Do plants freeze upon uncertainty shocks?*

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This version: February 15, 2015

Abstract

Following the real option literature, whether or not uncertainty shocks drive business cycles depends on adjustment frictions. If plants freeze and remain inactive in response to increased uncertainty, real economic activity contracts. We show that a standard plant model with factor adjustment frictions identifies the importance of labor adjustment costs through the response of layoffs, quits and hiring on uncertainty shocks. Layoffs decline in response to a positive uncertainty shock when employment adjustment is sufficiently frictional, while layoffs increase otherwise. Empirically, we show that higher uncertainty reduces hiring and quits, while it raises layoffs. This finding suggests that plants do not freeze employment adjustments upon uncertainty shocks. Different from investments, this renders employment responsive to policy changes. The model also suggests that economies with more flexible labor markets should experience more layoffs upon uncertainty shocks. Using labor flow data from France, Germany and UK, we obtain empirical evidence that supports this hypothesis.

Keywords: Uncertainty, real option, labor.
JEL Classification Numbers: J23, J63, D81.

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*The research leading to these results has received funding from the European Research Council under the European Research Council under the European Union's Seventh Framework Programme (FTP/2007-2013) / ERC Grant agreement no. 282740 and we are very grateful for financial support from the German Science Foundation through SFB/TR 15 and the Bonn Graduate School of Economics. We wish to thank Christian Bayer, Nicholas Bloom, Rüdiger Bachmann, and Felix Wellschmied for helpful comments and the participants at the Search and Matching Conference, Spring Meeting of Young Economis and MEF Workshop at the University of Bonn.

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1 Introduction

Uncertainty is high during recessions. One widely discussed channel that causes this correlation is that uncertainty leads to a decline in investment through a 'real options channel'. When investment is irreversible, firms will wait longer before they undertake investment projects. The same holds true for employment decisions if employment adjustment is subject to some fixed or linear costs. As firms postpone adjustment decisions, the factor allocation becomes more misallocated, which lowers aggregate output. Understanding the importance of these separate factor adjustment frictions is important for policy makers, as it determines the responsiveness of investment and employment to fiscal or monetary policy changes during periods of high uncertainty.

In this paper, we revise the real option literature with a special focus on labor markets. In particular, we replicate the model presented in Bloom (2009), but decompose the employment change into layoffs, quits and hiring.[1] This decomposition identifies the importance of employment adjustment costs.[2] Under (strongly) frictional employment adjustment, a positive uncertainty shock affects employment mainly through the employment-side real option channel. Firms wait longer until they adjust employment, which induces a decline in both layoffs and hiring. On the other extreme, when employment adjustment is frictionless, employment adjustment is driven by the firms' investment response. The capital-side real option channel induces firms to postpone investment decisions. In turn, labor demand falls primarily through increased capital misallocation, which implies higher layoffs and lower hiring.

Empirically, Bloom (2009) documents that upon a positive uncertainty shock, both output and employment fall. The present paper reasseses this evidence. We decompose the employment response to an uncertainty shock into the components of employment change, i.e. layoffs, quits, hiring. Our findings establish a new stylized fact for the US labor market: A positive shock to uncertainty reduces hirings and quits, while it raises layoffs.

Based on our identification, the empirical finding supports a model with weak employment adjustment frictions. The employment-side real option channel seems to be negligible as it contradicts the response of layoffs on positive uncertainty shocks. In other words, while plants postpone investment plans, they do not freeze their employment decisions, which renders employment responsive to policy interventions during periods

[1]The model in Bloom (2009) is a partial equilibrium model of the firm with non-convex adjustment costs and time-varying volatility.

[2]As shortcut, whenever we refer to employment adjustment frictions, we mean some fixed or linear costs, or a combination of both, that gives rise to real option effects.

of high uncertainty. We see this finding as complementary to Bloom et al. (2007), which argues that investments are fairly unresponsive to policy interventions, such as reduced interest rates on loans. Interestingly, as firms do not adjust their capital stock, the policy maker can raise employment through subsidizing labor expenses, while capital does not respond.

With (strong) labor adjustment frictions, an uncertainty increase renders plants' employment highly insensitive to changes in the price. In particular, this holds true for the first few periods after the uncertainty shock, where the employment-side real option effect dominates and plants freeze employment. This has been discussed in Bloom (2009) and explicitly shown in Bloom et al. (2014). Therefore, we argue that our identification is robust to general equilibrium effects. In similar vein, if financial frictions primarily interact with uncertainty shocks by changing relative factor prices, our identification is also robust to a model with financial friction (in addition to the factor adjustment frictions).

An additional empirical contribution of our paper is to assess the response of labor flows across countries. We find that worker flows in the UK match closely the behavior of their US counterparts. For France, we obtain that hiring and quits decline in response to a positive uncertainty shock. Contrary to the US finding, layoffs decline on impact. Further, we analyzed German job flows and find results comparable to the US. While for the US, our results suggest fixed costs on labor to be of little importance, the international comparison shows that the general model is right in describing the behavior for different adjustment cost levels. In particular, the empirical findings corresponds to measures of labor market rigidities, that find the French labor market to be significantly more rigid than the US (or UK) labor market.[3] Beyond that, our results suggest that employment is less responsive to policy changes in France.

An implication of joint frictions in both factor adjustments, is that an increase in uncertainty distorts not only the capital-output ratio but also the capital-labor ratio. Quantitatively, there is an open debate whether uncertainty is a likely and important driver of business cycles. While Bloom (2009) and Bloom et al. (2014) find seizable effects of uncertainty shocks on real economic activity, Bachmann and Bayer (2013) conclude with the opposite result. Among other dimension, these studies differ in that employment adjustment is only frictional in the former two papers. A conjecture may be that the presense of frictions in both factors may amplify the uncertainty effects of output. We

[3]A measure of labor market rigidities has been constructed by the Fraser Institute, called 'Labor Market Regulations Index'. It displays large differences between the US and UK on the one side, and France and Germany on the other side.

find this amplification to be quantitatively negligible in the model.

Our emprical estimation strategy is to assess the response of worker flows (layoffs, quits and hiring) on uncertainty using structural VARs. We consider a five-variate model including worker flows, uncertainty and real GDP. Our baseline identification assumption is that neither innovations to worker flows, nor uncertainty shocks, do contemporaneously affect real GDP.[4] Our results of falling hiring and increasing layoffs further sheds light on the mechanism underlying the drop of aggregate employment in response to positive uncertainty shocks, as documented for example in Bloom (2009). We also estimated the response of job flows, and find that job creation falls and job destruction rises to positive uncertainty shocks.

This study is related to a growing literature that analyzes the macroeconomic effects of uncertainty shocks. The literature has discussed several mechanisms through which uncertainty affects economic activity.[5] Our analysis abstract from financial frictions, risk aversion and nominal rigidities which have been associated as alternative transmissions channel through which uncertainty may affect the economic activity. We see our study as complementary to these channels. In a model with financial frictions where firms can default on their debt, an uncertainty increase rises the default probability, and thus interest rates. This effect leads plants to lower their labor demand, whereby layoffs increase. In a model with risk averse households, an increase in uncertainty leads households to increase savings and reduce consumption for precautionary reasons. This transmission channel is often studied in combination with nominal rigidities, where higher uncertainty induce households to supply more labor for a given level of wage for precautionary reasons, which reduces plant's marginal cost of production. This channel combined with nominal rigidities implies an increase of markups over marginal costs, which yields a decline of consumption and investment. In contrast to the aforementioned frictions,

[4] We use labor flow data from United States based on the database developed by Davis et al. (2012), who extend the worker flows of private sector establishments provided by the Job Opennings and Labor Turnover (JOLTS) and Business Employment Dynamics (BED) data back until 1990. As benchmark uncertainty measure, we use the time series estimated by Jurado et al. (2013). We prefer this measure as it controls for the forecastable component of economic indicators. Our empirical findings are robust against alternative uncertainty measures used in the literature, such as implied stock market volatility, inter-quantile range of firm profit growth and policy uncertainty.

[5] These include (1) the Oi-Hartman-Abel effect (Oi (1961), Hartman (1972), Abel (1983)), (2) real option effects (Bernanke (1983), Dixit and Pindyck (1994), Caballero and Engel (1999)), (3) frequency margin effect (Bloom (2009), Bachmann and Bayer (2014)), (4) financial frictions (Christiano et al. (2010), Arellano et al. (2012), Gilchrist et al. (2013)), (5) precautionary savings (Basu and Bundick (2012), Born and Pfeifer (2013), Fernandez-Villaverde et al. (2011)), and (6) search frictions (Schaal (2012), Guglielminetti (2013), Leduc and Liu (2014)). Further, studies providing empirical findings on the effect of uncertainty in the economy include Bachmann et al. (2013), Leahy and Whited (1996), Guiso and Parigi (1999), Ramey and Ramey (1995), Stein and Stone (2013), Handley and Limo (2012), Baker and Bloom (2013).

the theoretical implications of an economy with search frictions and time-varying uncertainty are different. Mortensen and Pissarides (1994) shows analytically that the match surplus strictly increase in uncertainty, which leads to an increase of hiring.
The remainder of this paper proceeds as follows: Section 2 presents the firm model and discusses the identification of employment adjustment frictions. Section 3 describes our dataset, econometric approach and documents the empirical findings. Finally, Section 4 concludes. An Appendix follows with robustness results and details on data sources and definitions.

2 Model

In this section, we study the effect of uncertainty shocks in a firm model with a special focus on worker flows. In particular, we replicate the model proposed by Bloom (2009) and we decompose the change in employment into layoffs, quits and hiring. We show that the model implies remarkably different effect of uncertainty shocks on worker flows when varying the degree of labor adjustment frictions in the economy. This model therefore allows us to identify the importance of employment adjustment frictions.

2.1 Factor adjustment friction model

We consider a partial equilibrium model of the firm and we assume that each firm operates a finite number of plants.[6] Each plants is monopolistically competitive and maximizes profits subject to a set of capital and labor adjustment costs. We assume that plants optimize independent of each other. Suppose the plant faces the revenue function

$$R(A,K,L,H) = A^{\frac{1}{\epsilon}}(K^{\alpha}(LH)^{1-\alpha})^{\frac{\epsilon-1}{\epsilon}}, \tag{1}$$

where K denotes the capital stock, L the number of employees, and H average hours worked per employee. The implicit markup is $\epsilon/(\epsilon-1)$ and A denotes a profitability shock

$$A_{ijt} = A_t^M A_{it}^F A_{ijt}^P, \tag{2}$$

[6] This reflects the firm structure in Compustat data, and the target moments in the model calibrations are computed from Compustat data.

which is composed of an aggregate (macro-level) component, A_t^M, a shock to each firm i, A_{it}^F, and a shock to each plant j within firm i, A_{ijt}^P. The components of the profitability shocks follow exogenous processes

$$A_t^M = A_{t-1}^M(1 + \sigma_{t-1}W_t^M) \tag{3}$$

$$A_{it}^F = A_{it-1}^F(1 + \mu_{it} + \sigma_{t-1}W_{it}^F) \tag{4}$$

$$A_{ijt}^P = A_{ijt-1}^P(1 + \sigma_{t-1}W_{ijt}^P), \tag{5}$$

respectively, where firm-level profitability has a stochastic trend, μ_{it}, and profitability shocks are independently distributed

$$(W_t^M \quad W_{it}^F \quad W_{ijt}^P)' \sim \mathcal{N}(0, I). \tag{6}$$

Aggregate uncertainty σ_t and the firm-level trend μ_{it} follow a 2-state Markov chain, respectively.

$$\sigma_t \in \{\sigma_L, \sigma_H\}, \quad \text{where } Prob(\sigma_{t+1} = \sigma_j | \sigma_t = \sigma_k) = \pi_{kj}^\sigma \tag{7}$$

$$\mu_{it} \in \{\mu_L, \mu_H\}, \quad \text{where } Prob(\mu_{it+1} = \mu_j | \mu_t = \mu_k) = \pi_{kj}^\mu \tag{8}$$

Wages are assumed to be a function of hours worked with $w(H) = w_1(1 + w_2 H^\gamma)$, which provides firms the possibility of not only adjusting the number of workers but also the hours worked. Production factor adjustment is subject to the adjustment costs function

$$\begin{aligned} C(A,K,L,H,I,E) = {} & 52w(40)C_L^P(E^+ + E^-) + (I^+ - (1 - C_K^P)I^-) \\ & + (C_L^F 1\{E \neq 0\} + C_K^F 1\{I \neq 0\})R(A,K,L,H) \\ & + C_L^Q L(E/L)^2 + C_K^Q K(I/K)^2. \end{aligned} \tag{9}$$

C_L^P and C_K^P capture partial irreversibilities, where the former is a cost linear in the number of workers hired or fired and the latter is a repurchase cost of disinvestments.[7] C_L^F and C_K^F quantify fixed disruption costs, a fixed share of revenues, and C_L^Q and C_K^Q

[7] We implicitely assume that adjustment costs C_L^P are proportional to wages arising from 40 hours worked per week, irrespective of the actual number of hours worked. This assumption dramatically simplifies the model solution.

capture quadratic adjustment costs. The plant problem is

$$
\begin{aligned}
& V(A, K, L, \sigma, \mu) \\
&\quad = \max_{\{I,E,H\}} \Big\{ R(A, K, L, H) - C(A, K, L, H, I, E) - w(H)L \\
&\qquad + \frac{1}{1+r}\mathbb{E}\big[V(A', K(1-\delta_K) + I, L(1-\delta_L) + E, \sigma', \mu')\big] \Big\},
\end{aligned} \tag{10}
$$

where I denotes investments, E adjustments in the number of employees, and H hours worked per employee.[8] Notice that the labor force declines by a constant share δ_L if plants do not hire (or fire). We assume δ_L to be the quit rate. Consequently, positive E denotes hirings while negative E captures layoffs.

2.2 Model calibration

Table 1 presents the model calibration. The first part contains predefined parameters, with standard assumptions for α, ϵ, δ_K, r. The wage function is specified such that wages are minimized at 40 hours per week and the wage is normalized to unity. A critical assumption is the relative magnitude of the uncertainty shock σ_H, because together with the probability of the shock π^{σ}_{LH} and its persistence π^{σ}_{HH} it determines how likely uncertainty shocks drive sizable business fluctuations. We assume that an uncertainty shock doubles the level of uncertainty. We consider an annual quit rate of 10%. The low value of quit rate in the model aims to reflect separations which are exogenous with respect to the productivity draws of the firm, such as retirement, family reasons or disease. The average firm level growth is set to 2% and a symmetric transition matrix is assumed for the firm trend. Corresponding to Compustat data, each firm is assumed to operate 250 plants.

The remaining model parameters are estimated by matching a set of firm-level correlations computed from Compustat data. The moments, presented in Table 7 in the Appendix of this paper, describe the joint behavior of investment rates, employment growth rates, and sales growth rates. In particular, the standard deviation, skewness, auto-correlation and joint (lagged) correlations of these three variables are targeted.

Reflecting the purpose of this study to investigate the impact of uncertainty shocks on worker flows and investigate the role of labor adjustment frictions to shape these responses, we estimate the full model allowing for adjustment frictions in both production

[8] For computational reasons, the plant value may be further simplified by maximizing out the choice of hours worked, which is a static decision problem. Further, the value function is homogeneous in (A, K, L), which can be exploited to factor out one of these state variables. See Bloom (2009) for more details.

Table 1

Set model parameters				
Parameter	Value			Explanation
α	1/3			Capital share in output
ϵ	4			Markup of 33%
w_1	0.8			Hourly wages minimized at 40 hours/week
w_2	2.4e-9			Wage bill equals unity at 40 hours
σ_H	$2 \times \sigma_L$			Uncertainty shock doubles baseline uncertainty
π^{σ}_{LH}	1/36			Uncertainty shock once every 36 years
π^{σ}_{HH}	0.71			Half-life of uncertainty shock 2 months
$(\mu_H + \mu_l)/2$	0.02			Average real growth rate of 2% annualy
π^{μ}_{LH}	π^{μ}_{HL}			Firm-level trend transition matrix symmetric
δ_K	0.1			Capital depreciation 10% annualy
δ_L	0.1			Exogenous labor attrition 10% annualy
r	6.5%			US firm-level discount rate
N	250			Firms operate 250 plants
Estimated model parameters				
	Adjustment Cost Specification			
Parameter	CapLab(E)	Cap	Cap(E)	Explanation
C^P_K	33.9	33.9	42.7	Investment resale loss (%)
C^F_K	1.5	1.5	1.1	Fixed investment cost (% annual sales)
C^Q_K	0	0	0.996	Quadratic capital adjustment cost
C^P_L	1.8			Per capita hiring/firing cost (% annual wages)
C^F_L	2.1			Fixed hiring/firing cost (% annual sales)
C^Q_L	0			Quadratic labor adjustment cost
σ_L	0.443	0.443	0.413	Baseline level of uncertainty
$\mu_H - \mu_L$	0.121	0.121	0.122	Spread of firm trend
π^{μ}_{HL}	0	0	0	Transition of firm trend
γ	2.093	2.093	2.221	Curvature of hours/wage function

factors (CapLab(E)), and when allowing for capital frictions only (Cap(E)). We further consider a third specification, where we use the estimated parameters from the full model specification while setting to zero the labor friction parameters (Cap). Specifically the comparison between CapLab(E) and Cap provides the main intuition for the differential impact of labor adjustment frictions. The comparison also allows us to assess the amplification of the second moment shock on output through the labor market friction. Cap(E) is helpful to assess the fit of the model when employment frictions are abstracted from.

The first eight moments in Table 7 presented in the Appendix A.1 include the second and third moments of investment rates, and the correlation of investment rate with lagged sales and employment growth. Thus, these moments crucially pin down the capital adjustment frictions, while the subsequent eight moments pin down labor adjustment frictions. Importantly, the model fit is basically unaffected when turning off labor frictions, i.e. comparing model CapLab(E) with model Cap. Re-estimating the model when excluding labor frictions, i.e. model Cap(E), worsens the fit of these moments considerably, in particular the lagged correlations with sales and employment growth. [9]

Even though it has not been a target of the model calibration to match the observed monthly layoff and hiring rate in US, the model without labor frictions performs surprisingly well in replicating empirical worker flow rates. The average layoff rate in the model is 1.6% and the hiring rate 3.9% compared to 1.2% and 3.4% empirically, see Davis et al. (2012). On the other side, the model with labor frictions is not close in this dimension, with an average layoff rate of 0.1% and hiring rate of 1.5%.

2.3 Results

In this subsection, we compare the impulse responses upon an unexpected increase of uncertainty in the model with both adjustment frictions, CapLab(E), and when excluding labor frictions, Cap. We refer the reader to the Appendix A.3 for the responses of the re-estimated model with capital frictions only, Cap(E). The effects are qualitatively very similar to the Cap model.

Comparing CapLab(E) with Cap, we observe that in both models hirings and quits falls initially. Layoffs, however, decline initially in CapLab(E) while layoffs increase in Cap. The difference is explained by the employment-side real option effect. When

[9] In order to compensate for the fact that the lagged correlation of employment growth with investment rates and sales growth decline by a lot when shutting off labor frictions. Therefore, re-estimating the model without labor frictions yields significant quadratic capital adjustment costs to increase these lagged correlations.

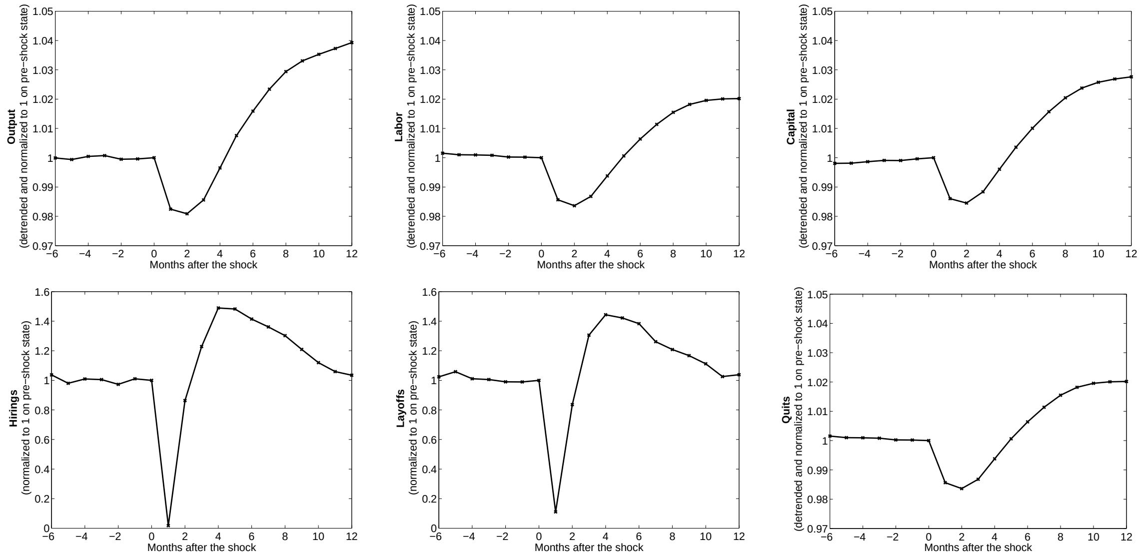


Figure 1: Impulse response functions on a positive uncertainty shock in the capital and labor adjustment costs model, CapLab(E).

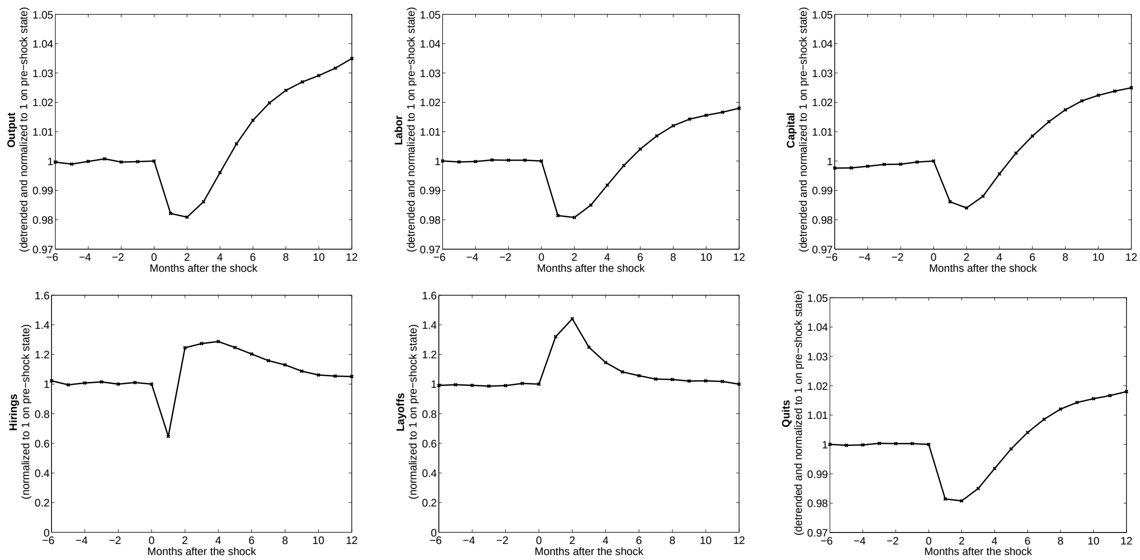


Figure 2: Impulse response functions on a positive uncertainty shock in the capital adjustment costs model, Cap.

uncertainty increases in the model with both frictions, plants do not only postpone investment decisions but they also freeze employment costly adjustments. In turn, both hiring and layoffs fall in that model. In the model, where labor adjustment is frictionless, layoffs increase because the inaction on the investment margin induces more plants to have its capital depreciate which shifts the emplyoment change distribution to the left accordingly. We picture this in Figure 3.

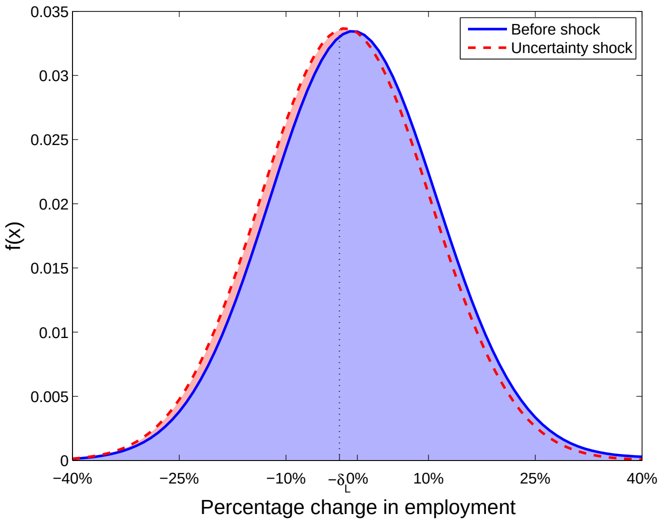


Figure 3: Change in the distribution of employment growth upon uncertainty shock

Accordingly, the mechanism for the decline in hiring differs across the two models although the response is qualitatively very similar. In CapLab(E), hiring decreases because plants freeze employment adjustments. In Cap, however, hiring decreases because of the shift in the employment change distribution induced by plants freezing investment plans.[10]

Importantly, general equilibrium effects are unlikely to affect the firm responses to uncertainty shocks substantially, see Bloom (2009) and Bloom et al. (2014). The reason is that firms freeze, which makes capital adjustments relatively inelastic to factor prices.

Through the lens of the model, the impulse responses of uncertainty shocks on worker flows allows us to identify the relative importance of labor frictions in the economy. Moreover, we are able to assess if higher uncertainty leads to more inactivity at the employment policy. If these frictions are sufficiently strong, an unexpected rise of uncertainty leads to a drop in worker flows as more plants freeze in order to avoid incurring

[10] As with worker flows, the model with labor frictions predicts a decrease of job flows upon an uncertainty shock. While the model without labor frictions predicts an increase of job destruction and a decline of job creation given an unexpected rise in uncertainty.

costs at the current period that would have to be reversed in the near future. However, if labor frictions are sufficiently weak, an uncertainty shock leads plants to actively change their employment policy, and thus, inducing an increase of layoffs and a decrease of hiring.

Under the existence of capital and labor adjustment frictions, an uncertainty increase distorts not only the capital-output ratio but also the capital-labor ratio. Thus, we should expect stronger effect of uncertainty on output when the economy is subject to both frictions. Surprisingly, the output response to uncertainty under both model specifications behaves similarly. Output falls under both scenarios to about 2% with respect to the pre-shock period and relative to trend growth.[11] Through the lens of our model we can conclude that capital frictions are the crucial channel through which uncertainty affects output, while amplification through labor frictions is minor.

While the behavior of worker flows during the first few periods after the shocks is mainly explained by real option effects (both capital-side and employment-side), the response in the subsequent periods is characterized by the frequency effect. By frequency effect, we name the fact that higher realized volatility in the proftability distribution means that plants hit the inaction barrier more often and adjust thus more frequently. Apart from the extensive margin effect, larger realized volatility also implies that on the intensive margin average layoffs and hiring increases. The two effects drive both layoffs and hiring up under both models, which is a noticeable feature in Figure 1 and 2.

3 Empirical Evidence

The theoretical model presented in the previous section implies different effects of uncertainty shocks on worker flows depending on the relative importance of labor frictions in the economy. Furthermore, these results lead to different implications with regard to plants freezing. In order to shed light on this topic, we estimate the empirical effect of uncertainty shocks in US, UK, France and Germany. In particular, the empirical evidence consists of three parts. First, we briefly describe the datasets and variables used for this study. Second, we present the estimation methodology and assess the response of worker flows from uncertainty shocks in the US. Third, we examine the effect of uncertainty on labor flows in UK, France, and Germany relative to US.

[11] As this may be due to the fact that labor frictions are marginal in the present calibration, we repeat the exercise with signficantly larger labor friction parameters, and we similarly found only slightly larger output losses as compared to the model without labor frictions.

3.1 Data Description

The labor flow data for US is drawn from Davis et al. (2012), who extend the worker flows of private sector establishments provided by JOLTS (Job Opennings and Labor Turnover) and BED (Business Employment Dynamics) back until 1990. The dataset contains time series of quits, hirings and layoffs at quarterly frequency for the period 1990-2010.

Worker flow time series for the United Kingdom are based on Labour Force Survey (LFS) for the period 1995-2013. The LFS is a quarterly survey of households living in the United Kingdom and collects information from individuals on issues related with employment for five successive quarters. One of the advantages of this survey consists in the detailed questions on worker flows. More precisely, every worker who has left a job within the last three months is asked for the underlying reason about this job separation. We identify layoffs whenever the worker left because the employer closed down, cut staff or the temporary job ended. Further, we consider a job separation to be a quit whenever the worker resigned or left the job for family or health reasons. Finally, we recognize hiring as those new employee-employer relations which are not older than three months.

We obtain aggregate data on worker flows at quarterly frequency for the period 1999-2013 in France from *Déclarations mensuelles des mouvements de main-d'œuvre* (DMMO) and *Enquête sur les mouvements de main-d'œuvre* (EMMO). The former consists of mandatory declarations for private sector establishments with 50 or more employees about the worker flows movements. The information provided by EMMO complements the data from DMMO. It reports worker movements from a representative sample of private sector establishments between 10 to 49 workers.

For Germany, the data available to us is limited to job flows. However, as these variables are also informative on the relation between labor flows and uncertainty, we consider them for the analysis. We construct job flows at quarterly frequency for the period 1975-2006 in Germany using the Establishment Labor Flow Panel (ELFLOP). This dataset is based on the mandatory resports every plant has to submit to the social security agency, when an employment relationship begins or ends. It provides aggregate job flows for the universe of German establishments at the regional, industry, plant-age and plant-size level.[12]

Our results are based on seasonally adjusted labor flow data.[13]

[12]Following Davis and Haltiwanger (1999), we define job creation as the gross number of new jobs added by expanding and new establishments, and job destruction as the gross number of jobs destroyed by contracting and exiting establishments.

[13]We seasonally adjust the quarterly data of United Kingdom, Germany and France using X12-

Throughout this study, we think of uncertainty shocks as mean-preserving spreads in the distribution of profitability shocks. To be more precise, the literature has distinguished between micro uncertainty and macro uncertainty, where the formers refers to the distribution of idiosyncratic plant-level or firm-level profitability shocks, while the latter refers to profitability shocks common to all plants or firms. As uncertainty is not directly observable, the literature has relied primarily on financial markets and survey indicators to construct uncertainty estimates. These measures include realized and implied stock market volatility, the interquartile range of firm profit growth, and the cross sectional dispersion of forecast about macroeconomic indicators.

In the next section, we empirically assess the relation between uncertainty and labor flows in the US using the macro uncertainty series constructed in Jurado et al. (2013). The authors argue for the importance to distinguish between variability and predictability of an economic indicator. Stock market volatility, for example, may vary due to changes in the capital requirements even though there is no change in the level of uncertainty. Taking this into account, they estimate macro-uncertainty as the average conditional volatility of the unforecastable component of several macroeconomic and financial indicators of the US.

Regarding the European countries in our sample, we also rely on proxies of uncertainty suggested by the literature. As for the United Kingdom, this is the principal component of financial and survey based indicators of economic uncertainty, see Haddow et al. (2013). For Germany, we use the cross-sectional dispersion of the expectation with respect to domestic production for manufacturing firms, see Bachmann et al. (2013). For France, we use realized stock market volatility.

We refer to the appendix for the empirical results using alternative proxies of uncertainty, using stock market levels instead of output, and further details on data sources and definitions.

3.2 Uncertainty and Worker Flows: United States

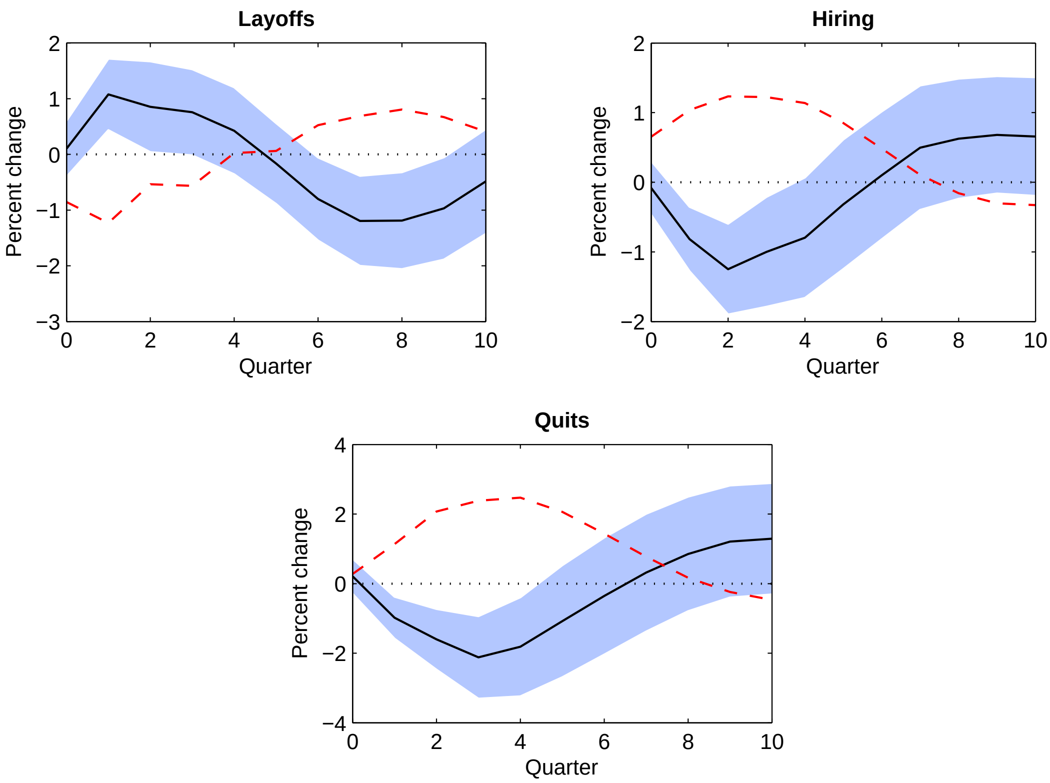
To assess the impact of uncertainty shocks on worker flows, we allow for the dynamic interaction between GDP, uncertainty and worker flows by estimating a structural vector autorregressive (sVAR) models. The frequency of the series in the sVAR is quarterly, estimated with 4 lags, and all variables are standardized and logarithmized.

We consider a five-variate model, including hiring, quits, layoffs, uncertainty and GDP. We identify the impact of structural shocks using short run restrictions and following

ARIMA, while the US data is provided deseasonalized.

above ordering. In specific, we assume that shocks to the worker flow variables and shocks to uncertainty do not impact on GDP contemporaneously. We further restrict worker flow shocks not to affect uncertainty in the same period. We are agnostic about the causal ordering within the worker flow variables, respectively, since its ordering has no impact on the impulse response functions for the first two shocks in the estimated model.[14] The proposed sVAR model 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: Impulse response functions from an uncertainty shock: Worker flows



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 a five-variate sVAR with uncertainty ordered second and worker flow variables last. We use macro uncertainty from Jurado et al. (2013). Shaded regions represent 90% confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

[14]For further details, see Christiano et al. (1999).

Table 2 shows the impulse responses of worker flows to a positive uncertainty shock (solid black line) and to a GDP shock (dash-dot red line), respectively. Empirically, uncertainty has 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 and quits. These responses may be explained by both a model with capital frictions only, but also by a model with additional strong employment adjustment frictions as discussed in Section 2.
However, the positive response of layoffs from an uncertainty shock is not compatible with a model that attributes an important role to employment adjustment frictions. Interestingly, the worker flow variables respond to an uncertainty shock in the same way as to a negative productivity shock.[15] In line with these results, we find that job creation falls and job destruction increases upon a positive uncertainty shock. [16] Our findings are robust to various uncertainty measures, filtering options and changes on the identifying restrictions of the sVAR. Further, the reaction of layoffs and hiring from an uncertainty shock are robust when we focus on continuing plants.[17]

Table 3: Variance decomposition from an uncertainty shock

	Hirings	Quits	Layoffs
1 quarter	0.6%	0.7%	1.1%
2 quarters	10.6%	10.2%	12.3%
4 quarters	22.1%	20.5%	18.4%
8 quarters	21.0%	18.9%	27.6%

Note: All variables are detrended with HP-filter (λ=1600). The forecast-error variance decomposition is based upon the estimation of a five-variate sVAR for worker flows.

We further assess to what extent time-varying uncertainty explains fluctuations of worker flows. For that purpose, we compute the forecast error variance of each worker variable. Table 3 shows that innovations to uncertainty are responsible for at least 18% of the volatility in worker flow variables within the first year. Interestingly, the importance of uncertainty shocks to account for fluctuations in all three worker flows is of very simi-

[15]In the same direction as our results, Leduc and Liu (2014) provide evidence that an uncertainty shock act as a negative demand shock as it raises unemployment and inflation.

[16]The figures are provided in the Appendix. In specific, we estimate a structural VAR containing GDP, uncertainty, job creation and job destruction. We find that an unexpected increase of uncertainty leads to more job destruction and less job creation (see Table 12).

[17]More details are provided in Appendix A.5.

lar quantitative importance. These results suggest that uncertainty is a quantitatively important factor to explain the behavior of worker flows.

Through the lens of the model presented in Section 2, our empirical findings allow us to arrive at two main conclusions for the US. First, labor frictions are relatively small such that uncertainty shocks affects the economy mostly through capital frictions. Second, plants do not freeze employment adjustments upon an unexpected rise of uncertainty. It is important to point out that our empirical findings do not imply that labor frictions are non-existent in US. It rather suggest that these frictions are rather small and more precisely smaller than as calibrated in Bloom (2009). Another interpretation is that the labor adjustment frictions appear sufficiently small such that abstracting from them does not seem to impair the model fit.

3.3 Effect of Uncertainty Shocks Across Countries

Our theoretical results show that the degree of labor frictions matters for the qualitative and quantitative effect of uncertainty on worker flows. In fact, we should expect lower reaction of layoffs and job destruction in countries with stricter labor market regulations relative to countries with flexible labor markets, *ceteris paribus*.[18] This is due to the fact that when stricter regulation raises labor adjustment costs, this leads to a stronger role of the employment-side real option effect.

We study the impact of uncertainty on labor flows for UK, Germany, and France vis-a-vis the US. We estimate the sVAR model for each country separately and the impulse response functions presented in Appendix A.6. The UK data shows a behavior of worker flows fairly similar to the US with layoffs significantly increasing while hirings and quits significantly decreasing. The German data allows us only to compare job flows, but the results are qualitatively similar to the US with job creation (destruction) significantly decreasing (increasing). As for France, we find that layoffs decline on impact from an uncertainty shock. Through the lens of the model, this finding implies that labor frictions in France are stronger and an uncertainty shocks induces more plants to freeze their employment decisions.

Furthermore, we assess the quantiative difference in the response of labor flows as compared to the US. To do so, we estimate the sVAR model from each country separately and obtain the mean response from a one standard deviation uncertainty shock. Then,

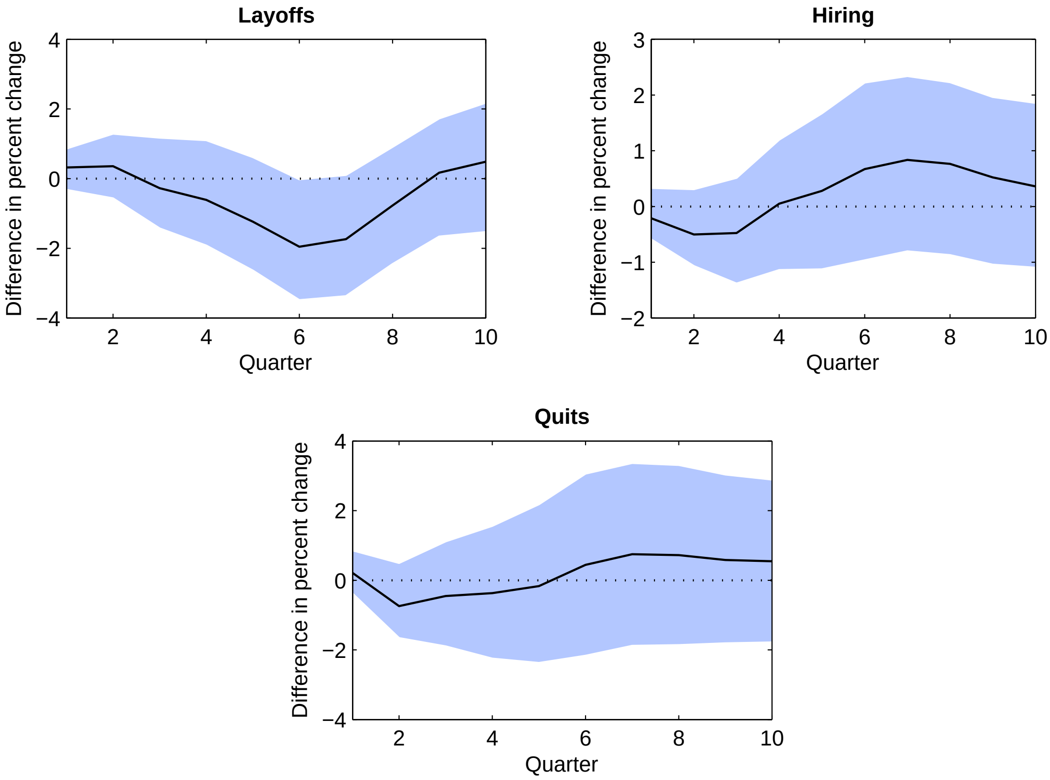
[18]This holds only true to the extent that labor market regulation affects the employment adjustment costs. This is clearly the case with restrictions imposing firing costs on firms, but less clearly so with minimum wages. In the following, we think of more labor market regulation as more frictional labor adjustment.

using as reference the mean response in US, we subtract the mean response of the country under interest. We bootstrap over this difference to obtain confidence intervals.[19] The *relative* impulses responses from an uncertainty shock across countries are presented in Table 4, 5, and 6. Layoffs and job destruction increase significatively more in US vis-a-vis France and Germany. For UK, we do not find significant difference relative to US.

While for the US, our results suggest fixed costs on labor to be of little importance, the international comparison shows that the general model is right in describing the behavior of labor flows for different labor adjustment cost levels. The differential response to uncertainty shocks in France is not surprising given that layoffs decrease in the estimated sVAR model. Furthermore, holding the response of quits constant and assuming that plants do not hire and layoff workers within the same period, the smaller increase of job destruction in Germany vis-a-vis US, suggests that labor regulations in Germany leads more plants to adopt a *wait-and-see* behavior for emplyoment changes when uncertainty rises.

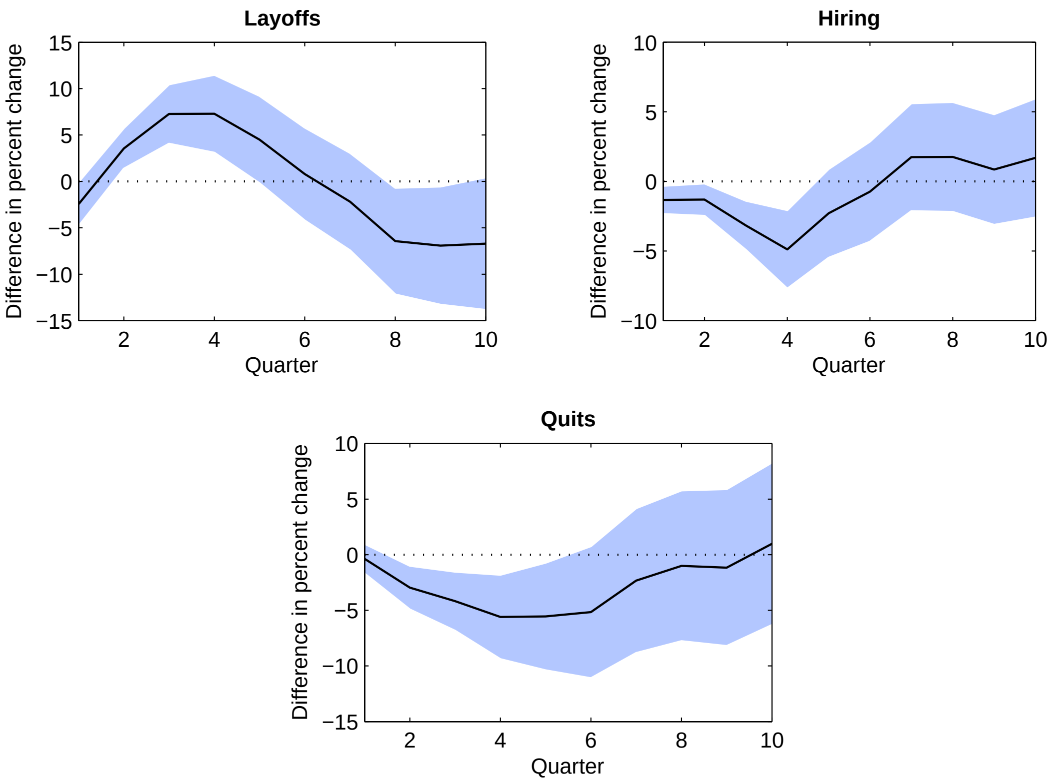
[19]For comparison purposes, we demean and normalize each uncertainty proxy by its standard deviation.

Table 4: Impulse response functions from an uncertainty shock: US vs. UK (Private sector)



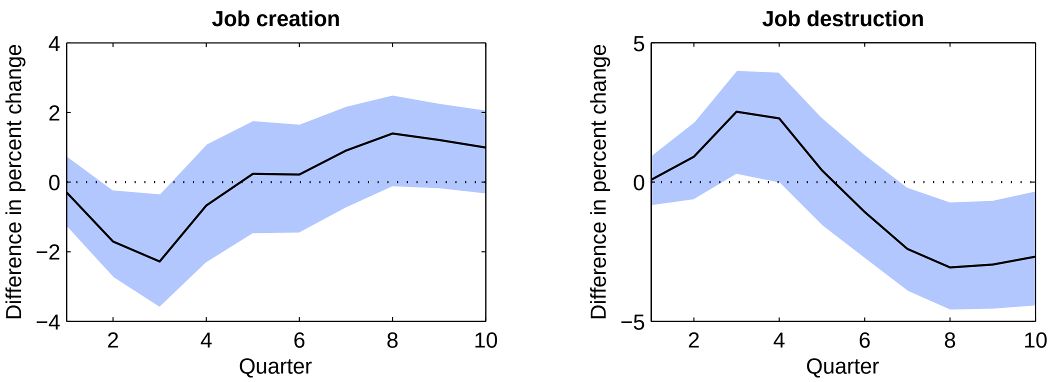
Note: Difference in impulse response from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with uncertainty ordered second and worker flow variables last. We use macro uncertainty from Jurado et al. (2013) for US and principal component of uncertainty from Haddow et al. (2013) for UK. Shaded regions represent 90% standard error confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

Table 5: Impulse response functions from an uncertainty shock: US vs. France (Manufacturing)



Note: Difference in impulse response from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with uncertainty ordered second and worker flow variables last. We use macro uncertainty from Jurado et al. (2013) for US and realized stock market volatility for France. Shaded regions represent 90% standard error confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

Table 6: Impulse response functions from an uncertainty shock: US vs. Germany (Manufacturing)



Note: Difference in impulse response from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a four-variate sVAR with uncertainty ordered second and worker flow variables last. We use macro uncertainty from Jurado et al. (2013) for US and ex-ante forecast dispersion of future production from Bachmann et al. (2013) for Germany. We concentrate the analysis on manufacturing due to the fact that the proxy of uncertainty in Germany is constructed based on a survey in the manufacturing sector. Shaded regions represent 90% standard error confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

4 Conclusion

This paper revises the real option literature with a special focus on labor markets. We replicate the model presented in Bloom (2009), but decompose the employment change into layoffs, quits and hiring. This decomposition identifies the importance of employment adjustment costs. Under frictional employment adjustment, a positive uncertainty shock affects employment mainly through the employment-side real option channel. Plants wait longer until they adjust employment, which induces a decline in both layoffs and hiring. On the other extreme, when employment adjustment is frictionless, employment adjustment is driven by the plants' investment response. The capital-side real option channel induces plants to postpone investment decisions. In turn, labor demand falls primarily through increased capital misallocation, which implies higher layoffs and lower hiring. Understanding the importance of capital and employment adjustment frictions separately is important for policy makers, as it determines the responsiveness of investment and employment to fiscal or monetary policy changes during periods of high uncertainty.

Empirically, our findings establish a new stylized fact for the US labor market: A positive shock to uncertainty reduces hirings and quits, while it raises layoffs. Further, job creation falls and job destruction rises. Based on our identification, the empirical finding supports a model with weak employment adjustment frictions. The employment-side real option channel seems to be negligible as it contradicts the response of layoffs on positive uncertainty shocks. In other words, while plants postpone investment plans, they do not freeze their employment decisions, which renders employment responsive to policy interventions during periods of high uncertainty. We see this finding as complementary to Bloom et al. (2007), which argues that investments are fairly unresponsive to policy interventions, such as reduced interest rates on loans. Interestingly, as firms do not adjust their capital stock, the policy maker can raise employment through subsidizing labor expenses, while capital does not respond.

Additionally, we assess the response of worker flows and job flows across countries. For the UK, we find that worker flows match closely the behavior of their US counterparts. For France, we obtain that hiring and quits decline in response to a positive uncertainty shock. Contrary to the US finding, layoffs decline on impact. Further, German job flows behave comparably to the US. While for the US, our results suggest fixed costs on labor to be of little importance, the international comparison shows that the general model is right in describing the behavior for different adjustment cost levels. In particular, the empirical findings corresponds to measures of labor market rigidities, that find the

French labor market to be significantly more rigid than the US (or UK) labor market. Beyond that, our results suggest that employment is less responsive to policy changes in France.

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A Appendix

A.1 Target moments

Table 7: Target moments

Moments	Data	CapLab(E)	Cap	Cap(E)
Correlation $(I/K)_{it}$ with $(I/K)_{it-2}$	0.328	0.268	0.276	0.343
Correlation $(I/K)_{it}$ with $(I/K)_{it-4}$	0.258	0.221	0.224	0.254
Correlation $(I/K)_{it}$ with $(\Delta L/L)_{it-2}$	0.208	0.205	0.201	0.233
Correlation $(I/K)_{it}$ with $(\Delta L/L)_{it-4}$	0.158	0.173	0.163	0.167
Correlation $(I/K)_{it}$ with $(\Delta S/S)_{it-2}$	0.260	0.283	0.274	0.322
Correlation $(I/K)_{it}$ with $(\Delta S/S)_{it-4}$	0.201	0.211	0.201	0.225
Standard deviation $(I/K)_{it}$	0.139	0.149	0.148	0.129
Skewness $(I/K)_{it}$	1.789	1.785	1.740	1.697
Correlation $(\Delta L/L)_{it}$ with $(I/K)_{it-2}$	0.188	0.195	0.098	0.136
Correlation $(\Delta L/L)_{it}$ with $(I/K)_{it-4}$	0.133	0.154	0.096	0.109
Correlation $(\Delta L/L)_{it}$ with $(\Delta L/L)_{it-2}$	0.160	0.149	0.054	0.077
Correlation $(\Delta L/L)_{it}$ with $(\Delta L/L)_{it-4}$	0.108	0.121	0.052	0.054
Correlation $(\Delta L/L)_{it}$ with $(\Delta S/S)_{it-2}$	0.193	0.212	0.099	0.130
Correlation $(\Delta L/L)_{it}$ with $(\Delta S/S)_{it-4}$	0.152	0.149	0.083	0.096
Standard deviation $(\Delta L/L)_{it}$	0.189	0.211	0.250	0.228
Skewness $(\Delta L/L)_{it}$	0.445	0.581	0.236	0.151
Correlation $(\Delta S/S)_{it}$ with $(I/K)_{it-2}$	0.203	0.219	0.162	0.218
Correlation $(\Delta S/S)_{it}$ with $(I/K)_{it-4}$	0.142	0.150	0.118	0.152
Correlation $(\Delta S/S)_{it}$ with $(\Delta L/L)_{it-2}$	0.161	0.166	0.095	0.129
Correlation $(\Delta S/S)_{it}$ with $(\Delta L/L)_{it-4}$	0.103	0.118	0.080	0.092
Correlation $(\Delta S/S)_{it}$ with $(\Delta S/S)_{it-2}$	0.207	0.240	0.171	0.205
Correlation $(\Delta S/S)_{it}$ with $(\Delta S/S)_{it-4}$	0.156	0.154	0.105	0.124
Standard deviation $(\Delta S/S)_{it}$	0.165	0.161	0.177	0.162
Skewness $(\Delta S/S)_{it}$	0.342	0.161	0.464	0.162
Criterion		404	819	625

A.2 Job flows responses in the model

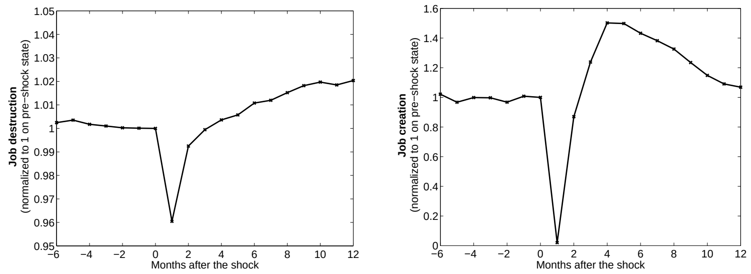


Figure 4: Labor & Capital adjustment costs model (CapLab(E))

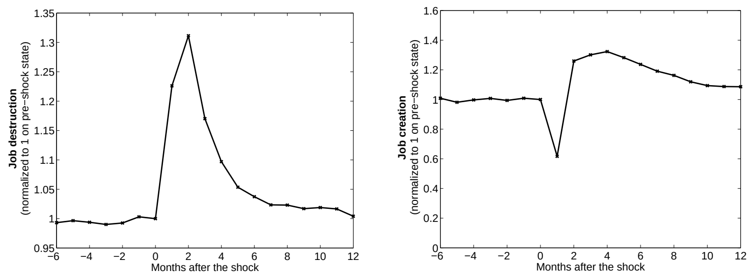


Figure 5: Capital adjustment costs model (Cap)

A.3 Capital adjustment cost model based on the re-estimation of the model

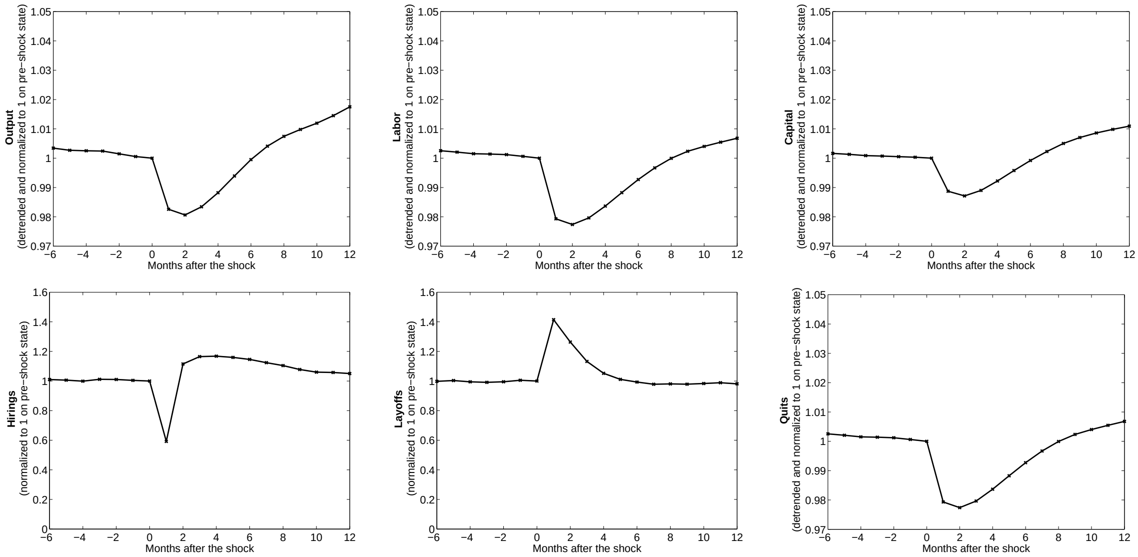


Figure 6: Capital adjustment costs model (Cap(E))

A.4 Data Sources and Description

Table 8: United States

Variable	Description	Source
Jur-Macro	Common variation in the unforecastable component of a large number of economic indicators. Data available from 1960M1-2011M12. We use quarterly averages of the monthly series.	Jurado et al. (2013)
Jur-Firm	Common variation in the unforecastable component of firm profit growth. Data available from 1970Q3-2011Q2.	Jurado et al. (2013)
Stock	Chicago Board of Options Exchange VXO index of percentage implied volatility, on a hypothetical at the money S&P100 option 30 days to expiration. We use quarterly averages of the monthly series.	CBOE
IQR	Inter-quantile range of firm sales growth based on Compustat firms. Data available from 1962Q1-2010Q3.	Bloom et al. (2013)
Pol	Economic Policy Uncertainty Index. Consist on an index of three components. First, coverage of policy-related economic uncertainty. Second, the number of federal tax code provisions to be expired in future years. Third, disagreement among economic forecasters with respect to the evolution of macroeconimc variables. Data available from 1985M1-2014M7.	Baker et al. (2013)
Worker flows	The worker flows are based upon JOLTS establishment microdata and growth rate densities from the Business Employment dynamics.	Davis et al. (2012)
Job flows	Gross job gains and gross job losses, decomposed by continuing, entering and exiting establishment, available from 1990Q2-2013Q4.	BEA
GDP	Inflation adjusted value of goods and services in United States. Data available from 1947Q3-2014Q2.	FRED

Table 9: United Kingdom

Variable	Description	Source
Uncertainty	Principal component analysis of a set of uncertainty proxies. Among them, the FTSE option-implied volatility, dispersion of company earning and gdp growth forecasts and sterlin option-implied volatility. Data available from 1985M3-2014M3. We use quarterly averages of the monthly series.	Haddow et al. (2013)
Worker flows	We construct worker flows in UK using the labor force survey. Whenever a person change the job or the employment status within the quarter, the survey asks for the reason of this change and when it has occurred. We identify layoffs as the E (employment) to E and E to U (unemployment) movements that are because the worker has been made redundant, dismissed or temporary job ended. Furthermore, quits are E to E and E to U movements where the worker have resigned, gave up for health or family reasons. Finally, total hiring is constructed as U to E and E to E movements. We deseasonalize the data using X12-ARIMA. Data available from 1995Q1-2013Q3.	LFS

Table 10: Germany

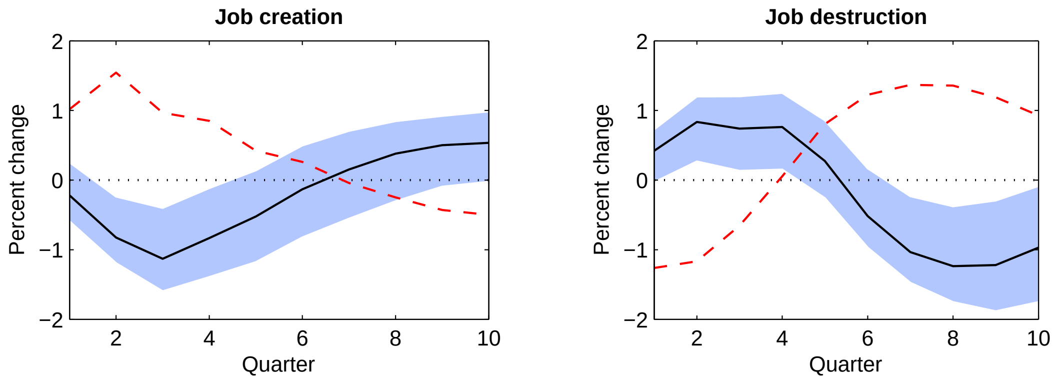
Variable	Description	Source
Uncertainty	Cross sectional manufacturing survey forecast disagreement with respect to the growth of domestic production in the next three months. The data is available for the period 1980M1 2010M12	Bachmann et al. (2013)
Job flows	We obtain job flows in Germany using the Establishment Labor Flow Panel (ELFLOP). It contains information on gross job gains and job losses by plant size and age for the universe of German establishments. The ELFLOP covers the time period 1975Q2-2006Q4.	Seth (2013)

Table 11: France

Variable	Description	Source
Uncertainty	Monthly standard deviation of the daily CAC40 index. We use quarterly averages of the monthly series.	Bloomberg
Worker flows	We construct worker flows in France using the DMMO-EMMO survey, which contains information of all workforce movements for a given establishment employment more than 9 employees in France. For each movement, we know the legal form of the contract and the reason of separation. The data is available for the period 1999Q1-2010Q4.	DMMO-EMMO

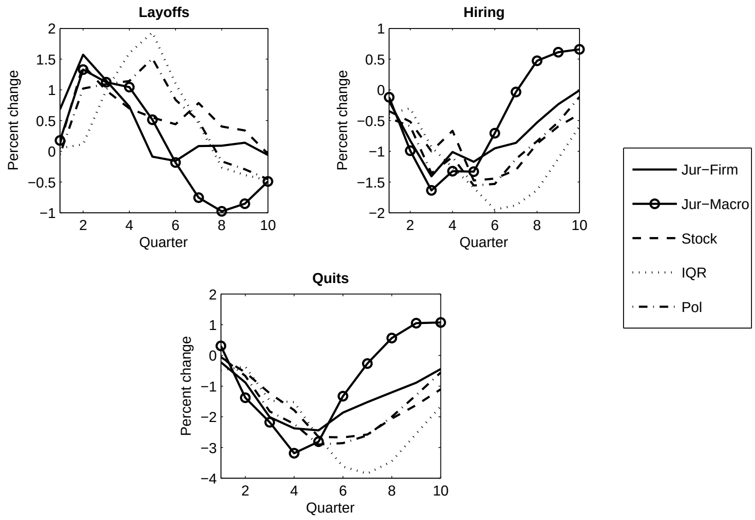
A.5 Robustness Tests

Table 12: Impulse response functions from an uncertainty shock: Job flows



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 a four-variate sVAR with uncertainty ordered second and job flow variables last. We use macro uncertainty from Jurado et al. (2013). Shaded regions represent 90% confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

Table 13: US: IRFs of worker flows from an uncertainty shock using different proxies of uncertainty

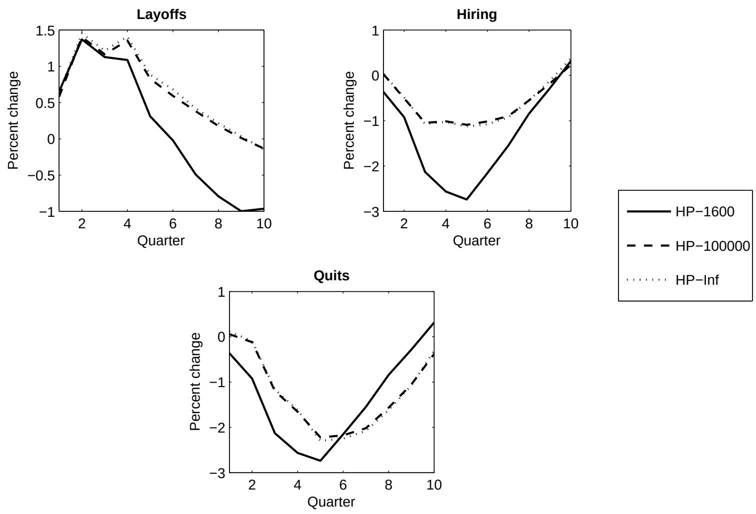


Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with uncertainty ordered second and worker flow variables last. We use different proxies of uncertainty: Jur-Firm (firm level uncertainty based on Jurado et al. (2013)), Jur-Macro (macro uncertainty based on Jurado et al. (2013)) Stock (S&P500 implied volatility), IQR (IQR firm sales growth from Compustat firms), POL (policy uncertainty based on Baker et al. (2013)). All variables are in logs and detrended with HP-filter (λ=1600).

Table 14: US: IRFs of job flows from an uncertainty shock using different proxies of uncertainty

Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a four-variate sVAR with uncertainty ordered second and job flow variables last. We use different proxies of uncertainty: Jur-Firm (firm level uncertainty based on Jurado et al. (2013)), Jur-Macro (macro uncertainty based on Jurado et al. (2013)) Stock (S&P500 implied volatility), IQR (IQR firm sales growth from Compustat firms), POL (policy uncertainty based on Baker et al. (2013)) All variables are in logs and detrended with HP-filter (λ=1600).

Table 15: US: IRFs of worker flows from an uncertainty shock under different filtering alternatives

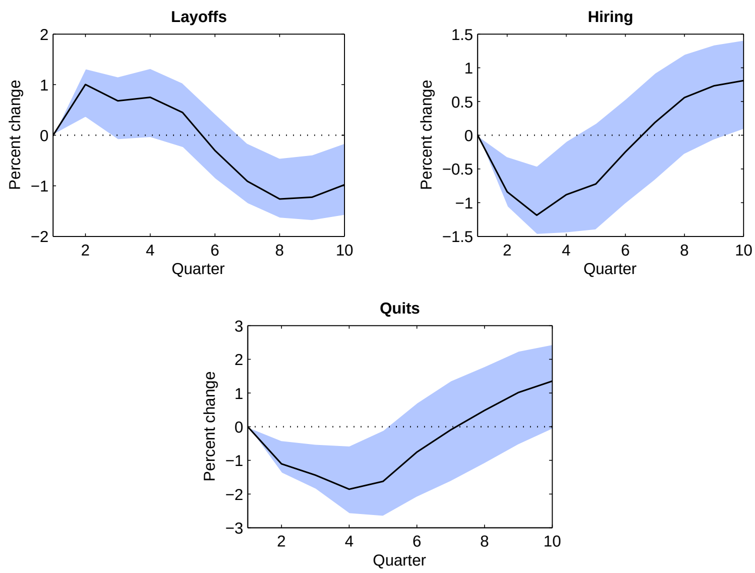


Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with uncertainty ordered second and worker flow variables last. We use Jur-Macro uncertainty. All variables are in logs and detrended under different filtering alternatives.

Table 16: US: IRFs of job flows from an uncertainty shock under different filtering alternatives

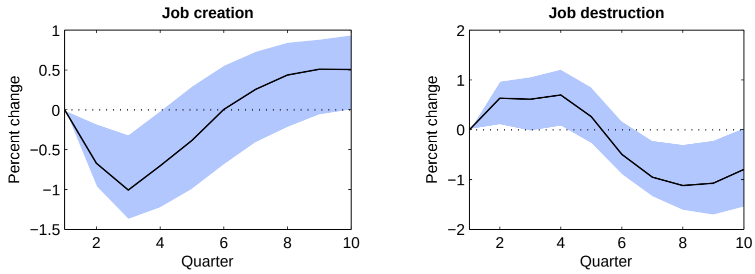
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a four-variate sVAR with uncertainty ordered second and job flow variables last. We use Jur-Macro uncertainty. All variables are in logs and detrended under different filtering alternatives.

Table 17: US: IRFs of worker flows from an uncertainty shock under different ordering assumption



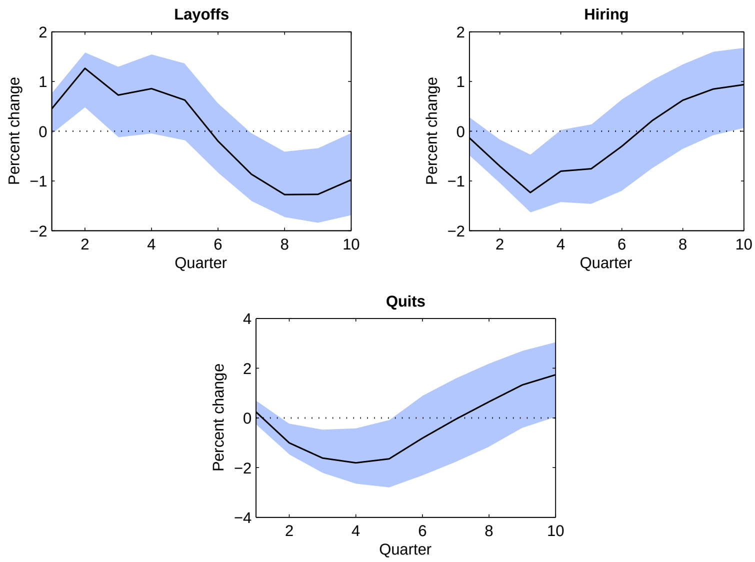
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with worker flows ordered first, gdp second and uncertainty last. We use macro uncertainty from Jurado et al. (2013). Shaded regions represent 90% confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

Table 18: US: IRFs of job flows from an uncertainty shock under different ordering assumption



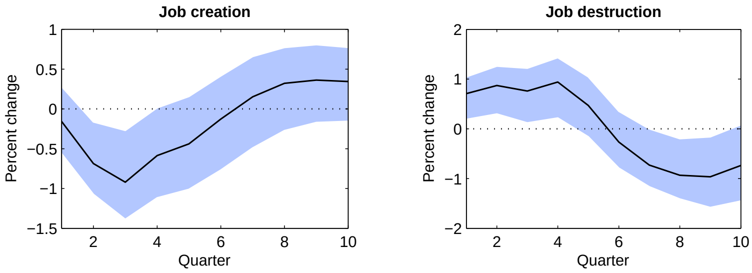
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a four-variate sVAR with job flows ordered first, gdp second and uncertainty last. We use macro uncertainty from Jurado et al. (2013). Shaded regions represent 90% confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

Table 19: US: IRFs of worker flows from an uncertainty shock using stock market level instead of GDP



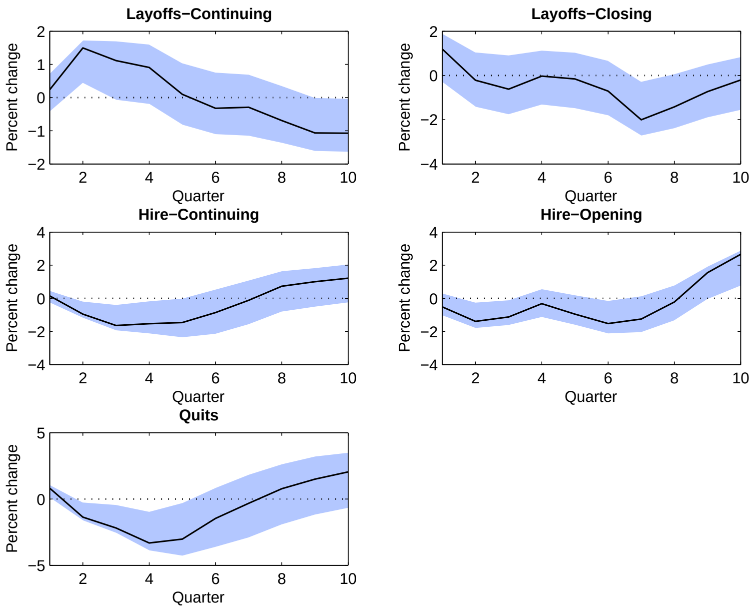
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with stock market level ordered first, worker flows second and uncertainty last. We use macro uncertainty from Jurado et al. (2013). Shaded regions represent 90% confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

Table 20: US: IRFs of job flows from an uncertainty shock using stock market level instead of GDP



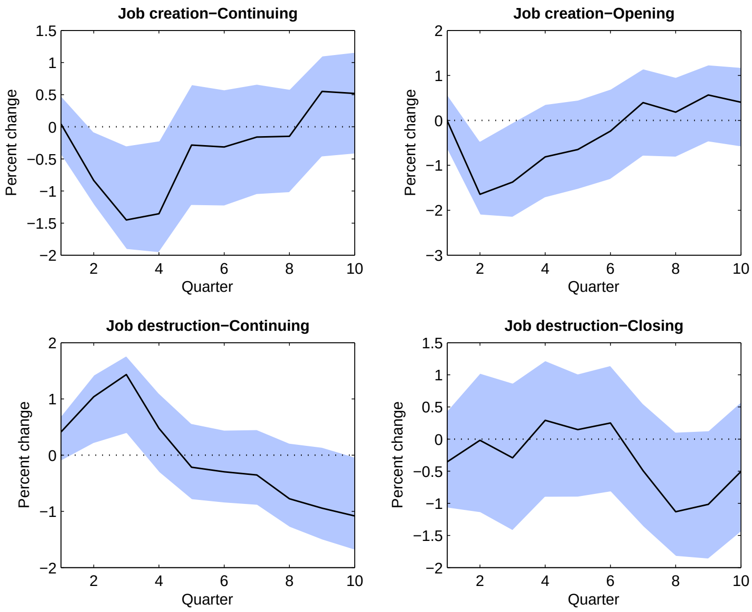
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a four-variate sVAR with stock market level ordered first, job flows ordered second and uncertainty last. We use macro uncertainty from Jurado et al. (2013). Shaded regions represent 90% confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

Table 21: US: IRFs of worker flows from an uncertainty shock controlling for entry and exit



Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a seven-variate sVAR with uncertainty ordered second and worker flow variables last. We use macro uncertainty from Jurado et al. (2013). Shaded regions represent 90% confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

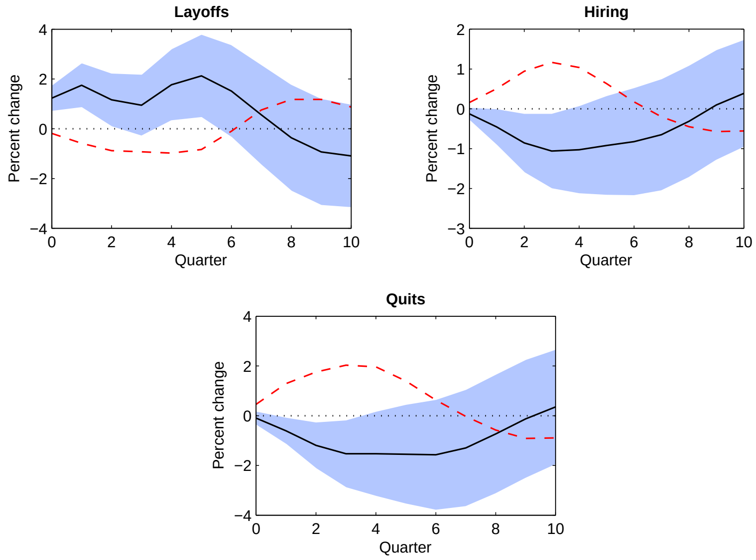
Table 22: US: IRFs of job flows from an uncertainty shock controlling for entry and exit



Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a six-variate sVAR with uncertainty ordered second and job flow variables last. We use macro uncertainty from Jurado et al. (2013). Shaded regions represent 90% confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

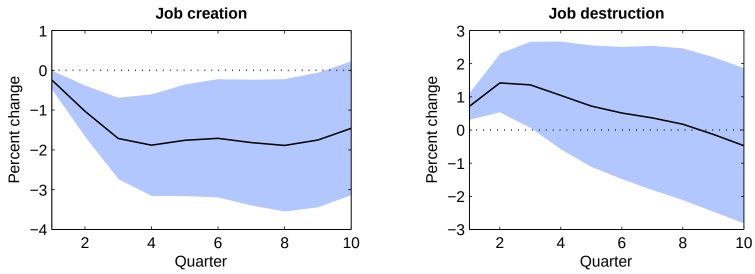
A.6 Uncertainty shocks across countries

Table 23: UK: Impulse response functions from an uncertainty shock (All economy)



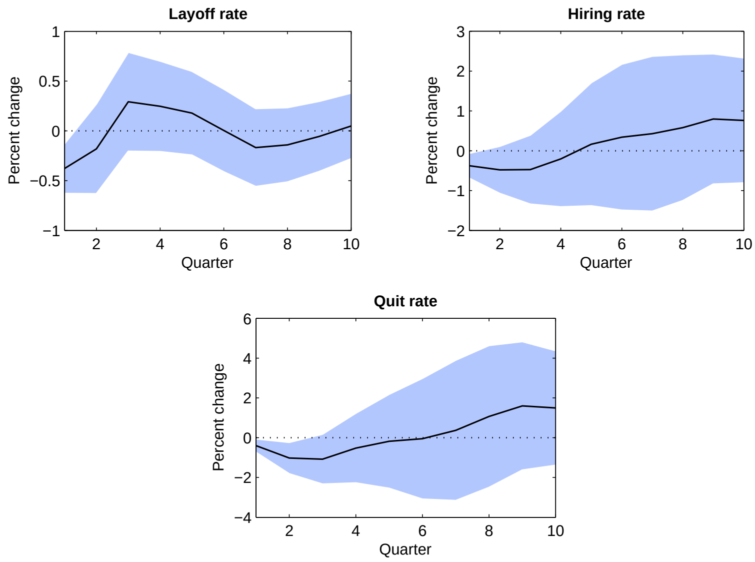
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with uncertainty ordered second and worker flow variables last. We use principal component of uncertainty based on Haddow et al. (2013). Shaded regions represent 90% confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

Table 24: Germany: Impulse response functions from an uncertainty shock (Manufacturing)



Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a four-variate sVAR with uncertainty ordered second and the job flow variables last. We use ex-ante forecast dispersion of future production from Bachmann et al. (2013) as proxy of uncertainty. Shaded regions represent 90% confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).

Table 25: France: Impulse response functions from an uncertainty shock (Manufacturing)



Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with uncertainty ordered second and the worker flow variables last. We use stock market volatility as uncertainty. Shaded regions represent 90% confidence interval from an uncertainty shock based on Kilian (1998) bootstrap. All variables are in logs and detrended with HP-filter (λ=1600).