data	Model
Mean v_t/u_t	0.29	0.290
Mean Separation rate	0.005	0.005
Mean Job-to-job transition rate	0.010	0.010
Mean Job finding rate	0.101	0.106
Std. Separation rate	0.090	0.091
Persistence Separation rate	0.662	0.553

Note: The sample period for data is 2005Q3-2016:Q4. The targets for separations, the job-to-job transition rate and the job finding rate are from the quarterly series provided by the Labor Force Survey (AKU), The series for v/u is computed using monthly data provided by the Labor Force Survey (AKU) and the Unemployment Board Statistics, respectively. To compute the persistence and standard deviation for separations, we take logs and HP filter the series for separations with a penalty parameter of 1,600.

Table 10: Comparison of Moments, Sweden

	u_t	Job find. rate	Sep. rate	v_t	v_t/u_t
		Standard Deviation			
Data	0.085	0.077	0.0910	0.175	0.247
Model	0.109	0.031	0.0912	0.118	0.199
		Correlation with Labor Productivity			
Data	−0.153	0.461	−0.656	0.628	0.498
Model	−0.656	0.959	−0.439	0.959	0.919

Note: All variables are logged and HP-filtered with a penalty parameter equal to 1,600. The sample period for data is 2005Q3-2016:Q4. Unemployment and vacancies is quarterly averages of monthly data from the Labor Force surveys and the Unemployment Board Statistics, respectively. The job finding and separation rates are constructed from quarterly series provided by the Labor Force Survey (AKU), SCB. Labor productivity is from the National Accounts and on a quarterly frequency.