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# Do plants freeze upon uncertainty shocks?\*

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[Preliminary version]

## Abstract

Following the real option literature, whether or not uncertainty shocks drive business cycles depends on the degree of adjustment frictions. The more plants freeze and remain inactive in response to increased uncertainty, the stronger the adverse effects on the economic activity. Using quarterly labor flow data of U.S. establishments, we find that an unexpected increase in uncertainty reduces hirings, quits and job creation, while it raises layoffs and job destruction. Our finding suggests that plants remain active as a result of uncertainty shocks. A partial equilibrium model with capital and labor adjustment costs can not explain our empirical results. Surprise increases in uncertainty leads plants to freeze investment and labor policies. We are able to rationalize our findings using a version of this model without labor adjustment frictions. As uncertainty increases, more plants adopt a wait-and-see policy for investment. This, in turn, reduces capital through depreciation of the existing capital stock, and thereby lowers labor demand, which implies more layoffs and less hiring. The model implies that economies with flexible labor market regulations should experience more layoffs and job destruction upon an uncertainty shock with respect to economies with stricter regulations. Using additional labor flow data from Germany, France 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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# 1 Introduction

Uncertainty shocks may cause economic recessions. As uncertainty rises, the option value of waiting increases and plants optimally freeze investments and employment decisions. Such *wait-and-see* behavior reduces GDP through two main channels. First, higher inactivity decreases the aggregate capital from depreciation. Second, the allocation of production factors worsens. Whether or not uncertainty shocks explain sizable business cycle fluctuations depends importantly on the strength of these real option effects.

In this paper, we analyze 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 effect of uncertainty on worker and job flows.

In particular, we assess the response of labor flows (layoffs, quits, hiring, job destruction and job creation) on uncertainty by estimating conditional correlations and structural VARs.<sup>1</sup> We set up a simple regression model, where we control for real GDP to obtain conditional correlations of worker and job flows with uncertainty. We further estimate two structural vector autorregressive models. First, we consider a five-variate model including worker flows, uncertainty and real GDP. Second, we estimate a four-variate model containing job flows, uncertainty and real GDP. Our baseline identification assumption is that neither innovations to labor flows, nor uncertainty shocks, do contemporaneously affect real GDP.<sup>2</sup>

We find that hiring, quit, and job creation are negatively correlated with uncertainty, while layoffs and job destruction positively co-move with uncertainty, after controlling for real GDP. When estimating the impulse responses on structural uncertainty shocks based on the VAR models, we find qualitatively the same significant relations. Our empirical finding constitutes new stylized fact for the U.S. labor market: A positive shock to uncertainty reduces hirings, quits and job creation, while it raises layoffs and job destruction. Interestingly, these labor flow variables respond to an uncertainty increase

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<sup>1</sup>Following the literature, we define job creation as the gross number of new jobs added by expanding and new establishments. Further, we define job destruction as the gross number of jobs destroyed by contracting and exiting establishments.

<sup>2</sup>We use labor flow data from United States based on a recently developed database from Davis et al. (2012), who extend the job and worker flows of private sector establishments provided by the Job Openings 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.

in the same way as to a negative productivity shock.<sup>3</sup>

The models from Bloom (2009), Bloom et al. (2014) and Bachmann and Bayer (2013) are natural candidates to explain our empirical results. They consider a model with time-varying volatility and non-convex adjustment costs to explain the effect of uncertainty on aggregate employment, capital and output. However, they differ in the markets which are subject to frictions and their main results. While the former two papers include capital and labor adjustment frictions and find sizable effect of uncertainty, the latter study considers only capital frictions and do not find that uncertainty is a major source of business cycle fluctuations. This distinction may be crucial to arrive at the opposite conclusions. If an uncertainty shock induces plants to freeze investment and labor policies, this amplifies the effect of uncertainty shocks on output as it distorts the capital-output and the capital-labor ratio.

We compare the effect of uncertainty shocks on labor flows varying the degree of labor adjustment frictions. In particular, we consider a model, where we allow for labor frictions, and a second where we explicitly rule out such friction. Both models are subject to capital adjustment frictions and identical otherwise. For comparability reasons, we closely follow Bloom (2009) in setting the model up.

Based on the model with adjustment costs on both factors of production we obtain, contrary to our empirical results, a decline of job destruction and layoffs from an unexpected increase in uncertainty. As hiring and layoffs is costly in the model, plants may decide to freeze in order to avoid paying layoff (hiring) costs that would have to be reverted in the near future. In contrast, when labor is not (or only weakly) frictional, the response of layoffs is fundamentally different. As uncertainty increases, more plants freeze their investment decisions. This reduces capital through depreciation of the existing capital stock, and thereby lowers labor demand, which implies more layoffs and less hiring, in concordance with our empirical results. Surprisingly, we find similar and sizable effect of uncertainty shocks on output in both model specifications, allowing us to conclude that capital friction is the crucial channel through which uncertainty affects output in the model.

The model implies that economies with flexible labor market regulations should experience more layoffs and job destruction upon an uncertainty shock with respect to economies with stricter regulations.<sup>4</sup> Using French, German, and UK labor flow data,

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<sup>3</sup>Several studies have documented the pro-cyclical behavior of hirings, quits and job creation, and the counter-cyclical behavior of layoffs and job destruction. See for instance Fujita and Nakajima (2013), Hall and Lazear (1984), Shimer (2005) and Solon et al. (2009).

<sup>4</sup>We do not have a prediction with respect to the difference of hiring and job creation between countries with stricter vs. flexible labor market regulations. A model with or without labor adjustment

we find that layoffs and job destruction increase significantly less in France, and Germany vis-a-vis the US response. In the case of UK, we do not find significant difference relative to US. Given that especially the French and German labor market are more rigid than the US, this may be seen as further support of the model implication.

This study is related to a growing literature that analyzes the macroeconomic effects of uncertainty shocks. First, we contribute to the discussion whether uncertainty drives business cycles. While Bloom (2009) and Bloom et al. (2014) include capital and labor adjustment frictions and find sizable effects of uncertainty shocks on the real economic activity, Bachmann and Bayer (2013) abstracts from the labor friction, and finds that uncertainty shocks are unlikely an important driver of business cycles. Interestingly our model with only capital adjustment costs can account for an important drop and rebounds in output upon uncertainty shocks of around 2%.<sup>5</sup>

Second, our paper is related to the literature on employment and investment under uncertainty.<sup>6</sup> To the best of our knowledge, we are the first to provide evidence that the *wait-and-see* policy, under unexpected higher uncertainty, is dominated at the layoff decision.

Our analysis abstract from financial frictions, search 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.<sup>7</sup> We explore how well a model with risk neutral agents that are subject

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frictions predicts a decrease of these worker flows upon an uncertainty shock.

<sup>5</sup>Is important to recognize that Bachmann and Bayer (2013) present impulse responses from the model at yearly frequency, while we document responses upon uncertainty shocks at monthly frequency. If we aggregate the effects at yearly frequency, we do not find sizable effects of uncertainty on output.

<sup>6</sup>Some examples are: (1) Oi-Hartman-Abel effect (Oi (1961), Hartman (1972) and Abel (1983)), (2) real option effect (Bernanke (1983), Dixit and Pindyck (1994), Caballero and Engel (1999) and Bloom (2009)), (3) frequency margin effect (Bloom (2009) and Bachmann and Bayer (2014)), (4) financial frictions (Christiano et al. (2010), Arellano et al. (2012) and Gilchrist et al. (2013)), (5) precautionary savings (Basu and Bundick (2012), Born and Pfeifer (2013) and Fernandez-Villaverde et al. (2011)) and (6) search frictions (Schaal (2012), Guglielminetti (2013) and Leduc and Liu (2014)). Additionally, other studies who provide empirical findings on the effect of uncertainty in the economy are 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).

<sup>7</sup>If an economy is subject to financial frictions, an increase in uncertainty rises the debt repayment costs as the probability of default increases given limited contract enforceability. This effect leads plants to reduce their size, in order to decrease the default risk. On the other side in a model with risk aversion, an increase in uncertainty leads households to increase savings and reduce consumption for precautionary reasons. This transmission channel is commonly 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 imply an increase of markups over marginal costs, which yields a decline of consumption and investment. In contrast to the mentioned frictions, the theoretical implications of an economy with search frictions and time-varying uncertainty are different. Mortensen and Pissarides

to non-convex factor adjustment costs is able to rationalize our empirical findings. The remainder of this paper proceeds as follows: Section 2 describes our dataset, econometric approach and provides the empirical findings. Section 3 presents the adjustment frictions model and the differential responses when varying the degree of labor adjustment frictions. Finally, Section 4 concludes. An Appendix follows with robustness results and model derivations.

## 2 Empirical Evidence

The empirical evidence consist in three main sections. First, we briefly describe the datasets and variables used for this study. Second, we assess the response of job and worker flows from uncertainty shocks in US. Third, we examine the effect of uncertainty on labor flows in countries with different degree of labor market regulations.

### 2.1 Data Description

#### 2.1.1 Labor Market Flows

Our results are based on seasonally adjusted labor flows data from United States, United Kingdom, Germany and France.<sup>8</sup>

The data for United States is drawn from Davis et al. (2012), who extend the job and 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 job creation, job destruction, quits, hirings and layoffs at quarterly frequency for the period 1990-2010.

The information of worker flows in United Kingdom is based on LFS (Labour Force Survey) 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 on the detailed questions on worker flows. More precisely, every worker who have left a job within the 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

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(1994) shows analytically that the match surplus strictly increase in uncertainty, which leads to an increase of hiring and job creation.

<sup>8</sup>We seasonally adjust the quarterly data of United Kingdom, Germany and France using X12-ARIMA. The aggregate time series for United States are provided seasonalized.

the worker resign or left the job for family or health reasons. Finally, we recognize hiring as those new employee-employer relations which are not older than the three months. We construct job flows at quarterly frequency for the period 1975-2006 in Germany using the ELFLOP (Establishment Labor Flow Panel). The source used to construct this dataset is based on the mandatory reports from every plant, elaborated to the social security agency whenever the employment relationship begins and ends. This database provide aggregate job flows for the universe of German establishments at the regional, industry, plant-age and plant-size level.

Finally, we obtain aggregate data on worker flows at quarterly frequency for the period 1999-2013 in France from DMMO and EMMO (*Déclarations mensuelles des mouvements de main-d'œuvre* and *Enquête sur les mouvements de main-d'œuvre*). The former consist 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.

### 2.1.2 Uncertainty

Throughout the study, we think about uncertainty as a mean-preserving spread in the productivity distribution. The literature have distinguished between two types of uncertainty processes: micro-uncertainty and macro-uncertainty. The former refers to time-varying idiosyncratic productivity dispersion, while the second alludes to time-varying volatility in the aggregate productivity.

While uncertainty is not directly observable, the literature has relied primarily on financial market and survey indicators to get an approximation of this variable. As an example, we could find realized and implied stock market volatility, inter-quartile range of firm profit growth, cross sectional dispersion of forecast about macroeconomic indicators, among others.

In the next section, we will empirical assess the relation between uncertainty and labor flows in US using the estimated macro-uncertainty series proposed by Jurado et al. (2013). The authors argue about the importance to distinguish between variability and predictability of an economic indicator. For example, stock market volatility may vary due to changes in the capital requirements even though there is no change in the level of uncertainty. Thus, they estimate macro-uncertainty as the average conditional volatility from the unforecastable component of several macroeconomic and financial indicators from US.

Unfortunately, we do not have equivalent measures of uncertainty for the rest of the countries under interest. Still, we rely on proxies of uncertainty that have been used already in the literature. We will consider, as a measure of uncertainty in United Kingdom, the principal component of financial and survey based indicators of economic uncertainty (Haddow et al. (2013)). For Germany, we use the cross-sectional dispersion on the expectation with respect to domestic production for manufacturing firms (Bachmann et al. (2013)). Finally, for France, we will use realized stock market volatility.

We refer to the appendix for the empirical results using alternative proxies of uncertainty and further details on data sources and definitions.

## 2.2 Uncertainty and Labor Market Flows: United States

Let us consider first the simple correlations of uncertainty and labor market flows, presented in Table 1. The displayed correlations are conditional on fluctuations of real GDP to control for potential spurious correlations, as the variables under interest co-move with the business cycle. Thus, we use a simple regression model including uncertainty and real GDP as regressors and standardize all variables to have unit-variance for this exercise. Conditional on first moment fluctuations, uncertainty is negatively correlated with hiring and job creation, while layoffs and job destruction co-move positively with uncertainty. This finding is qualitatively equivalent when using alternative proxies of micro and macro uncertainty.

Table 1: Correlation between uncertainty and labor flow variables

	Hiring	Quits	Layoffs	Job Creation	Job Destruction
Uncertainty	-0.14 (0.06)	0.07 (0.06)	0.62 (0.07)	-0.33 (0.08)	0.68 (0.08)
GDP	0.83 (0.05)	0.83 (0.06)	-0.42 (0.09)	0.64 (0.07)	-0.17 (0.07)
$R^2$	0.72	0.31	0.69	0.30	0.51
Period	1990q2-2010q2				

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

In order to allow for a richer (dynamic) interaction between GDP, uncertainty and labor flows we will estimate two structural vector autoregressive (sVAR) models. The



frequency of the series in the sVAR is quarterly, estimated with 4 lags, and all variables enter the systems in logs. First, we consider a five-variate model, including worker flow variables (hiring, quits and layoffs), uncertainty and GDP. Second, we estimate a four-variate model containing job flows (job creation and destruction), uncertainty and GDP. We identify the impact of structural shocks using short run restrictions by assuming that shocks to the worker (job) flow variables and shocks to uncertainty do not impact on GDP contemporaneously. We further restrict worker (job) flow shocks not to affect uncertainty in the same period. We are agnostic about the causal ordering within the worker (job) flow variables since its ordering has no impact on the impulse response functions for the first two shocks in the estimated model.<sup>9</sup>

Importantly, the proposed sVAR models 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 and 3 shows the impulse responses of worker flows and job 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 job creation. These responses are qualitatively consistent with the *wait-and-see* policy emphasized in Bloom (2009): an uncertainty shock expands the region of inaction of plants until the future becomes more certain.

However, the positive response of layoffs and job destruction from an uncertainty shock is not compatible with the importance of this channel. Instead, the *wait-and-see* effect is dominated at the layoff decision.<sup>10</sup> Furthermore, as quits decrease on impact from an unexpected rise of uncertainty, allows us to conclude that the rise of job destruction is not driven (only) by plants which stop replacing workers whenever they quit. Interestingly, the labor flow variables respond to an uncertainty shock in the same way as to a negative productivity shock.<sup>11</sup>

Moreover, we assess the contribution of uncertainty shocks to the forecast error variance of each worker and job flow variable. Table 4 shows that innovations to uncertainty are responsible for at least 19% of the volatility in labor flow variables. This share is

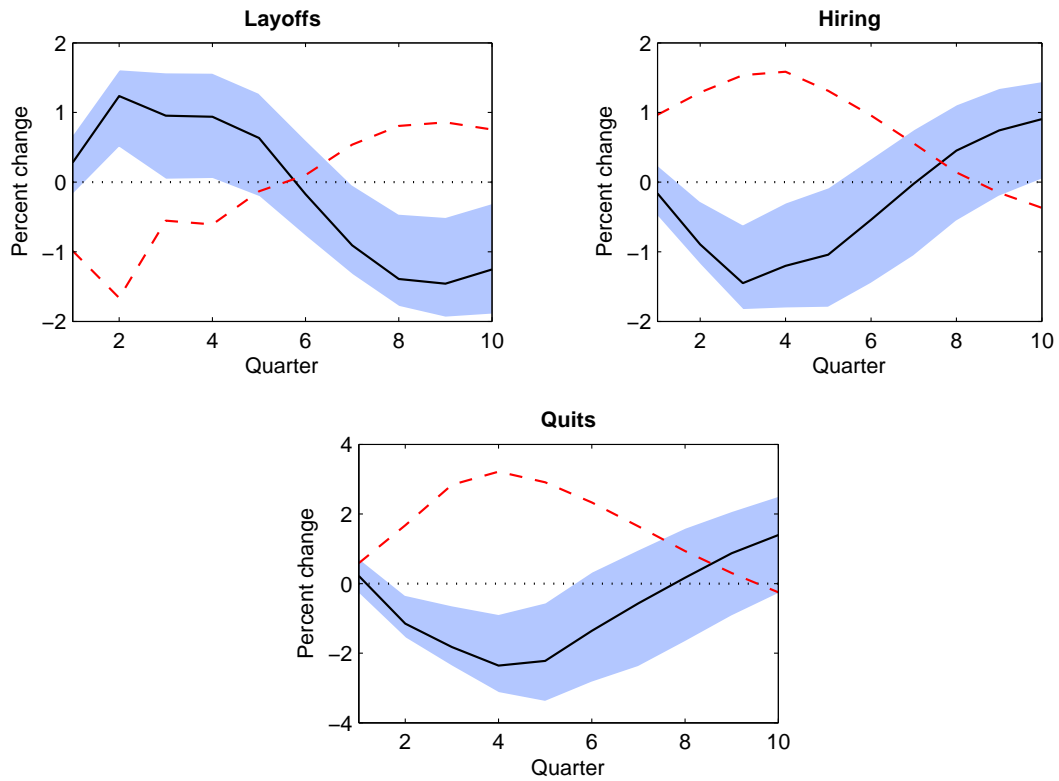
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<sup>9</sup>For further details, see Christiano et al. (1999).

<sup>10</sup>We think about layoffs as a voluntary termination of the contract from the employer side, which has direct costs on the plants through, for example, severance payments.

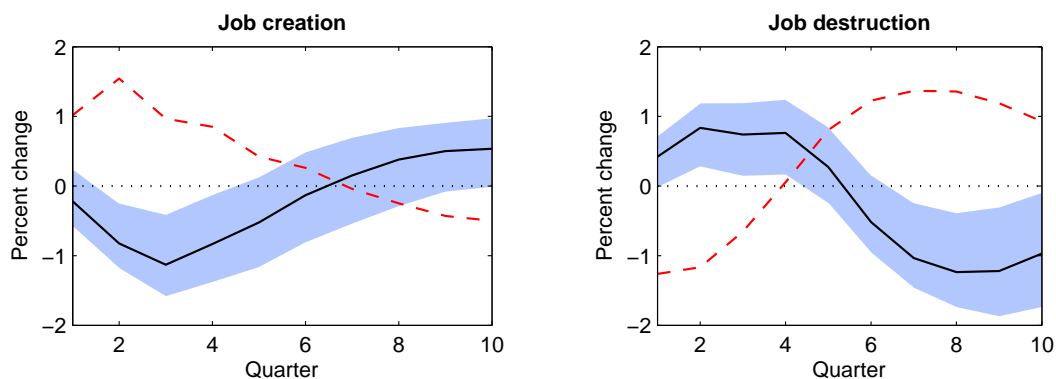
<sup>11</sup>In the same direction as our results, Leduc and Liu (2014) provide evidence that an uncertainty shock act as a negative demand shock as it raises unemployment and inflation.

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 ( $\lambda=1600$ ).

Table 3: 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 ( $\lambda=1600$ ).

Table 4: Variance decomposition from an uncertainty shock

	Hirings	Quits	Layoffs	Job creation	Job destruction
1 quarter	0.6%	0.7%	1.1%	1.0%	2.9%
2 quarters	10.6%	10.2%	12.3%	8.0%	9.7%
4 quarters	22.1%	20.5%	18.4%	19.7%	18.1%
8 quarters	21.0%	18.9%	27.6%	19.9%	23.6%

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

especially high for layoffs and job destruction. These results suggest that uncertainty is a quantitatively important factor to explain the evolution of labor flows.

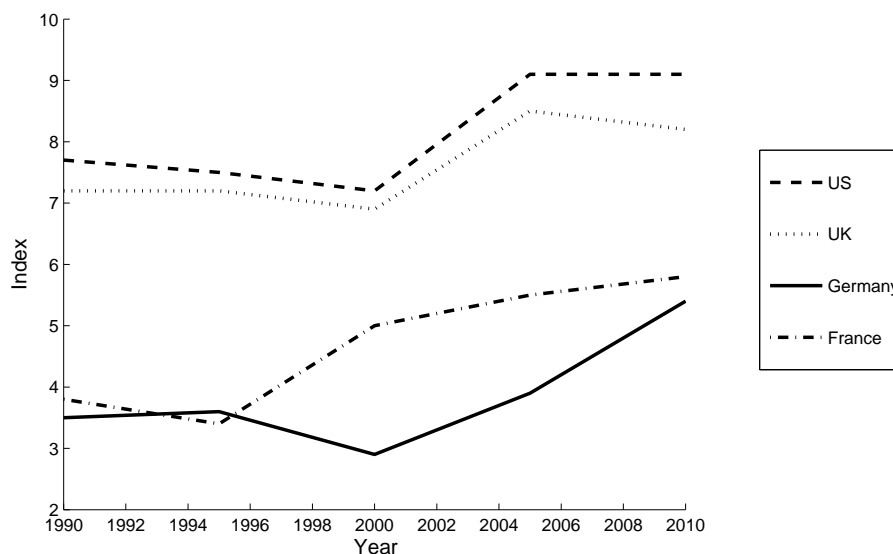
Our findings are robust under an alternative uncertainty and first moment measures, filtering options and changes on the identifying restrictions of the sVAR. Further, the reaction of layoffs and hiring from an uncertainty shock are robust when we focus on continuing plants. More details are provided in Appendix B.

### 2.3 Effect of Uncertainty Shocks Across Countries

In this section, we will try to understand to what extent different degrees of labor market regulations lead to distinct reactions of labor flows upon uncertainty shocks using data from UK, Germany and France (in addition to US).

Based on the index of labor market regulations by the Fraser Institute (Gwartney et al. (2012)), we can distinguish two groups in Table 5. The degree of labor regulation is low and similar in UK and US. On the other side, the labor market in France and Germany has been, throughout the last decades, more rigid.

Table 5: Fraser Institute Labor Market Regulations Index



Note: The index consists of six subindicators that measure the influence of hiring regulations and minimum wages, hiring and firing regulations, centralized collective bargaining, hours regulation, mandated cost of worker dismissal and conscription. The indicator is normalized to range from 0 to 10, with higher scores representing higher economic freedom and less regulation.

In order to compare quantitatively the effect of uncertainty shocks across countries we

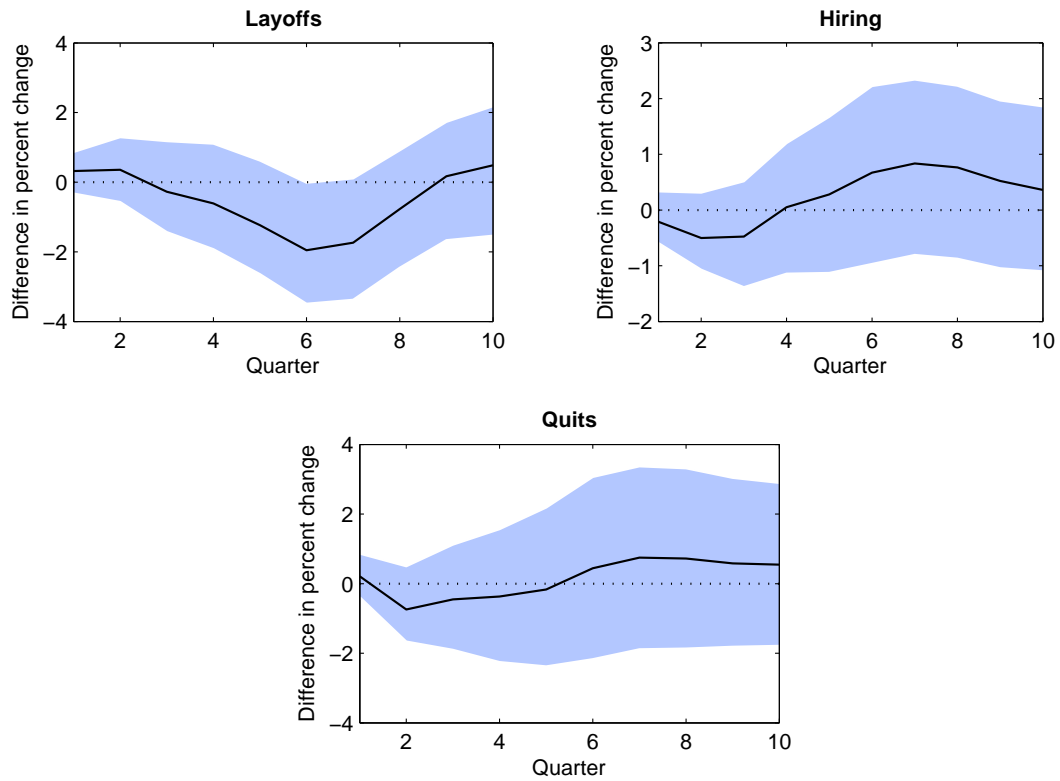
proceed with three steps. First, we estimate the sVAR model from each country separately and obtain the mean response from a one standard deviation uncertainty shock. Second, using as reference the mean response in US, we subtract the mean response of the country under interest. Third, we bootstrap over this difference to obtain confidence intervals.<sup>12</sup>

The impulses responses from an uncertainty shock across countries are presented in Table 6, 7 and 8. Layoffs and job destruction increase significantly more in US vis-a-vis France and Germany. For UK, we do not find significant difference relative to US.

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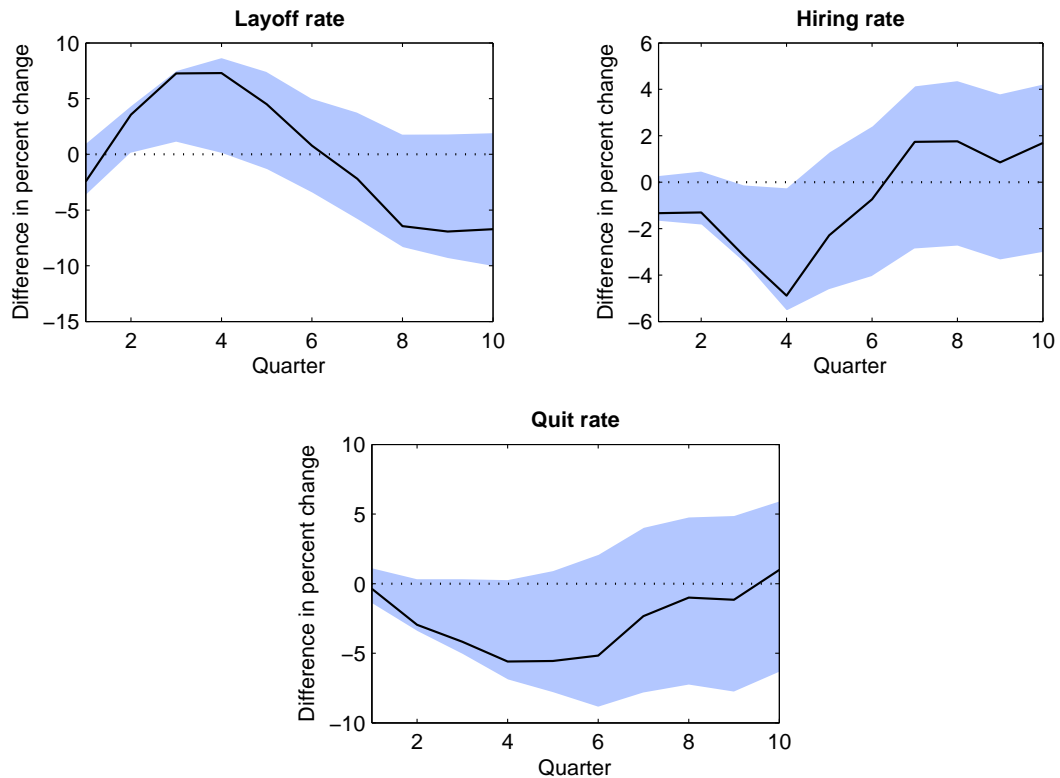
<sup>12</sup>For comparison purposes, we demean and normalize each uncertainty proxy by its standard deviation.

Table 6: Impulse response functions from an uncertainty shock: US vs. UK (Private sector)



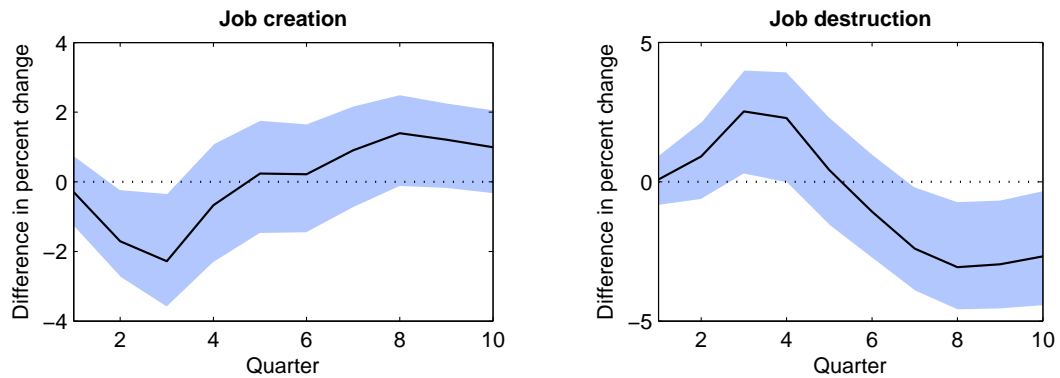
Note: Difference in impulse response from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with uncertainty ordered second and worker flow variables last. We use macro uncertainty from Jurado et al. (2013) for US and principal 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 ( $\lambda=1600$ ).

Table 7: 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 ( $\lambda=1600$ ).

Table 8: 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 ( $\lambda=1600$ ).



### 3 Theory

While Bloom (2009) and Bloom et al. (2014) find uncertainty shocks to be a quantitatively important factor in explaining business cycle fluctuations, Bachmann and Bayer (2013) conclude this to be unlikely the case. These two groups notably differ in the way they model factor adjustment frictions. While the former includes capital and labor adjustment frictions, the latter allows for capital frictions only. This distinction may be crucial to arrive at the opposite conclusions. If an uncertainty shock induces plants to freeze investments and labor policies, this amplifies the effect of uncertainty shocks on GDP. Not only does an uncertainty shock distort the capital-output ratio, but also the capital-labor ratio.

In the following, we compare the effect of uncertainty shocks on labor flows varying the degree of labor adjustment frictions. In particular, we consider a model where we allow for labor frictions, and a second where we explicitly rule out such friction. Both models are subject to capital adjustment frictions and identical otherwise. For comparability reasons, we closely follow Bloom (2009) in setting up the model.

#### 3.1 Factor adjustment friction model

We consider a partial equilibrium model of the firm. Reflecting the firm structure in Compustat data, we assume that each firm operates a finite number of plants. Each plant is monopolistically competitive and maximizes profits subject to a set of capital and labor adjustment costs. For simplicity, we will assume that plants optimize independent of each other. The model allows for time-varying uncertainty and adjustment costs are such that wait-and-see behavior arises when uncertainty increases.

Suppose each plant faces the revenue function

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

where  $\epsilon/(\epsilon - 1)$  is the markup and  $A$  denotes a profitability shock

$$A_{ijt} = A_t^M A_{it}^F A_{ijt}^P, \quad (2)$$

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 profitability shocks follow

exogenous processes

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

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

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

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

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

Aggregate uncertainty  $\sigma_t$  and the firm-level trend  $\mu_{it}$  follow a 2-state Markov chain, respectively.

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

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

Wages are assumed to be a function of hours worked with  $w(H) = w_1(1 + w_2H^\gamma)$ , 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

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

$C_L^P$  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.<sup>13</sup>  $C_L^F$  and  $C_K^F$  quantify fixed disruption costs, a fixed share of revenues, and  $C_L^Q$  and  $C_K^Q$  capture quadratic adjustment costs. We assume that each plant optimizes independently

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<sup>13</sup>We implicitly 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.

its plant value

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

For computational reasons, the plant value may be further simplified by maximizing out the choice of hours worked, which is basically 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.<sup>14</sup>

Notice that the labor force declines by a constant share  $\delta_L$  if plants do not hire (or fire). We assume  $\delta_L$  to be the quit rate. Consequently, a positive  $E$  denotes hirings while a negative  $E$  captures layoffs. Furthermore, job creation (job destruction) is the change of employment from those plants than increase (decrease) their size. We study the transmission of uncertainty shocks with a special focus on these labor flows.

### 3.2 Model calibration

Table 9 presents the model calibration. The first part contains predefined parameters, with standard assumptions for  $\alpha$ ,  $\epsilon$ ,  $\delta_K$ ,  $r$ . 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  $\sigma_H$  because together with the probability of the shock  $\pi_{LH}^\sigma$  and its persistence  $\pi_{HH}^\sigma$  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.<sup>15</sup> 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 10, describe the

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<sup>14</sup>See Bloom (2009) for more details.

<sup>15</sup>We leave for future work the role of endogenous quits in this model setup. Schaal (2012) considered a multi-worker search and matching model with endogenous worker flows to assess the role of uncertainty shocks on unemployment. His model predicts, contrary to our empirical results, an increase of quits from an unexpected increase of uncertainty.

Table 9

<i>Set model parameters</i>				
Parameter	Value	Explanation		
$\alpha$	1/3	Capital share in output		
$\epsilon$	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		
$\sigma_H$	$2 \times \sigma_L$	Uncertainty shock doubles baseline uncertainty		
$\pi_{LH}^\sigma$	1/36	Uncertainty shock once every 36 years		
$\pi_{HH}^\sigma$	0.71	Half-life of uncertainty shock 2 months		
$(\mu_H + \mu_L)/2$	0.02	Average real growth rate of 2% annually		
$\pi_{LH}^\mu$	$\pi_{HL}^\mu$	Firm-level trend transition matrix symmetric		
$\delta_K$	0.1	Capital depreciation 10% annually		
$\delta_L$	0.1	Exogenous labor attrition 10% annually		
$r$	6.5%	US firm-level discount rate		
$N$	250	Firms operate 250 plants		
<i>Estimated model parameters</i>				
Parameter	Adjustment Cost Specification			Explanation
	CapLab(E)	Cap	Cap(E)	
$C_K^P$	33.9	33.9	42.7	Investment resale loss (%)
$C_K^F$	1.5	1.5	1.1	Fixed investment cost (% annual sales)
$C_K^Q$	0	0	0.996	Quadratic capital adjustment cost
$C_L^P$	1.8			Per capita hiring/firing cost (% annual wages)
$C_L^F$	2.1			Fixed hiring/firing cost (% annual sales)
$C_L^Q$	0			Quadratic labor adjustment cost
$\sigma_L$	0.443	0.443	0.413	Baseline level of uncertainty
$\mu_H - \mu_L$	0.121	0.121	0.122	Spread of firm trend
$\pi_{HL}^\mu$	0	0	0	Transition of firm trend
$\gamma$	2.093	2.093	2.221	Curvature of hours/wage function

Table 10: 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

joint behavior of investment rates, employment growth rates, and sales growth rates. In particular, the standard deviation, skewness, auto-correlation and mutual (lagged) correlations of these three variables are targeted.

Reflecting the purpose of this study to investigate the role of labor adjustment frictions, we estimate the model when allowing for both adjustment frictions (CapLab(E)) and when allowing for capital frictions only (Cap(E)). Furthermore, we consider a third specification where we use the estimated parameters under the full model specification and we shut off the labor frictions (Cap). We do so for two reasons. First, it allows us to compare the effect on output under the two model specifications and assess the relevance of labor frictions. Second, the first eight moments in Table 10 have an important role to pin down the capital adjustment frictions and the fit remains almost equivalent when not considering labor frictions. However, when re-estimating the model excluding labor frictions, the fit of these moments worsens. This is due to the fact that the estimated capital frictions increase considerably with respect to the baseline model in order to improve the fit of the rest of the moments.

### 3.3 Results

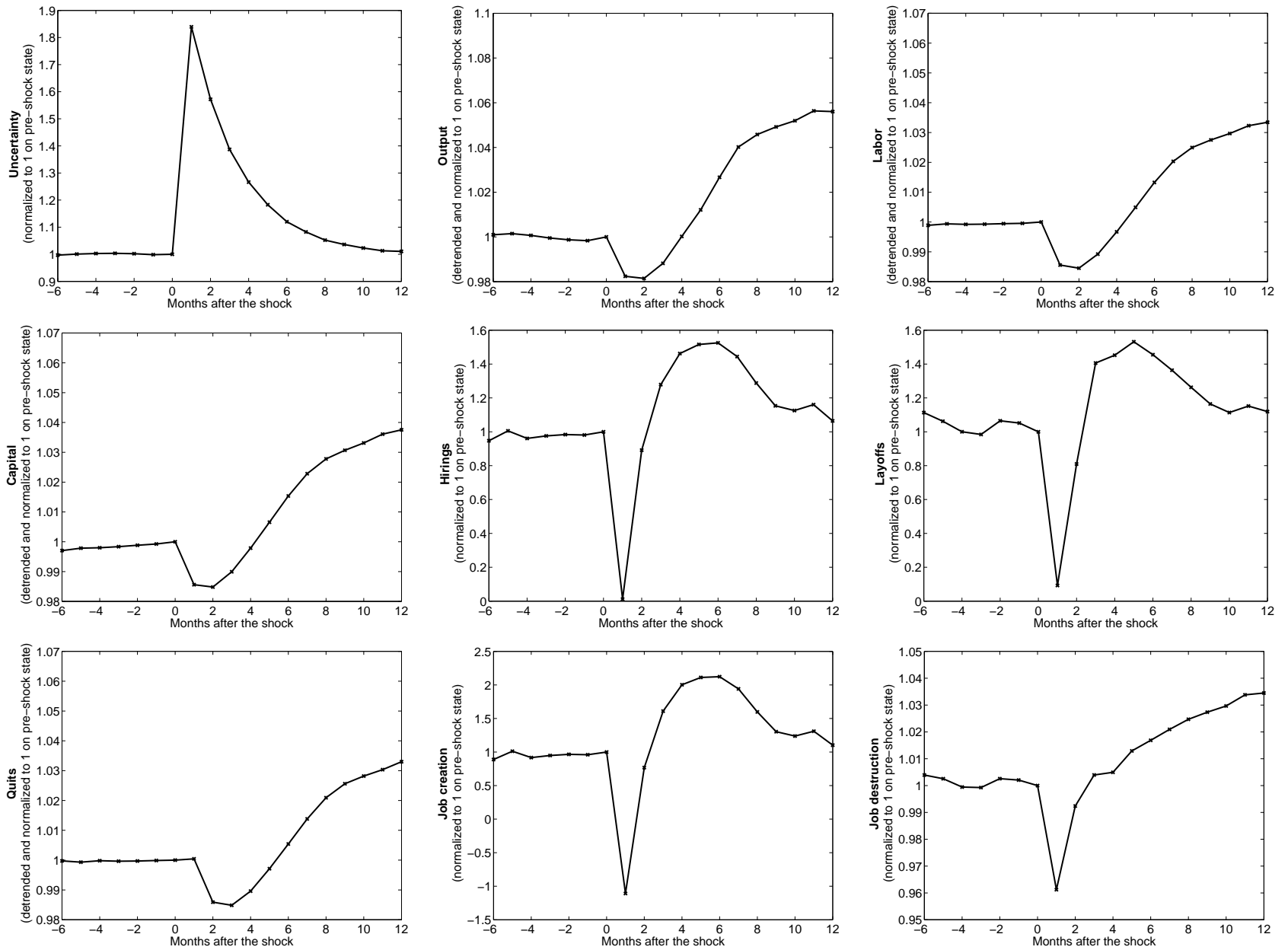


Figure 1: Labor & Capital adjustment costs model (CapLab(E))

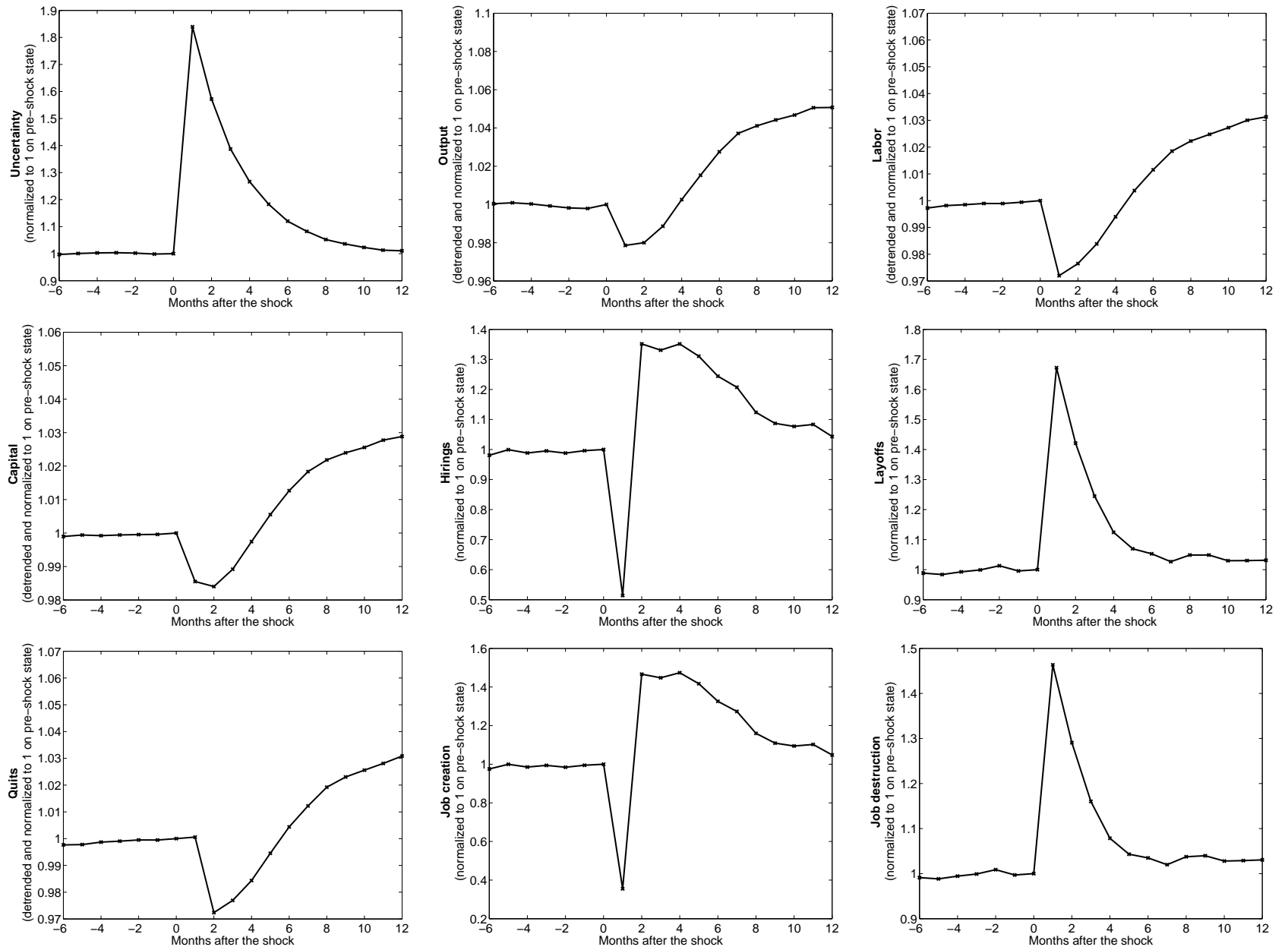


Figure 2: Capital adjustment costs model (Cap)



In this section we will compare the impulse responses upon an unexpected increase of uncertainty in the model where we allow for both adjustment frictions (CapLab(E)) and when exclude labor frictions (Cap). We refer the reader to the Appendix C for the results of the re-estimated model with capital frictions (Cap(E)) as the effects are qualitatively the same as the "Cap" model.

Quite surprisingly, the output response to uncertainty is almost the same on impact during the first 3 months after the shock. Output falls under both scenarios to about 2% with respect to the pre-shock period and relative to trend growth. Through the lens of our model we can conclude that capital frictions are the crucial channel through which uncertainty affects output.

To obtain a better understanding of the effect from labor frictions, we compare the lower plots in Figure 1 and 2. With labor frictions, all labor flows decrease on impact, in other words, plants adopt a *wait-and-see* policy at the labor decision. In the subsequent periods, higher realized volatility slowly drives up labor flows.

In the model without labor frictions, hiring and job creation also falls on impact, but this is due to plants freezing investments, whereby the capital stock decreases. The most notable difference between the two model specifications is with respect to layoffs and job destruction. While in the former specification these two variables decrease, the model with capital frictions implies an increase of layoffs and job destruction from an uncertainty shock. Given that an unexpected rise of uncertainty increases the inactivity of plants with respect to investments, the capital stock decreases through depreciation. This, in turn, leads to a shift to the left in the distribution of employment growth, as seen in Figure 3.

Our theoretical results provide us an interesting implication: the reaction of layoffs and job destruction in countries with stricter labor market regulations should be smaller with respect to countries with flexible labor markets. This is due to the fact that under stricter labor regulations, labor adjustment costs are larger, which leads to a stronger role of the *wait-and-see* at the labor margin.

Based on the empirical evidence provided in Section 2.3, we find that layoffs and job destruction increase significantly less in France, and Germany vis-a-vis the US response. For UK, we do not find significant difference relative to US. Given that the French and German labor market are more rigid than the US, this may be seen as support of this model implication.

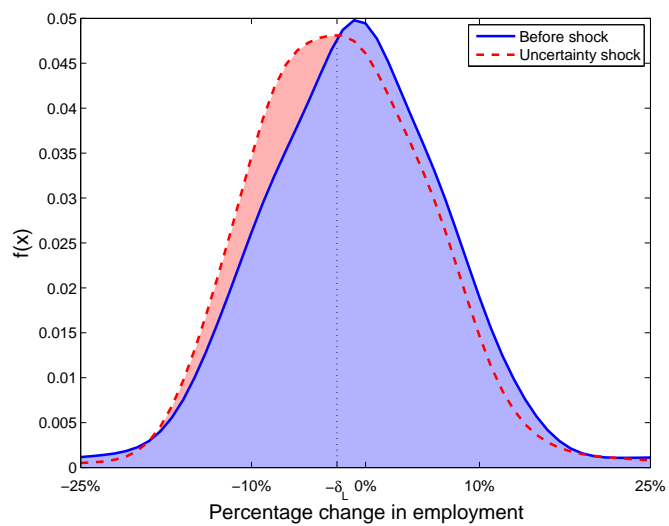


Figure 3: Change in the distribution of employment growth upon uncertainty shock

## 4 Conclusion

Whether or not uncertainty shocks may be an important driver of business cycle fluctuations depends on the strength of the *wait-and-see* policy.

Using labor flow data from US we document new stylized facts on the effects of uncertainty shocks in the economy. A structural uncertainty shock significantly reduces hiring and job creation. These responses are consistent with the *wait-and-see* emphasized in Bloom (2009): an uncertainty shock expands the region of inaction of plants until the future becomes more certain. However, the positive response of layoffs and job destruction from an uncertainty shock is not compatible with the importance of this channel. Instead, we provide evidence that the *wait-and-see* effect is dominated at the layoff decision.

In order to rationalize our empirical findings, we consider two alternative models. In particular, we consider a model where we allow for labor frictions, and a second where we explicitly rule out such friction. Both models are subject to capital adjustment frictions and identical otherwise.

Based on the model with adjustment costs on both factors of production we obtain, contrary to our empirical results, a decline of hiring and layoffs from an unexpected increase in uncertainty. As hiring and layoffs is costly in the model, plants may decide to freeze in order to avoid paying layoff (hiring) costs that may have to be reverted in the near future. In contrast, when labor is not frictional, the response of layoffs is fundamentally different. As uncertainty increases, more plants freeze their investment decisions. This reduces capital through depreciation of the existing capital stock, and thereby lowers labor demand, which implies more layoffs and less hiring, in concordance with our empirical results. Surprisingly, we find similar and sizable effect of uncertainty on output in both model specifications. Through the lens of our model we can conclude that capital frictions are the crucial channel through which uncertainty affects output. Our model provides a testable implication: the reaction of layoffs and job destruction in US upon uncertainty shocks should be larger relative to countries with stricter labor regulations. This is due to the fact that under stricter labor regulations, labor adjustment costs are larger, which strengthen the value of inactivity at the labor margin.

Using French, German, and UK data, we find that layoffs and job destruction increase significantly less in France, and Germany vis-a-vis the US response. For UK, we do not find significant difference relative to US. Given that the French and German labor market are more rigid than the US, this may be seen as further support of the model implication.

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## A Data Sources and Description

Table 11: 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 macroeconomic 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 12: 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 13: 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)

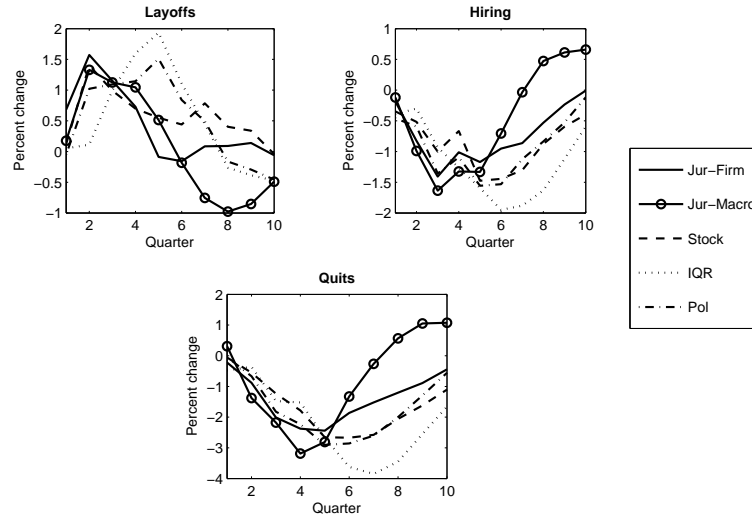
Table 14: France

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



## B Robustness Tests

Table 15: US: IRFs of worker flows from an uncertainty shock using different proxies of uncertainty



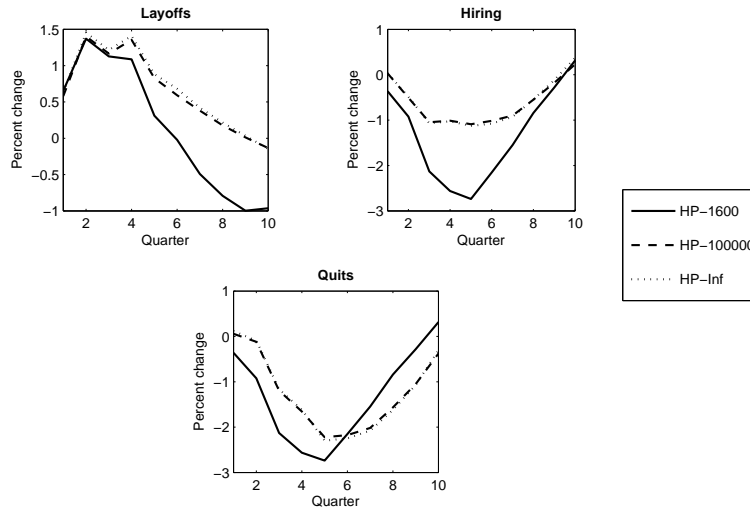
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with uncertainty ordered second and worker flow variables last. We use different proxies of uncertainty: Jur-Firm (firm level uncertainty 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 ( $\lambda=1600$ ).

Table 16: 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 ( $\lambda=1600$ ).

Table 17: US: IRFs of worker flows from an uncertainty shock under different filtering alternatives



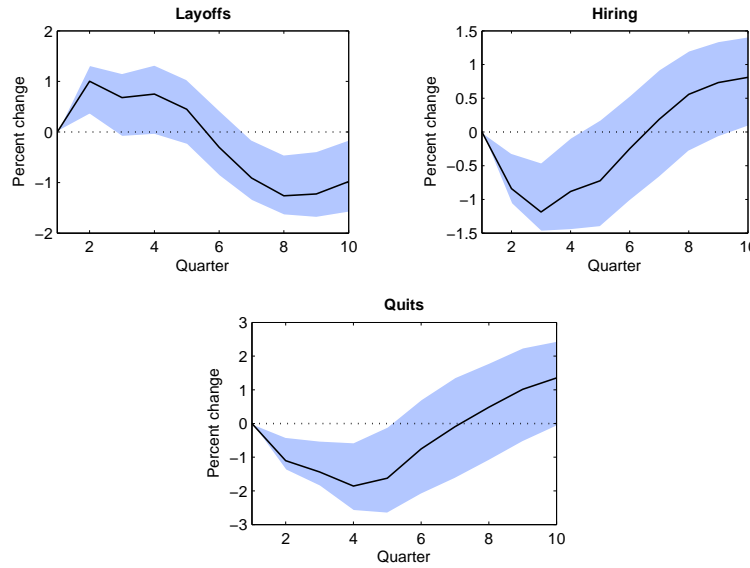
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with uncertainty ordered second and worker flow variables last. We use Jur-Macro uncertainty. All variables are in logs and detrended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

Table 18: US: IRFs of job flows from an uncertainty shock under different filtering alternatives



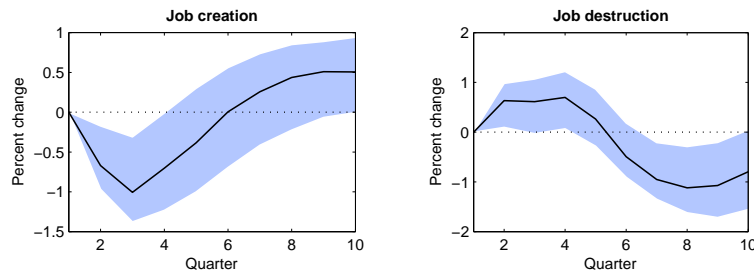
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a four-variate sVAR with uncertainty ordered second and job flow variables last. We use Jur-Macro uncertainty. All variables are in logs and detrended under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

Table 19: US: IRFs of worker flows from an uncertainty shock under different ordering assumption



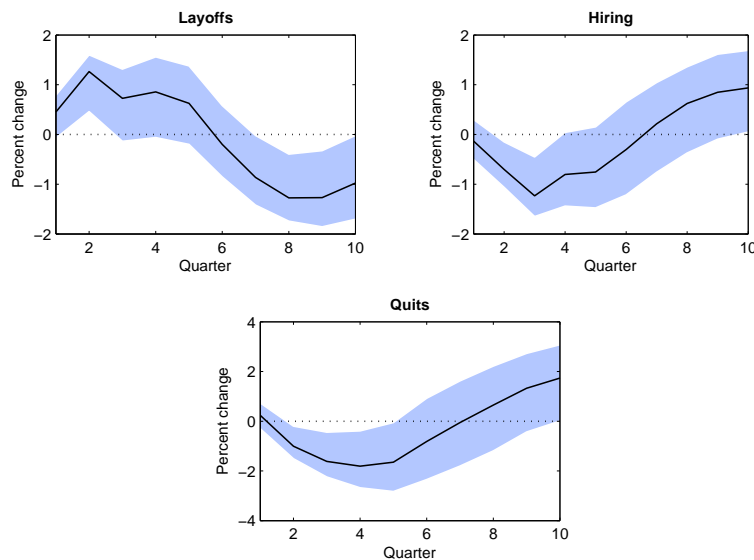
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with worker flows ordered first, gdp second and uncertainty last. We use macro uncertainty from Jurado et al. (2013). Shaded regions represent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

Table 20: US: IRFs of job flows from an uncertainty shock under different ordering assumption



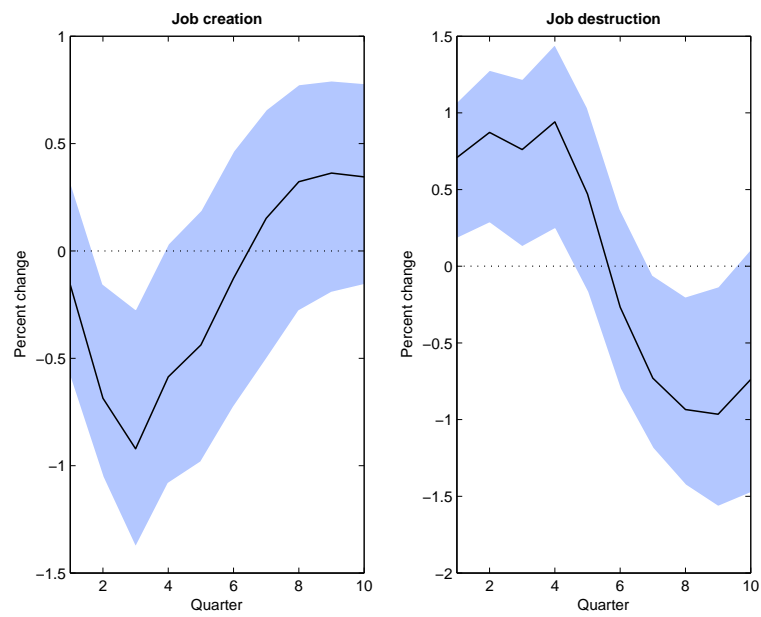
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a four-variate sVAR with job flows ordered first, gdp second and uncertainty last. We use macro uncertainty from Jurado et al. (2013). Shaded regions represent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

Table 21: US: IRFs of worker flows from an uncertainty shock using stock market level instead of GDP



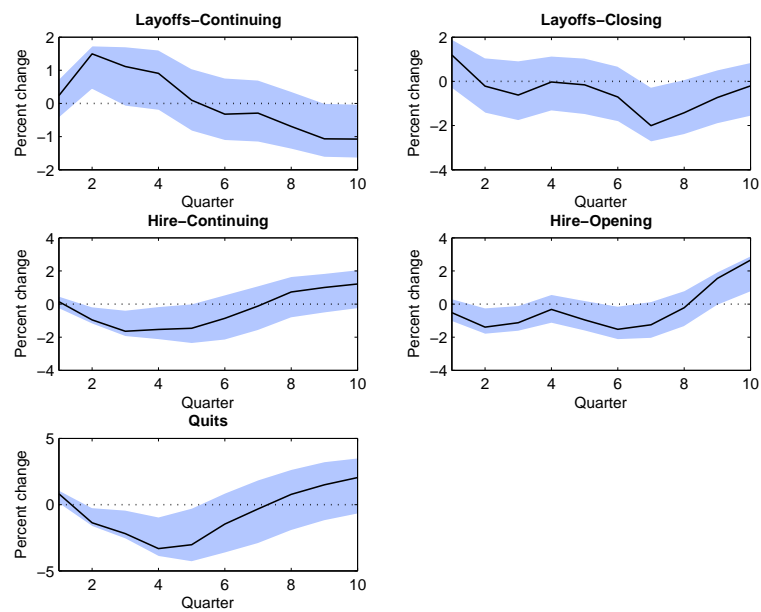
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a five-variate sVAR with stock market level ordered first, worker flows second and uncertainty last. We use macro uncertainty from Jurado et al. (2013). Shaded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

Table 22: US: IRFs of job flows from an uncertainty shock using stock market level instead of GDP



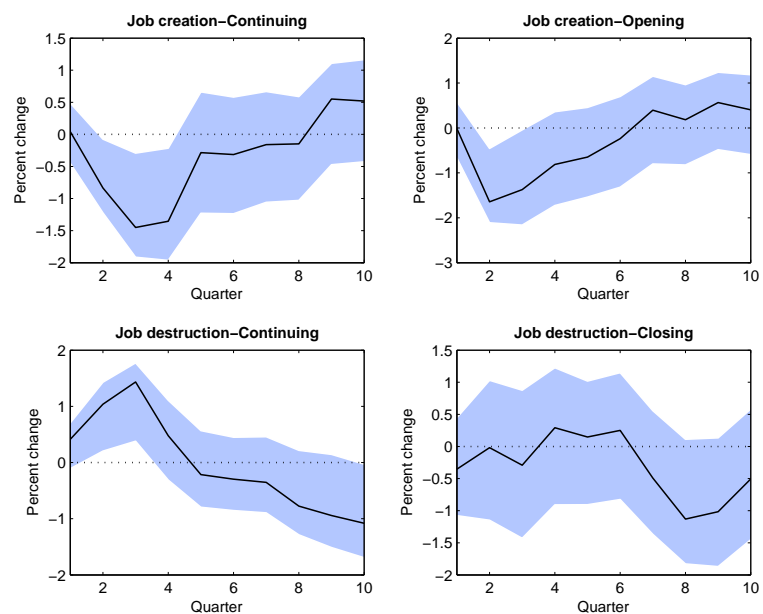
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a four-variate sVAR with stock market level ordered first, job flows ordered second and uncertainty last. We use macro uncertainty from Jurado et al. (2013). 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 ( $\lambda=1600$ ).

Table 23: US: IRFs of worker flows from an uncertainty shock controlling for entry and exit



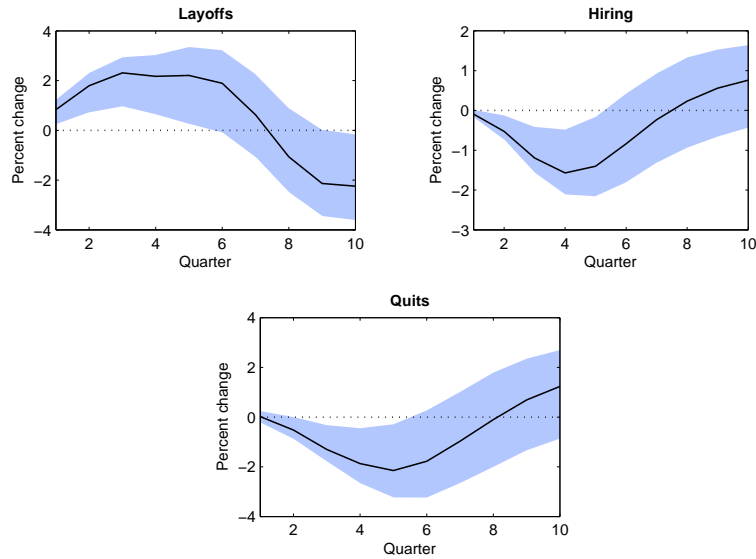
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a seven-variate *s*VAR with uncertainty ordered second and worker flow variables last. We use macro uncertainty from Jurado et al. (2013). Shaded regions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

Table 24: US: IRFs of job flows from an uncertainty shock controlling for entry and exit



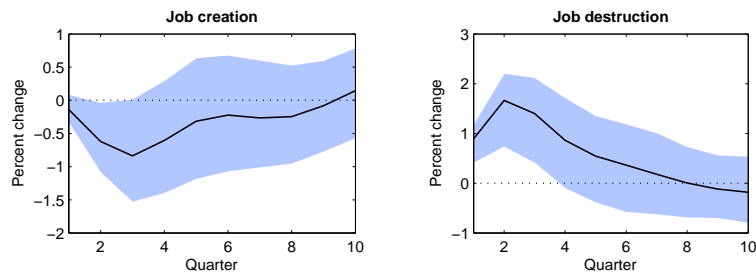
Note: Impulse response functions from a one standard deviation uncertainty shock (solid black line). The impulse responses are obtained estimating a six-variate sVAR with uncertainty ordered second and job flow variables last. We use macro uncertainty from Jurado et al. (2013). Shaded regions represent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

Table 25: 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 ( $\lambda=1600$ ).

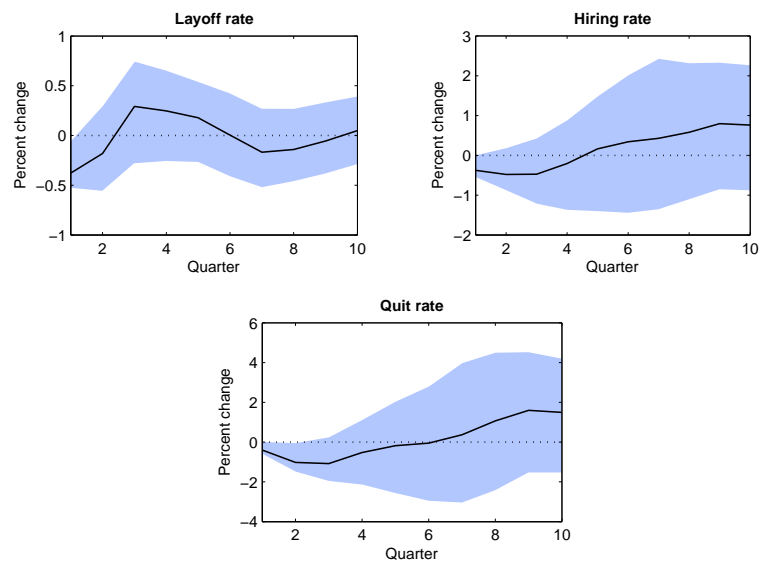
Table 26: Germany: Impulse response functions from an uncertainty shock (Manufacturing)



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 ( $\lambda=1600$ ).



Table 27: 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 ( $\lambda=1600$ ).

## C Capital adjustment cost model based on the re-estimation of the model

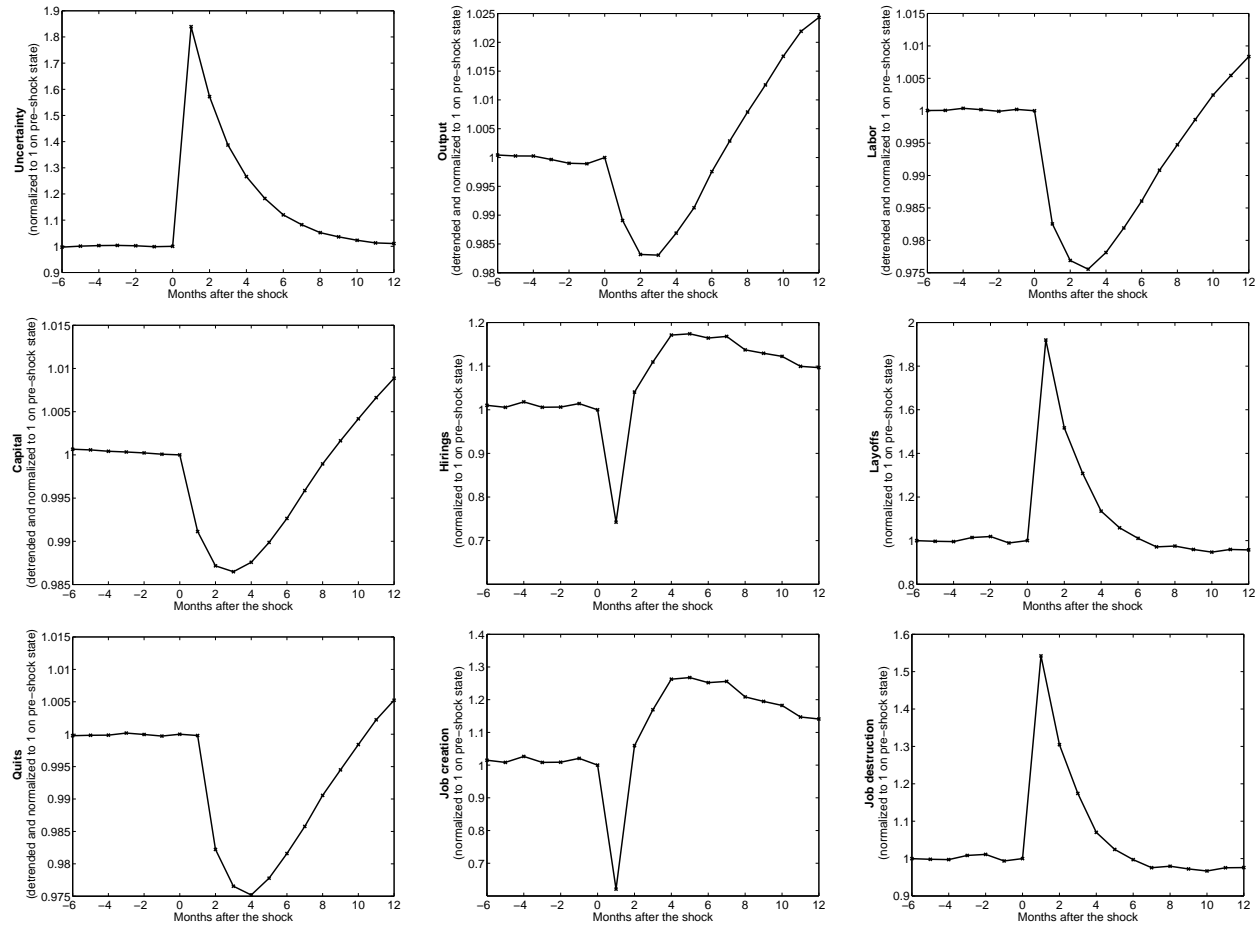


Figure 4: Capital adjustment costs model (Cap(E))