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Do plants freeze upon uncertainty shocks?

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Do plants freeze upon uncertainty shocks?*

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Abstract

Using quarterly worker flow data of U.S. establishments, we find that an unexpected increase in uncertainty reduces hirings and quits, while it raises layoffs. This finding suggests that the real option effect of uncertainty is less important for employment decisions. Hence plants do not freeze in response to uncertainty shocks. To explain our findings, we propose a multi-worker plant search and matching model with decreasing returns to scale and financial frictions. As a result of unexpected uncertainty increase, plants reduce their employment size in order to decrease the default risk that arises from higher uncertainty in the economy.

Keywords: Uncertainty, real option, search and matching, worker flows.

JEL Classification Numbers: J23, J63, D81.

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1 Introduction

A recent literature has argued that uncertainty may cause economic recessions. Higher uncertainty increases the option value of waiting and through this channel plants freeze investment and employment decisions until the future becomes clearer. To the extent that recessions are driven by wait-and-see effects, public policies envisaged to smooth economic recessions may only have limited effect on plants' decisions.

In this paper, we study the importance of the wait-and-see effect for employment decisions. It has been well documented that aggregate employment decreases upon positive uncertainty shocks, see for example Bloom (2009). The underlying mechanisms of this relation, however, are still unclear, and to better understand them, we study the worker flow components of net job creation: hirings, quits, layoffs. Does employment change because plants freeze, that is reduce hirings and layoffs, or because plants actually increase layoffs? Furthermore, how do quits react to uncertainty changes and how do these three margins interact with each other?

Based on a plant model with non-convex (labor) adjustment costs, we propose a simple decomposition of the different channels through which uncertainty affects employment. We focus on separations, which is generally composed of quits and layoffs. While quits are strongly affected by general equilibrium effects (wage, labor market tightness), we suppose layoffs are rather unaffected by such effects.¹ Consequently, we can reduce the number of potential channels through which uncertainty affects layoffs to three: (1) real option effect, (2) frequency effect, and (3) intensive margin effect. An increase in uncertainty raises the option value of waiting and thereby widens the adjustment triggers (real option effect), but at the same time plants hit their adjustment triggers more often (frequency effect), and the average adjustment conditional on adjusting is larger (intensive margin effect).

We focus on the relation of micro-uncertainty with hirings, quits, and layoffs using (conditional) correlations and structural VARs. Simple correlations may provide only limited insights. One obvious concern is that uncertainty correlates with the business cycle, which may render any correlation spurious. In order to account for this problem, we use regression models, where we control for real GDP to obtain conditional correlations of worker flows with uncertainty. Further, we allow for more dynamic interaction using a structural VAR. We identify the structural shocks assuming that innovations to the worker flows (quits, layoffs, hirings) do not contemporaneously affect GDP and

¹Abstracting from general equilibrium effects allows us to characterize the layoff decision as a solution to a plant problem in partial equilibrium.

neither do shocks to uncertainty.

We exploit a recently developed database from Davis et al. (2012), who extend the worker flow measures provided by Job Openings and Labor Turnover Survey (JOLTS) back until 1990. The dataset contains time series for quits, hirings and layoffs at quarterly frequency. As for micro-level uncertainty, we consider the measure suggested by Jurado et al. (2013) that is based on the cross sectional dispersion of firm profit growth. We prefer their measure as it controls for the forecastable components of uncertainty.²

Empirically, we find that hirings and quits are negatively correlated with uncertainty, while the correlation of the layoffs is positive. The correlations are all confirmed both when conditioning on GDP and when estimating the impulse responses on structural uncertainty shocks under VAR models. Our empirical finding constitutes a new stylized fact for the U.S. labor market. A positive uncertainty shock reduces hirings and quits, while it raises layoffs. Interestingly, these three worker flow variables respond to an uncertainty increase in the same way as to a negative productivity shock.³

In the context of real option effects, our paper provides an interesting implication. With respect to employment decisions, the real option effect seems dominated by the intensive margin and frequency effects.⁴ However, this is based on abstracting from some potentially important channels such as general equilibrium effects. To gain better understanding of the (un)importance of real option effects for plants' employment decisions, we suggest a general equilibrium model with search frictions that allows for endogenous quits and layoffs.

We first argue and show that standard search and matching models in the tradition of Mortensen and Pissarides (1994) have difficulties in generating the empirical behavior of quits, layoffs, and hirings. The reason is exactly the real option effect, which we have found to be empirically less important. An increase in the uncertainty of plant-level productivity raises the option value of maintaining the match and in turn, this lowers the layoff probability. Meanwhile, the constant returns to scale assumption implicit in these models eliminates any role for optimal plant size changing in uncertainty. In other words, there is no intensive margin effect on layoffs, quits, and hirings and as we show, this effect goes counter the real option effect.

Our explanation of the empirical findings is therefore based on a multi-worker

²Our findings are robust to alternative measures of uncertainty.

³A long line of studies have documented the pro-cyclical behavior of hirings and quits, and the counter-cyclical behavior of layoffs. See for instance Fujita and Nakajima (2013), Hall and Lazear (1984), Shimer (2005) and Solon et al. (2009).

⁴A related paper, Bloom et al. (2007) provides empirical evidence and theoretical explanation about the dominance of the real option effect for investment.

model with decreasing returns to scale, as proposed by Elsby and Michaels (2013) and Fujita and Nakajima (2013). In addition, we study the role of financial frictions as channel for uncertainty shocks. Limited contract enforceability implies that plants default whenever idiosyncratic productivity is sufficiently low. Therefore, debt repayment costs increase with the amount of debt the plant holds. Importantly, plants make decisions on employment and debt before observing the productivity realization. When uncertainty increases, expected profits conditional on remaining in the market rises, which gives incentives to plants to expand. However, at the same time, the probability of default increases. In our model, higher uncertainty leads plants to reduce their size, in order to decrease the default risk, which is a mechanism highlighted by Arellano et al. (2012). Thus, plants reduce hirings and increase layoffs upon an uncertainty shock, which is consistent with our empirical findings.

The literature on uncertainty and its effect on the economy has expanded considerably since the seminal papers of Hartman (1972), Abel (1983), Dixit and Pindyck (1994), and more recently, Bloom (2009). One of the implications of these studies is that whenever physical investment is (partly) irreversible, an increase in uncertainty raises the value of waiting until the future becomes clearer. Even though this channel leads to postpone investments and depress economic activity, the overall effect of uncertainty in the economy is still in dispute. Bachmann and Bayer (2014), in a heterogeneous agent model with fixed capital adjustment costs, did not find that firm-uncertainty is a major driver of business cycle fluctuations. The same main finding was obtained by Born and Pfeifer (2013) with a New Keynesian model featuring policy risk and uncertainty about technology. On the other side, Bloom et al. (2012), Fernandez-Villaverde et al. (2011) and Basu and Bundick (2012), find the opposite effect. That is, increased uncertainty about the future causes a prolonged contraction in economic activity. In addition, Arellano et al. (2012) and Gilchrist et al. (2013), conclude that time-varying uncertainty has a considerable negative effect in output when the economy faces financial frictions.

A difference between our paper and these studies is our focus on the effect of uncertainty on worker flows variables. This implies that we need to consider an heterogeneous-agent search and matching model to explain our empirical findings. Furthermore, as we want to study the importance of the real option effect (relative to the frequency and the intensive margin effect), we require non-convex adjustment costs on employment decisions and a multi-worker plant search and matching model. Using this framework, we provide evidence that the real option channel of waiting is dominated under the layoff decision.

Consequently, the theoretical part of our paper contributes to the recently de-

veloping literature that investigate the role of time-varying uncertainty in search and matching labor market models. To our best knowledge, there are three studies that analyze uncertainty shocks in model with search frictions. Schaal (2012) proposes a model with dynamic contracts, multi-worker firms, and endogenous quits and layoffs to explain the evolution of unemployment and labor productivity during the Great Recession in U.S. Even though the focus of his study is different from ours, this model predicts - contrary to our empirical evidence - an increase of hirings, quits and layoffs given an unexpected rise of uncertainty. Leduc and Liu (2012) provide evidence that an unexpected increase in uncertainty leads to a persistent increment in the unemployment rate and a decline in inflation rate. They develop a DSGE model that includes nominal rigidities and search frictions with exogenous separations. Guglielminetti (2013) includes search frictions in a standard RBC framework with exogenous separations, to explain the negative response of employment, vacancies and wages with respect to an uncertainty shock. Different from the latter two studies, in our model layoffs and quits are endogenous and the model addresses the empirical responses of these worker flows to uncertainty shocks that we found empirically.

The remainder of this paper proceeds as follows: Section 2 describe our dataset, econometric approach and provides the results. Section 3 sets up a basic search and matching model with endogenous layoffs and quits and discusses the channels of uncertainty shocks. Section 4 presents the multi-worker plant model with search and financial frictions and compares the theoretical predictions with respect to the empirical results. Finally, Section 5 concludes. An Appendix follows with robustness results and model derivations.

2 Empirical evidence

2.1 Three channels of uncertainty

Shocks to uncertainty induce changes in agents' behavior through a variety of channels, for example precautionary savings, real option, and financial frictions. Throughout this paper we think of uncertainty as mean-preserving spreads to the distribution of plant-level productivities that is common across plants.

In the following, we will focus on the channels present in a partial equilibrium model of the plant. We suppose an economy with non-convex factor adjustment frictions, that gives rise to a region where a plant does not adjust factor inputs, and argue that uncertainty shocks affect factor adjustments through three distinct channels. As

uncertainty increases, the *real option effect* implies that fewer plants adjust because the inaction region widens. Second, the *frequency effect* captures that plants move faster beyond the adjustment triggers and hence adjust more frequently. Third, the *intensive margin effect* accounts for the fact that conditional on adjusting, plants adjust substantially more.⁵

While the frequency and intensive margin effects imply a factor demand increase, the real option effect works into the opposite direction. Nevertheless, it may be wrong to conclude that the real option effect is dominated if there is more factor adjustment in response to a positive uncertainty shock. Under the presence of exogenous factor depreciation (e.g. capital depreciation or retirements), wait-and-see behavior may imply a reduction in aggregate factor input. See Appendix A for a formal decomposition.

Let us now analyze the specific role of uncertainty shocks on labor markets. Plant-level labor adjustment consists of separations and hirings. As hirings depend crucially on household decisions (e.g. precautionary labor supply) and general equilibrium effects, we cannot study the importance of the real options effect for hirings by using the decomposition into three channels. On the other side, separations are composed of layoffs, quits and other reasons such as retirements. From the plant’s perspective, the latter two are exogenous. Workers quit when they obtain an offer from another plant where the worker’s productivity is larger, and they retire when they pass a certain age. Therefore, total separations does not allow us to identify the importance of real option effects for the reasons stated above. Instead, we study the response of layoffs to uncertainty shocks. To the extent that layoffs and quits do not interact non-linearly with uncertainty, this allows us to study the role of the real options effect on layoff decision. If layoffs decrease in uncertainty, the real option effect is the dominating channel. Else if layoffs increase, the real option effect is dominated by frequency and intensive margin effects.

In Section 3, we suggest a search and matching model with endogenous layoffs and quits, which allows us to relax the assumptions, this decomposition is based upon. In particular, such model accounts for general equilibrium effects.

2.2 Data sources and variables

To conduct our empirical analysis, we exploit a recently elaborated dataset by Davis et al. (2012), who construct synthetic data of worker flows in private sector back until 1990 and at quarterly frequency. Exploiting the data from Business Employment

⁵In Bloom (2009), the frequency effect is labelled ‘volatility effect’ and the real options effect ‘uncertainty effect’ without separating between the intensive and extensive margin, which work into opposite directions.

Dynamics (BED), they expand the information provided at Job Openings and Labor Turnover Survey (JOLTS), and construct worker flows time series from 1990 until 2010. In particular, we use hirings, quits, and layoffs. Further, we require a measure of micro-level uncertainty and our baseline measure is the one provided by Jurado et al. (2013) (in the following JLN uncertainty). Their uncertainty estimate is the average forecast error variance with respect to h-quarter profit growth of Compustat firms,

$$u_{it}(h) = \text{Var}(y_{it+h} - E[y_{it+h}|I_t] | I_t) \quad , \text{ and } \quad \bar{u}_t(h) = \frac{1}{N} \sum_{i=1}^N u_{it}(h)$$

where y_{it} denotes firm profit growth, $u_{it}(h)$ is the h-quarter ahead forecast error variance for firm i and $\bar{u}_t(h)$ is the measure of micro-level uncertainty. We use the 4-quarter ahead forecast as baseline specification.

As an alternative uncertainty measure, we consider the VXO index provided by the Chicago Board of Options Exchange, that is the hypothetical at the money S&P100 option 30 days to expiration. We aggregate the variable at quarterly frequency using the average of the index within the months of the quarter. This measure has also been used in Bloom (2009) and reflects macro-level uncertainty. Finally, we use real GDP at quarterly frequency. For our analysis, all variables are detrended using Hodrick-Prescott filter with $\lambda = 1600$.

2.3 Estimation and results

The goal of this paper is to analyze the relation between micro-uncertainty and worker flows. First, we compute simple correlations between JLN uncertainty and worker flows and the results thereof are presented in Table 1. We find a negative and significant correlation hirings and quits with uncertainty, while layoffs co-move positively with uncertainty. However, we should notice that the presented correlations may be spurious as all these variables co-move with the business cycle.

Thus, we estimate the correlation of worker flows with uncertainty while controlling for GDP. We use a simple regression model including JLN uncertainty and GDP as regressors and standardize all variables to have unit-variance. The correlations of hirings and layoffs are robust against controlling for GDP, while for quits the correlation is still negative but not significant.⁶

Third, we use a more structural approach and allow for dynamic interaction be-

⁶In Appendix B, we also show that the positive correlation between layoffs and uncertainty is robust when considering only continuing plants.

Table 1: Relation between uncertainty and worker flow variables

	Hirings		Separations		Quits		Layoffs	
Uncertainty	-0.60 (0.09)	-0.23 (0.07)	-0.17 (0.11)	0.19 (0.11)	-0.51 (0.10)	-0.07 (0.08)	0.51 (0.10)	0.39 (0.14)
GDP		0.67 (0.08)		0.63 (0.10)		0.77 (0.08)		-0.21 (0.13)
R^2	0.36	0.67	0.02	0.30	0.26	0.66	0.25	0.29
Period	1990q2-2010q2							

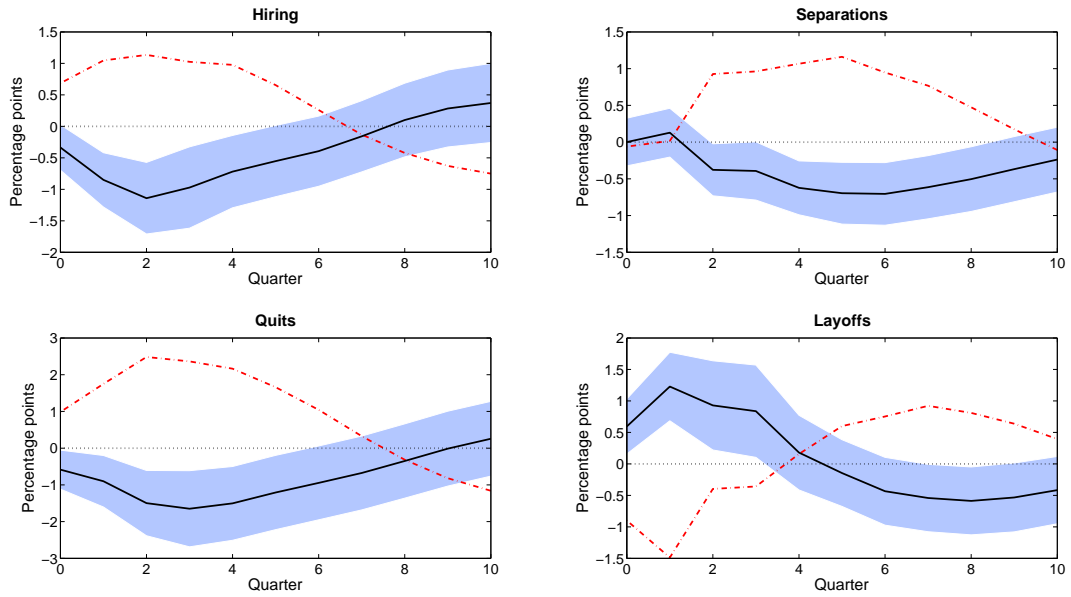
Note: All variables are in logs and detrended with HP-filter ($\lambda=1600$). Robust standard errors in parentheses.

tween worker flows, uncertainty, and GDP by estimating a structural vector autoregressive model (sVAR) model. We use a three-variate model for each worker flow variable in combination with uncertainty and GDP. Our time series are at quarterly frequency and we estimate the sVAR models with four lags. We identify the impact of structural shocks by assuming that shocks to the worker flow variable and shocks to uncertainty do not impact on GDP contemporaneously. We further restrict worker flow shocks not to affect uncertainty on impact.⁷ This causal ordering allows us to identify innovations to uncertainty that are orthogonal to first moment shocks (changes in business cycle conditions). These uncertainty shocks may arise, for example, from greater unpredictability of revenues or costs, or from higher uncertainty about access to credit and financial markets.

Table 2 shows the impulse responses of separation, hirings, quits and layoffs to an uncertainty shock (solid black line) and to a GDP shock (dash-dot red line). Empirically, various uncertainty measures have been shown not to be strongly persistent with a half-life of a year. Therefore, we focus on the impulse responses within the first four quarters. A structural uncertainty shock significantly reduces hirings, while the response of separations is insignificant within the first four quarters. Interestingly, the two components of separations, layoffs and quits, respond significantly to the shock, but in diametral directions. Quits decline, while layoffs increase upon a positive uncertainty shock. The results from the sVAR reveal a new stylized fact for the U.S. labor market. A positive uncertainty shock reduces hirings and quits, while it raises layoffs. Interestingly,

⁷In Appendix B we present the results when conversing the last identifying assumption.

Table 2: Impulse response functions from an uncertainty shock



Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line) and a GDP shock (dash-dot red line). The impulse responses are obtained estimating for each worker flow variable a three-variate sVAR with uncertainty ordered second and the worker flow variable last. We use JLN uncertainty and shaded regions represent 90% standard error confidence interval from an uncertainty shock. All variables are in logs and detrended with HP-filter ($\lambda=1600$).

these three worker flow variables respond to an uncertainty shock in the same way as to a negative productivity shock.

In the context of the previous discussion on three uncertainty channels, our empirical results provide an interesting implication. As layoffs increase upon an uncertainty shock, the real option effect seems to be dominated by the intensive margin and frequency effects. In other words, when plants decide on the optimal number of employees in response to a rise in uncertainty, wait-and-see behavior seems to be less important than it is for capital, where the real option channel has been shown to be crucial, see for example Bloom et al. (2007).

Table 3: Variance decomposition from an uncertainty shock

	Hirings	Separations	Quits	Layoffs
1 quarter	2.7%	0.0%	3.7%	5.5%
2 quarters	11.2%	0.5%	6.2%	15.6%
4 quarters	19.9%	5.3%	14.6%	21.8%
8 quarters	22.0%	17.3%	19.6%	21.5%

Note: All variables are detrended with HP-filter ($\lambda=1600$). The forecast-error variance decomposition is based upon the estimation of a three-variate sVAR consisting of GDP, uncertainty and the worker flow variable.

Moreover, we assess the contribution of uncertainty shocks to the forecast error variance of each worker flow variable. Table 3 shows that innovations to uncertainty are responsible for at least 17% of the volatility in worker flow variables. This share is especially high for layoffs and hirings. These results suggest that uncertainty is a quantitatively important factor which plays a significant role for hirings, layoffs and quits.

Our findings are robust under an alternative uncertainty measure, the VXO index, changing the identifying restrictions of the sVAR. Further, the reaction of layoffs from an uncertainty shock is robust when we focus on continuing plants. More details are provided in Appendix B.

3 Uncertainty shocks in a basic search and matching model

Let us first try to understand the different channels of uncertainty in a basic search and matching model. In order to analyze the relation between uncertainty shocks and

worker flows, we need a model that allows for endogenous layoffs and quits. Our basic model is similar to the textbook model in chapter 4 of Pissarides (2000). Different from that model, however, we assume that the offer-accepting probability for employed workers is not always one, but follow the modeling strategy of Jung and Kuhn (2012), and assume that a random non-monetary gain from switching jobs implies a non-trivial offer-accepting probability. In addition, we assume idiosyncratic productivity shocks and the dispersion of these shocks is the measure of uncertainty we will analyze subsequently.

We assume each period to consist of three stages. In stage one, plants observe an idiosyncratic productivity shock x that follows a logistic distribution

$$x \sim \text{logistic}(0, \psi_x), \quad (1)$$

with zero-mean and variance $\pi^2 \psi_x^2 / 3$. If the productivity draw is below a threshold level ω_x , a plant optimally lays off its workers. Else, the plant produces in stage two. In stage three, plants post vacancies to hire workers, and both unemployed and employed workers are searching for jobs. Conditional on obtaining an offer, the employed worker observes an idiosyncratic utility gain η_{eo} from switching to another plant. η_{eo} is also logistically distributed with mean κ_{eo} and scale parameter ψ_{eo} . For sufficiently large non-monetary job switching gains, the worker quits.

3.1 Model equilibrium

In the following, we directly present the model solution and refer to Appendix C for the model derivations. In equilibrium, the model's match surplus is

$$S = (1 - \pi_x) \left[a - f - b + \pi_{eo} q_{eo} \left(\kappa_{eo} - \frac{\Psi_{eo}}{q_{eo}} \right) + \frac{\Psi_x}{1 - \pi_x} + \left((1 - \pi_{eo} q_{eo})(1 - \mu) + (1 - \pi_{ue})\mu \right) \beta ES \right], \quad (2)$$

where β is the discount factor, and a , f and b denote average productivity, fixed operation costs, and the worker's value of home production, respectively. We assume that a plant may post a vacancy either on a market for employed workers or on a market for unemployed ones, while vacancy posting costs κ are the same on both markets. Following from a free-entry condition, π_{ue} is the probability of an unemployed worker to

receive a job offer

$$\pi_{ue} = \chi \left(\frac{\chi \beta (1 - \mu)}{\kappa} ES \right)^{\frac{1-\rho}{\rho}}, \quad (3)$$

where χ is the matching efficiency, and ρ the matching elasticity of a Cobb-Douglas matching function. μ denotes the worker's bargaining power. From the free-entry condition on the unemployed workers market, π_{eo} is the probability of an employed worker to receive a job offer

$$\pi_{eo} = \chi \left(\frac{\chi \beta (1 - \mu) q_{eo}}{\kappa} ES \right)^{\frac{1-\rho}{\rho}}. \quad (4)$$

Worker and plant jointly bargain for the wage, the productivity threshold of layoff, and the gain threshold of quits. Consequently, separations are efficient. This obtains as probability that the employed worker accepts an offer

$$q_{eo} = \left(1 + \exp \left\{ \frac{1}{\psi_{eo}} (\beta (1 - \mu) ES - \kappa_{eo}) \right\} \right)^{-1}. \quad (5)$$

The layoff probability is

$$\begin{aligned} \pi_x = \left(1 + \exp \left\{ \frac{1}{\psi_x} \left(a - f - b + \pi_{eo} q_{eo} \left(\kappa_{eo} - \frac{\Psi_{eo}}{q_{eo}} \right) \right. \right. \right. \\ \left. \left. \left. + \left((1 - \pi_{eo} q_{eo})(1 - \mu) + (1 - \pi_{ue})\mu \right) \beta ES \right) \right\} \right)^{-1}, \end{aligned} \quad (6)$$

and Ψ_x is the plant's option value of maintaining the match and not laying off the worker

$$\Psi_x = E(x|x > \omega_x) = -\psi_x \left((1 - \pi_x) \log(1 - \pi_x) + \pi_x \log(\pi_x) \right). \quad (7)$$

The employed worker's option value of accepting an outside offer is given by

$$\Psi_{eo} = E(\eta_{eo}|\eta_{eo} > \omega_{eo}) = -\psi_{eo} \left((1 - q_{eo}) \log(1 - q_{eo}) + q_{eo} \log(q_{eo}) \right). \quad (8)$$

3.2 Worker flows

Let us now define the worker flows as implied by this model. First, the stock of unemployed in period $t + 1$ is the sum of workers laid off in period t that did not find a job within the same period and period t unemployed workers that are not hired in the

current period

$$u_{t+1} = \pi_x(1 - \pi_{ue})(1 - u_t) + (1 - \pi_{ue})u_t. \quad (9)$$

Let us also define the within-period unemployment after layoffs at stage 1

$$\tilde{u}_t = u_t + \pi_x(1 - u_t). \quad (10)$$

We define layoffs as the number of workers transiting from employment into unemployment

$$L_t = \pi_x(1 - u_t). \quad (11)$$

Quits is the number of workers changing from one job to another

$$Q_t = \pi_{eo}q_{eo}(1 - \tilde{u}_t). \quad (12)$$

Finally, the hirings are given by the workers hired from both the pool of unemployed and unemployed workers

$$H_t = \pi_{ue}\tilde{u}_t + \pi_{eo}q_{eo}(1 - \tilde{u}_t). \quad (13)$$

3.3 Uncertainty shock

Let us now turn to the key topic, the response of worker flows on uncertainty shocks. In this model, shocks to uncertainty are unexpected changes in the dispersion of idiosyncratic productivity (x), which we denoted by ψ_x . Subsequently, we discuss different channels through which uncertainty shocks affect the labor market. In particular, a real option effect and a frequency effect are present. However, there is no intensive margin effect in a model with linear production technology.

3.3.1 Real option effect

If uncertainty increases, the expected productivity conditional on maintaining the match, that is the plant's option value of maintaining the match, Ψ_x , increases. The channel of a change in uncertainty ψ_x on worker flows through a change in Ψ_x is the real option channel. To highlight this real option channel, let us in the following abstract from all other effects of uncertainty shocks, for example on the unemployment rate or acceptance probability.

Consequently, an uncertainty increase raises the match surplus unambiguously. Furthermore, we may rewrite the layoff probability as a function of the layoff threshold for idiosyncratic productivity ω_x ,⁸

$$\pi_x = \left(1 + \exp \left\{ -\frac{\omega_x}{\psi_x} \right\} \right)^{-1}. \quad (14)$$

Below the threshold productivity, plants lay off workers while they maintain the match above that threshold. The threshold decreases in the match surplus and therefore the real option channel implies a decrease in the threshold when uncertainty increases. This effect closely corresponds to the real option effect discussed in the decomposition of uncertainty effects in the empirical section of this paper. In other words, higher uncertainty widens the inaction region (shifts the adjustment trigger of not laying off a worker to the left) and plants are more likely to not adjust and “freeze”. Obviously, this leads to a decline in π_x and therefore a decline in layoffs.

Furthermore, also the offer-acceptance probability (q_{eo}) declines from the real option effect and in turn, this leads to less quits. The job-finding probability of an unemployed worker (π_{ue}) increases in response to ψ_x . The impact of the real option effect on hirings (H) is therefore ambiguous as hiring increases from the increased job-finding probability, while it decreases from a lower offer-acceptance rate.

Importantly, we have abstracted from responses of stage 3 unemployment when going through the effects of the real option channel. This abstraction is important as it allows us to overcome the inherent time aggregation bias present in this type of models. For the model to be tractable, we assumed plants to first decide on layoffs, while quits and hirings are decided on in a later stage. The time aggregation bias arises as quits and hirings are affected by stage 1 layoffs through stage 3 unemployment. By abstracting from changes in stage 3 unemployment, we eliminate the time aggregation bias.

The fact that layoffs decrease through the real option channel reveals a generic problem of most search and matching models to generate our empirical finding that layoffs increase in uncertainty.

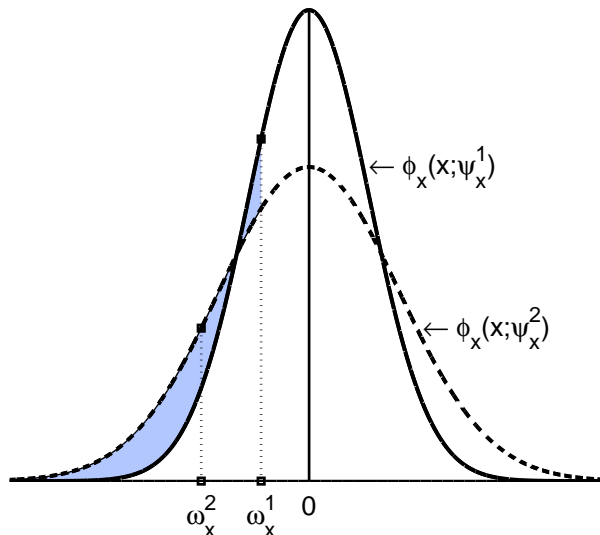
3.3.2 Frequency effect

The equation for π_x illustrates well another channel of uncertainty. Abstracting from the real option effect on ω_x , an increase in ψ_x increase π_x from its denominator, which captures the fact that, for larger dispersion of ψ_x the probability of extreme pro-

⁸Appendix C contains the details.

ductivity draws raises, which also raises the probability of layoffs.

Table 4: Real option and frequency effects of an uncertainty shock



In Table 4, we illustrate the differences between real option and frequency effects graphically. Suppose uncertainty increases from ψ_x^1 to ψ_x^2 , while the mean of the distribution remains unchanged at zero. The pdf for the two levels of uncertainty are plotted by the solid and dotted curves. Via the real option channel, the match surplus increases, which implies that the layoff threshold ω_x is shifted to the left. The frequency effect, on the other side, is the change in layoff probability for and unchanged layoff threshold. In our illustration, that corresponds to the differences in probability mass between the left and the right shaded areas.

4 Multi-worker model with financial frictions

(tba)

5 Conclusion

(tba)

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A Decomposition of uncertainty channels

To highlight the different channels through which uncertainty affects job destruction and to keep it simple, we want to think of a parsimonious model. There is a unit-mass of plants and these produce output using labor input L and facing idiosyncratic productivity z . The cross-sectional distribution of z is $G(z; \sigma)$, where σ is the uncertainty measure. Employment changes are subject to non-convex adjustment costs that give rise to real option effects. We denote the cross-sectional distribution of employment across plants by $H(L)$ and the joint distribution of productivity and labor by $F(z, L; \sigma)$. Independent of a plant's employment choice, every period some exogenous fraction of workers quits, which we denote by δ_L . We assume that an uncertainty shock represents an unexpected change from σ to σ' and that plants observe uncertainty in the period that it realizes (and not before). To keep our analysis tractable, we suppose that $H(L)$ is the ergodic distribution associated with σ before the uncertainty shock hits.

We let $JD(\sigma)$ denote aggregate job destruction and $JD(z, L; \sigma)$ denotes the number of jobs destroyed of a particular plant described by the pair (z, L) . First, we express aggregate job destruction in a convenient way.

$$\begin{aligned} JD(\sigma) &= \int_{z \times L} JD(z, L; \sigma) dF(z, L; \sigma) \\ &= \int_{z \times L} JD(z, L; \sigma) dF^{na}(z, L; \sigma, \sigma) + \int_{z \times L} JD(z, L; \sigma) dF^a(z, L; \sigma, \sigma). \end{aligned} \quad (15)$$

F^a denotes the distribution of F conditional on adjusting and F^{na} is the distribution conditional on not adjusting. Formally,

$$F^a(z, L; \sigma) = F(z, L; \sigma) \times 1\{JD(z, L; \sigma) \neq -\delta_L\}. \quad (16)$$

Note that adjusting shall be understood as incurring adjustment costs. We can further express job destruction as

$$JD(\sigma) = \#(na; \sigma) \varnothing(JD|na; \sigma) + \#(a; \sigma) \varnothing(JD|a; \sigma). \quad (17)$$

$\varnothing(JD|a; \sigma)$ denotes the average job destruction conditional on adjusting labor, while $\varnothing(JD|na; \sigma)$ is the average job destruction of non-adjusting plants that comes from the exogenous quit rate. $\#(na; \sigma)$ and $\#(a; \sigma)$ are the number of non-adjusting and adjusting plants, respectively. As we assume a unit mass of plants, this corresponds to the shares and $\#(na; \sigma) = 1 - \#(a; \sigma)$.

We can now study how and why aggregate job destruction reacts when uncertainty changes from σ to σ' .

$$\begin{aligned} JD(\sigma') - JD(\sigma) &= \#(na; \sigma') \varnothing(JD|na; \sigma') + \#(a; \sigma') \varnothing(JD|a; \sigma') \\ &\quad - \#(na; \sigma) \varnothing(NJC|na; \sigma) - \#(a; \sigma) \varnothing(NJC|a; \sigma) \end{aligned} \quad (18)$$

Further twisting the equation, we obtain

$$\begin{aligned} JD(\sigma') - JD(\sigma) &= (RO + FR) \left[\varnothing(JD|a; \sigma') - \varnothing(JD|na; \sigma') \right] \\ &\quad + \#(a; \sigma) IM(a) + \#(na; \sigma) IM(na), \end{aligned} \quad (19)$$

where we make use of the following definitions

$$RO = \#(a; \sigma', \sigma') - \#(a; \sigma', \sigma) \quad (20)$$

$$FR = \#(a; \sigma', \sigma) - \#(a; \sigma, \sigma) \quad (21)$$

$$IM(a) = \varnothing(JD|a; \sigma') - \varnothing(JD|a; \sigma) \quad (22)$$

$$IM(na) = \varnothing(JD|na; \sigma') - \varnothing(JD|na; \sigma). \quad (23)$$

RO denotes the real option effect, capturing changes in the share of adjusters that are due to the changed policy function, while FR denotes the frequency effect, capturing changes in the share of adjuster that are due to changes in the distribution productivity is drawn from. $IM(a)$ denotes the intensive margin effect, which captures the change in average JD conditional on adjusting. $IM(na)$ is the intensive margin effect of the firms not adjusting.⁹

Equation 19 is the key result of this decomposition exercise. Let us analyze the different terms supposing an uncertainty increase ($\sigma' > \sigma$). We know that under non-convex adjustment frictions, the option value of waiting increases when uncertainty raises, so RO is unambiguously negative. At the same time, $FR > 0$ because the isolated effect of higher realized volatility causes more plants to adjust.

⁹Note that, in order to arrive at equation 19, we can express the joint distribution of adjusting plants by

$$F^a(z, L; \sigma_1, \sigma_2) = F(z, L; \sigma_1) \times 1\{JD(z, L; \sigma_2) \neq -\delta_L l\},$$

where σ_1 captures the realized volatility effect and σ_2 the reaction of the plants' policy function in response to uncertainty. This distinction allows us to distinguish between FR and RO effects.

We further assume that the model is such that

$$\varnothing(JD|a; \sigma'), \varnothing(JD|na; \sigma'), \#(a; \sigma), \#(na; \sigma) > 0, \quad (24)$$

in other words, we assume that for both levels of uncertainty there exist adjusting and non-adjusting firms. On the intensive margin, we have $IM(a) > 0$, i.e. conditional on adjustment, firms adjust by more on average. This is because the tails of the productivity distribution are fatter and adjustment is monotonic in productivity. $IM(na)$ depends on the firm size distribution of non-adjusters. As we assume that in both periods the firm size distribution is identically the ergodic distribution for uncertainty level σ , we should expect $IM(na) = 0$.

Now the sign of the RO effect on the change in job destruction depends critically on the sign of $\Delta\varnothing := \varnothing(JD|a; \sigma') - \varnothing(JD|na; \sigma')$. For $\Delta\varnothing > 0$, the RO channel lowers JD when uncertainty is high, while for $\Delta\varnothing < 0$, the opposite is true. Theoretically, the sign of $\Delta\varnothing$ is ambiguous. In a model with exogenous labor attrition, the attrition rate is typically small. Thus non-adjusting firms destroy relatively few jobs. To the contrary, adjusting firms adjust by relatively much. Using these considerations to conjecture that $\Delta\varnothing > 0$ is unambiguous, however, because on average the non-adjusting firms are relatively larger in size.

To circumvent this issue, we focus solely on JD by adjusting firms, $JD^a = \int_{l \times z} JD(z, l; \sigma) dF^a(z, l; \sigma)$. Then, by the same decomposition we obtain:

$$JD^a(\sigma') - JD^a(\sigma) = (RO + FR) \varnothing(JD|a; \sigma') + \#(a; \sigma) IM(a) \quad (25)$$

This renders the RO effect unambiguous in being the only channel through which an uncertainty increase leads to less JD while the FR and IM channels imply the opposite response.

B Robustness tests

B.1 Additional reaction of labor variables from an uncertainty shock

Using the dataset from DFH and combining it with the information provided in BED, we construct a measure of layoffs for continuing plants, which is equivalent to layoffs after subtracting total job destruction of closing plants. As identifying assumption, plants that close their business do not hire workers within the quarter.

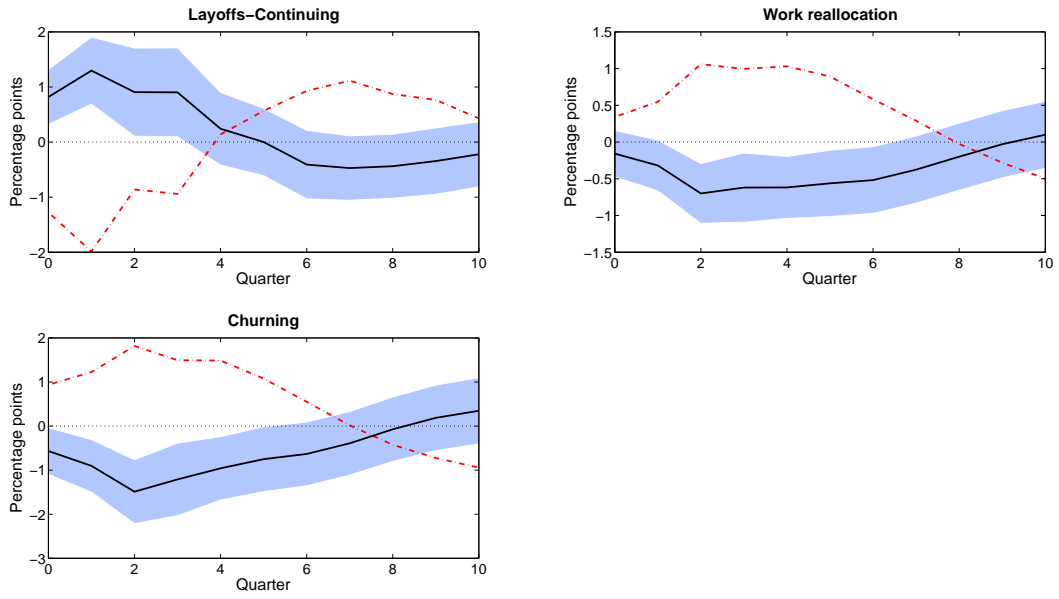
Given a surprise increase in uncertainty, net job creation displays a fall with a posterior recovery and rebound after 4 quarters since the shock. This response is qualitatively similar to the results provided by Bloom (2009) using employment and industrial production.

Table 5: Relation between uncertainty and further employment variables

	LC		WR		CH	
Uncertainty	0.53 (0.09)	0.40 (0.14)	-0.43 (0.10)	-0.03 (0.07)	-0.54 (0.09)	-0.13 (0.07)
GDP		-0.22 (0.14)		0.71 (0.08)		0.66 (0.08)
R^2	0.32	0.35	0.19	0.53	0.29	0.66
Period	1990q2-2010q2					

Note: All variables are in logs and detrended with HP-filter ($\lambda=1600$). Robust standard errors in parentheses.

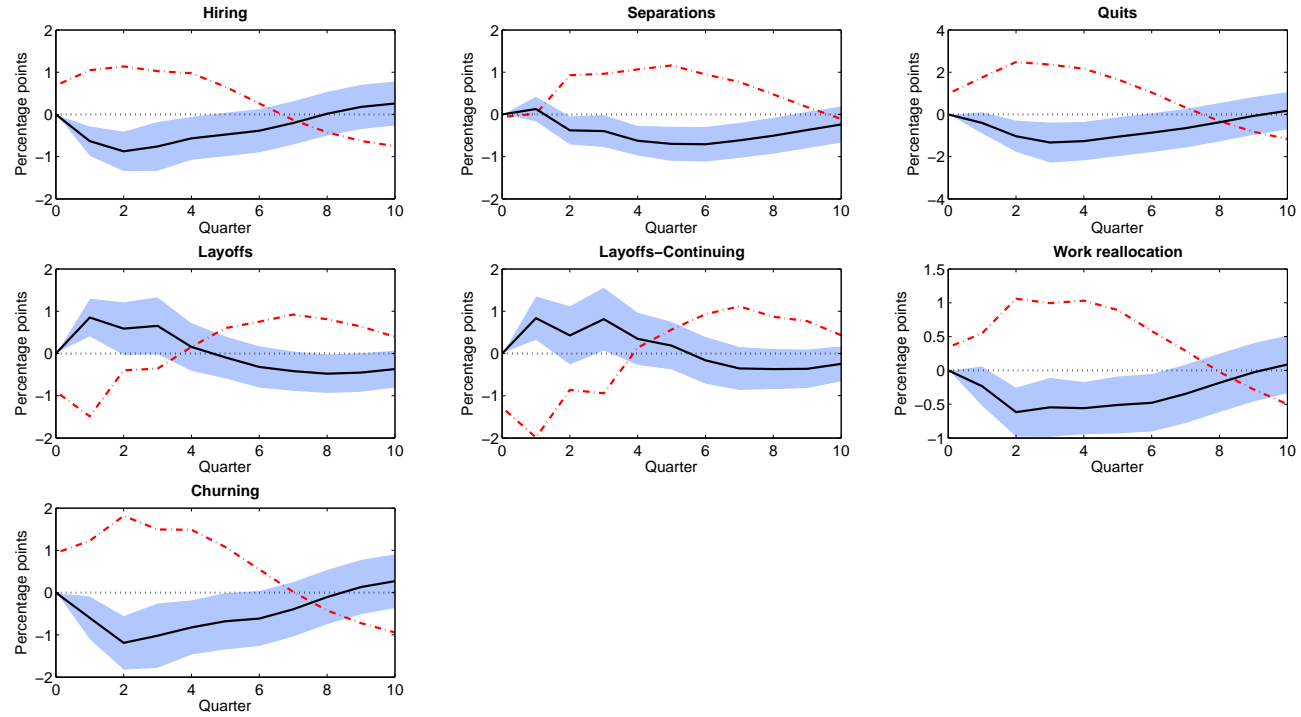
Table 6: Impulse response functions from an uncertainty shock



Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line) and a GDP shock (dash-dot red line). The impulse responses are obtained estimating for each worker flow variable a three-variate sVAR with uncertainty ordered second and the worker flow variable last. We use JLN uncertainty and shaded regions represent 90% standard error confidence interval from an uncertainty shock. All variables are in logs and detrended with HP-filter ($\lambda=1600$).

B.2 sVAR placing uncertainty last

Table 7: Impulse response functions from an uncertainty shock



Impulse response functions from a one standard deviation uncertainty shock (solid black line) and a GDP shock (dash-dot red line). The impulse responses are obtained estimating for each worker flow variable a three-variate sVAR with uncertainty ordered third and the worker flow variable second. We use JLN uncertainty and shaded regions represent 90% standard error confidence interval from an uncertainty shock. All variables are in logs and detrended with HP-filter ($\lambda=1600$).

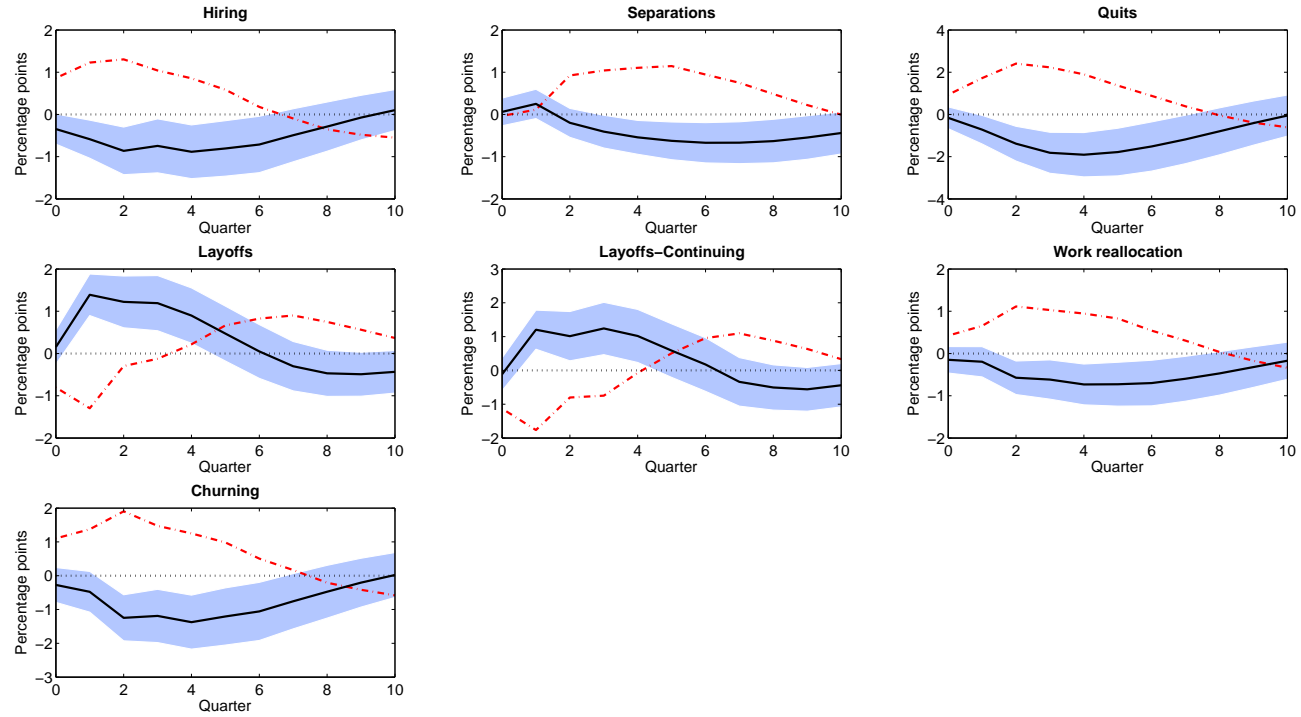
Table 8: Variance decomposition from an uncertainty shock

	Hirings	Separations	Quits	Layoffs
1 quarter	0.0%	0.0%	0.0%	0.0%
2 quarters	5.4%	0.4%	0.8%	6.1%
4 quarters	11.2%	5.3%	7.2%	9.5%
8 quarters	13.1%	17.2%	12.1%	9.8%

Note: All variables are in logs and detrended with HP-filter ($\lambda=1600$). The forecast-error variance decomposition is based upon the estimation of a three-variate sVAR consisting of GDP, uncertainty and the worker flow variable.

B.3 sVAR using VXO index as uncertainty measure

Table 9: Impulse response functions from an uncertainty shock



Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line) and a GDP shock (dash-dot red line). The impulse responses are obtained estimating for each worker flow variable a three-variate sVAR with uncertainty ordered second and the worker flow variable last. We use VXO index as uncertainty measure and shaded regions represent 90% standard error confidence interval from an uncertainty shock. All variables are in logs and detrended with HP-filter ($\lambda=1600$).

C Basic search and matching model with endogenous layoffs and quits

C.1 Timing of the model

A period consists of three stages. In stage 1, plants observe their idiosyncratic productivity draw and decide whether to maintain the match with the worker or lay off the worker. In stage 2, production takes place. In stage 3, plants post vacancies to hire a worker and during the same stage, workers can obtain an offer from a vacancy-posting plant and depending on idiosyncratic utility of switching jobs, they quit and leave the current match.

C.2 Plants

A plant's labor productivity is given by p and is distributed following a logistic distribution $p \sim \text{logistic}(a, \psi_x)$, where a denotes its mean and $\frac{\psi_x^2 \pi^2}{3}$ is the variance of p . As this distribution is common across plants, a denotes aggregate productivity and we can rewrite $p = a + x$, where

$$x \sim \text{logistic}(0, \psi_x) \quad (26)$$

denotes plant-level deviations from aggregate productivity, or idiosyncratic productivity shocks.¹⁰ We denote the *pdf* of x by ϕ_x . Plants incur fixed costs of operation f , they pay wages w , and the plant's match surplus is

$$\begin{aligned} J(a) &= \int_{\omega_x}^{\infty} (p(a, x) - w(a) - f + (1 - \pi_{eo}(a)q_{eo}(a))\beta EJ(a')) d\phi_x(x) \\ &= (1 - \pi_x(a)) \left(a - w(a) - f + \frac{\Psi_x(a)}{1 - \pi_x(a)} + (1 - \pi_{eo}(a)q_{eo}(a))\beta EJ(a') \right), \end{aligned} \quad (27)$$

where $\pi_x(a) = \text{Prob}(x < \omega_x)$ is the layoff probability. $\pi_{eo}(a)q_{eo}$ denotes the probability that the worker quits the match, and $\Psi_x(a)$ is the option value of maintaining the match

¹⁰Following the distributional assumption, labor productivity may accept negative values, which is - for good reason - not a common modeling approach. We could as well assume p to be log-logistically distributed, but that causes a huge loss of tractability and even worse, shocks to uncertainty ψ_x also affect the mean of p . We therefore stick to the assumption made and see this model only as illustration device.

(and not laying off the worker)

$$\Psi_x(a) = E(x|x > \omega_x) = -\psi_x\left((1 - \pi_x(a)) \log(1 - \pi_x(a)) + \pi_x(a) \log(\pi_x(a))\right). \quad (28)$$

C.3 Workers

The value of an employed worker (V^e) depends on the probability of being laid off and the wage she receives

$$V^e(a) = (1 - \pi_x(a)) \left(w(a) + \tilde{V}^e(a) \right) + \pi_x(a) V^u(a). \quad (29)$$

It further depends on the value of being unemployed (V^u) and the value of on-the-job search (\tilde{V}^e). We assume employed and unemployed workers to search free of costs, hence both types of workers always search. If an employed workers gets matched with a plant, the worker's acceptance depends on an idiosyncratic utility of switching. We denote this utility term by η_{eo} and assume it to be logistically distributed with mean κ_{eo} dispersion parameter ψ_{eo} and the cdf is given by ϕ_{eo} . The employed worker's value for on-the-job search is

$$\begin{aligned} \tilde{V}^e(a) &= \pi_{eo}(a) \int_{\omega_{eo}}^{\infty} (\beta EV^e(a') + \eta_{eo}) d\phi_{eo}(\eta_{eo}) \\ &\quad + \pi_{eo}(a) \int_{-\infty}^{\omega_{eo}} (\beta EV^e(a')) d\phi_{eo}(\eta_{eo}) \\ &\quad + (1 - \pi_{eo}(a)) \beta EV^e(a') \\ &= \pi_{eo}(a) q_{eo}(a) \left(\kappa_{eo} - \frac{\Psi_{eo}(a)}{q_{eo}(a)} \right) + \beta EV^e(a'), \end{aligned} \quad (30)$$

where $\pi_{eo}(a)$ is the probability of receiving an offer, and the threshold utility, above which the worker accepts to switch jobs is denoted by ω_{eo} . $q_{eo} = \text{Prob}(\eta_{eo} > \omega_{eo})$ is the offer-acceptance probability. We denote the option value of accepting an outside offer by

$$\Psi_{eo}(x) = E(\eta_{eo} | \eta_{eo} > \omega_{eo}) = -\psi_{eo} \left((1 - q_{eo}) \log(1 - q_{eo}) + q_{eo} \log(q_{eo}) \right). \quad (31)$$

The unemployed worker's value is

$$V^n(a) = b + \pi_{ue}(a) \beta EV^e(a') + (1 - \pi_{ue}(a)) \beta EV^n(a'), \quad (32)$$

where $\pi_{ue}(a)$ is the probability of receiving a job offer (when unemployed) and b denotes utility from home production when unemployed. The worker's match surplus is

$$\begin{aligned}\Delta(a) &= V^e(a) - V^n(a) \\ &= (1 - \pi_x(a)) \left(w(a) - b + \pi_{eo}(a) q_{eo}(a) \left(\kappa_{eo} - \frac{\Psi_{eo}(a)}{q_{eo}(a)} \right) \right. \\ &\quad \left. + (1 - \pi_{ue}(a)) \beta E \Delta(a') \right).\end{aligned}\tag{33}$$

C.4 Nash bargain

Assuming perfect commitment of worker and plant, they jointly bargain over wages and cut-off values for layoff and quit

$$(w, \omega_x, \omega_{eo}) = \arg \max_{w, \omega_x, \omega_{eo}} \Delta^\mu J^{1-\mu}.\tag{34}$$

For convenience we drop keeping track of aggregate productivity as function argument, and from the FOCs we obtain

$$(1 - \mu) \Delta = \mu J\tag{35}$$

$$w = \mu \left(a - f + \frac{\Psi_x}{1 - \pi_x} + (1 - \pi_{eo} q_{eo}) \beta (1 - \mu) ES \right)\tag{36}$$

$$\begin{aligned}& - (1 - \mu) \left(-b + \pi_{eo} q_{eo} \left(\kappa_{eo} - \frac{\Psi_{eo}}{q_{eo}} \right) + (1 - \pi_{ue}) \beta \mu ES \right), \\ \pi_x &= \left(1 + \exp \left\{ \frac{1}{\psi_x} \left(a - f - b + \pi_{eo} q_{eo} \left(\kappa_{eo} - \frac{\Psi_{eo}}{q_{eo}} \right) \right. \right. \right. \\ &\quad \left. \left. \left. + \left((1 - \pi_{eo} q_{eo}) (1 - \mu) + (1 - \pi_{ue}) \mu \right) \beta ES \right) \right\} \right)^{-1},\end{aligned}\tag{37}$$

$$q_{eo} = \left(1 + \exp \left\{ \frac{1}{\psi_{eo}} \left(\beta (1 - \mu) ES - \kappa_{eo} \right) \right\} \right)^{-1}.\tag{38}$$

Consequently, for ω_x we obtain

$$\omega_x = - \left(a - f - b + \pi_{eo} q_{eo} \left(\kappa_{eo} - \frac{\Psi_{eo}}{q_{eo}} \right) \left((1 - \pi_{eo} q_{eo}) (1 - \mu) + (1 - \pi_{ue}) \mu \right) \beta ES \right).$$

The total match surplus follows as

$$S = J + \Delta = (1 - \pi_x) \left[a - f - b + \pi_{eo} q_{eo} \left(\kappa_{eo} - \frac{\Psi_{eo}}{q_{eo}} \right) + \frac{\Psi_x}{1 - \pi_x} + \left((1 - \pi_{eo} q_{eo})(1 - \mu) + (1 - \pi_{ue})\mu \right) \beta ES \right]. \quad (39)$$

C.5 Free entry conditions

Workers can be hired by plants from two submarkets, the market of unemployed workers and the market of employed workers (searching on the job). We assume free entry for each market, such that the marginal plant is indifferent of posting a vacancy. The free entry condition for the unemployed workers market is

$$\kappa = \pi_{vu}(a) \beta EJ(a'), \quad (40)$$

where $\pi_{vu}(a)$ is the probability of filling a posted vacancy with an unemployed worker and κ denotes the cost of posting a vacancy, that we assume to be the same on both markets. On the market for employed workers the free entry conditions is

$$\kappa = \pi_{vo}(a) q_{eo}(a) \beta EJ(a'), \quad (41)$$

where $\pi_{vo}(a)$ is the probability of filling a vacancy with a worker that is currently employed. For each submarket, we assume a standard Cobb-Douglas matching function

$$m(a) = \chi v(a)^{1-\rho} u(a)^\rho, \quad (42)$$

where χ denotes matching efficiency. The implied job-filling rate on unemployed workers market is

$$\pi_{vu}(a) = \chi \theta_u(a)^{-\rho} \quad (43)$$

and on the employed workers market

$$\pi_{vo}(a) = \chi \theta_o(a)^{-\rho}. \quad (44)$$

Therefore, a worker's probability of receiving a job offer is given by

$$\pi_{ue}(a) = \chi \left(\frac{\chi\beta(1-\mu)}{\kappa} ES(a') \right)^{\frac{1-\rho}{\rho}}, \quad (45)$$

$$\pi_{eo}(a) = \chi \left(\frac{\chi\beta(1-\mu)q_{eo}(a)}{\kappa} ES(a') \right)^{\frac{1-\rho}{\rho}}, \quad (46)$$

on the two markets, respectively.