Do plants freeze upon uncertainty shocks?*

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Abstract

What explains the impact of uncertainty shocks on the economy? This paper uses highly disaggregated data on industry-level job flows to investigate the empirical relevance of various transmission channels of uncertainty shocks. The channels we consider are labor adjustment frictions, capital adjustment frictions, nominal ridigities, and financial frictions. For each channel, we derive testable implications regarding the response of job flows to uncertainty shocks. Empirically, uncertainty shocks lead to more job destruction and less job creation in more than 80% of all industries. The effect is significantly stronger in industries that face tighter financial constraints, which supports the financial frictions channel. In contrast, our evidence does not support the other three channels.

Keywords: Uncertainty shocks, job flows, financial frictions.

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1 Introduction

Two stylized facts have emerged over the last decade: Uncertainty is countercyclical[1] and uncertainty shocks are contractionary.[2] To rationalize the contractionary effects of uncertainty shocks, a number of transmission channels have been put forward. Two closely related channels build on capital and labor adjustment frictions. Higher uncertainty raises the real option value of waiting, firms postpone factor adjustment, which depresses real economic activity.[3] Another transmission channel builds on financial frictions. In the presence of borrowing limits, higher uncertainty raises the probability of insufficient funds. In response, firms downscale operations.[4] Yet another channel builds on rigid prices. In New Keynesian model environments, higher uncertainty motivates precautionary price setting, which raises markups.[5] While all of these four transmission channels have been shown to be potentially important in distinct quantitative macroeconomic models, we know little of their *empirical relevance*.[6]

To investigate the empirical relevance of these transmission channels, this paper derives testable implications of how frictions shape the responses of job creation and job destruction to uncertainty shocks.[7] For the US, we construct a long panel of job flows in highly disaggregated industries. Exploiting variation in the industry-level responses to uncertainty shocks, this paper provides empirical evidence that strongly supports the empirical relevance of financial frictions. In contrast, the data does not support an important role for the other three transmission channels.

Understanding which transmission channels are empirically relevant is of critical importance for both positive and normative questions. The nature of transmission determines the propagation and persistence generated by uncertainty shocks. On the normative side, the type of transmission channel matters for the design of policy, such as counter-cyclical stimulus policy. For example, if factor adjustment frictions are an important channel, an effective stimulus policy is an investment or hiring subsidy, which

[1]Measures of uncertainty include stock market volatility, macroeconomic forecast uncertainty, but also the cross-sectional dispersion in firm-level productivity or stock returns. These various measures are countercyclical and correlate positively with each other, see Bloom et al. (2018) for an overview.

[2]For empirical evidence on the effects of uncertainty shocks, see Bloom (2009), Bachmann et al. (2013b), Caggiano et al. (2014), Jurado et al. (2015), Baker et al. (2016) among many others.

[3]On capital adjustment frictions, see, e.g., Bloom (2009), Bachmann and Bayer (2013), Bloom et al. (2018). On labor adjustment frictions, see, e.g., Leduc and Liu (2016), Schaal (2017), Riegler (2018).

[4]On financial frictions, see, e.g., Arellano et al. (forthcoming) and Christiano et al. (2014).

[5]On price rigidities, see, e.g., Fernandez-Villaverde et al. (2015) and Basu and Bundick (2018).

[6]This paper focuses on the near-term effects of uncertainty shocks. Important long-run transmission channels include the Oi-Hartman-Abel effect and the growth options effect, see Bloom's (2014) survey.

[7]Following Davis and Haltiwanger (1992), job creation (job destruction) is the total employment change of plants with net employment gains (net employment losses).

targets plants close to their adjustment threshold, e.g., small plants as in Winberry (2018). If, instead, financial frictions are key, an effective policy intervention may target the financing conditions of firms close to default. If price rigidities are a key channel, adequate monetary policy rules are important, see Basu and Bundick (2018).

This paper contributes to the uncertainty literature by providing evidence on the empirical relevance of various transmission channels. To guide our empirical analysis, we propose four parsimonious models with labor adjustment frictions, capital adjustment frictions, price rigidities, and financial frictions, respectively. We show that these four channels all differ in their implications for the effects of uncertainty shocks on job flows. Given labor adjustment frictions, firms *freeze* (i.e., postpone) employment adjustment when uncertainty increases. This lowers both job creation and destruction. With capital adjustment frictions, plants freeze investment. This lowers job creation because the capital stock of non-investing plants depreciates. In the presence of financial frictions, higher uncertainty raises the value of liquidity buffers. Plants raise their liquidity buffers by downscaling operations, which lowers job creation and raises job destruction. Finally, rigid prices imply that uncertainty shocks raise markups. As a result, job creation falls and job destruction increases.

Importantly, the severity of these frictions shapes the response of job flows to uncertainty shocks. We show that larger labor adjustment costs amplify the decline in job creation and job destruction. Similarly, larger capital adjustment costs amplify the decline in job creation. Under financial frictions, the decline in job creation and increase in job destruction are amplified by more severe financial frictions, while more rigid prices dampen the job flow responses. These theoretical predictions provide testable implications, which we exploit in our empirical analysis.

Our empirical analysis builds on a panel of four-digit manufacturing industry job flows. A secondary contribution of our paper is to construct this panel, which is quarterly and ranges from 1972 through 2013. It combines data from the Longitudinal Research Database (LRD) and the Quarterly Workforce Indicators (QWI). First, we estimate the response of aggregate and industry-level job flows to uncertainty shocks. Both in the aggregate and in more than 80% of four-digit industries industries, job creation falls and job destruction increases.[8] The increase of job destruction *per se* is hard to reconcile with labor adjustment frictions as central transmission channel. Second, we exploit the variation in the job flow responses across industries. We ask whether this variation can

[8]This paper also contributes to the uncertainty literature being the first to provide evidence on the job flow responses to uncertainty shocks. Related work focuses on the unemployment rate, see Leduc and Liu (2016), and worker flows, see Guglielminetti (2016), Schaal (2017), Riegler (2018).

be understood through variation in the severity of frictions across industries in line with the theoretical predictions.

To study the interaction between job flow responses and frictions, we propose a number of proxies to measure the severity of frictions at the industry level. For example, we use the within-industry kurtosis of gross investment rates and employment growth as indicators of capital and labor adjustment costs, respectively. Larger adjustment costs lead to lumpier adjustment, which in turn raises the kurtosis.[9] For financial frictions, we consider measures of short-run liquidity needs and the firm age composition, to capture access to external finance, following a large literature, e.g., Rajan and Zingales (1998), Raddatz (2006), Hurst and Pugsley (2011), and Fort et al. (2013).

Empirically, we show that differences in the severity of financial frictions do explain significant differences in the job flow responses across industries. In line with our theoretical predictions, the job flow responses to uncertainty shocks are significantly stronger in industries with stronger measured financial frictions. The relation between differences in the severity of the other three frictions and job flow responses are either statistically insignificant, or significant but in opposition to our theoretical predictions. We hope that our findings provide guidance for future research on the effects of uncertainty shocks, and for the design of stimulus policy.

To summarize, we show that financial frictions are an important transmission channel of uncertainty shocks. Relatedly, Caldara et al. (2016) find that uncertainty shocks are particularly contractionary when worsening credit spreads. Closely related to the empirical approach of our paper is Samaniego and Sun (2018). Exploiting cross-industry and cross-country differences in depreciation rates, they argue that capital adjustment frictions are key for the transmission of uncertainty shocks.

The remainder of the paper is structured as follows: Section 2 provides the theoretical background. Section 3 describes the data. Section 4 outlines our estimation strategy and presents the empirical results. Section 5 concludes and an Appendix follows.

2 Theoretical background: frictions and uncertainty shocks

This paper first examines how the presence and severity of four distinct frictions shapes the response of job flows to uncertainty shocks. Importantly, we establish empirically testable predictions for the following channels: labor adjustment frictions, capital adjustment frictions, price rigidities, and financial frictions.

[9] Precisely these kurtosises have been used to estimate factor adjustment costs, see, for example, Caballero et al. (1997) and Bachmann and Bayer (2013).

2.1 Labor adjustment frictions

Ample evidence supports the presence of non-convex labor adjustment frictions.[10] We propose a parsimonious model to study the job flow response to an uncertainty shock under such frictions. Suppose an industry populated by a unit mass of plants. Plants produce output according to $y = z\ell^{\nu}$, where ℓ denotes labor and z plant-specific productivity, which follows a log-normal AR(1) process

$$\log z' = \rho_z \log z + \sigma_z \epsilon', \;\; \epsilon' \sim \mathcal{N}(0, 1), \tag{1}$$

where uncertainty σ_z is stochastic according to a two-point Markov chain

$$\sigma_z \in \{\sigma_z^L, \sigma_z^H\}, \text{ and } \Pr(\sigma_z' = \sigma_z^j | \sigma_z = \sigma_z^k) = \pi_{k,j}^{\sigma}. \tag{2}$$

An uncertainty shock occurs when σ_z switches from a low level σ^L to a high level σ^H. In this setup, deliberately borrowed from Bloom (2009) and Bloom et al. (2018), higher uncertainty is observed one period before it raises the volatility of productivity shocks.[11] The plant faces a dynamic labor adjustment problem subject to fixed disruption costs

$$\begin{aligned} V(\ell; z, \sigma_z) &= \max_{\ell'} \left\{ z\ell^{\nu} - w\ell - ac(\ell', \ell, z) + \beta \mathbb{E}\left[V(\ell'; z', \sigma_z') \,\middle|\, z, \sigma_z \right] \right\}, \\ ac(\ell', \ell, z) &= \theta^L \cdot z\ell^{\nu} \cdot \mathbb{1}\{\ell' \neq \ell\}, \end{aligned} \tag{3}$$

where parameter $\theta^L \geq 0$ governs the degree of labor adjustment frictions.[12] The presence of non-convex labor adjustment frictions is important for the transmission of uncertainty shocks. When uncertainty is high, the real option value of postponing labor adjustment increases. Both job creation and destruction fall as plants *freeze* employment. What is less obvious is how the job flow responses change in the degree of the labor adjustment friction, θ^L. We will come back to this question toward the end of this section.

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[10] Caballero et al. (1997) shows that the plant-level distribution of net employment growth has excess kurtosis, suggesting lumpy employment adjustment. Using indirect inference, Cooper and Willis (2009) and Bloom (2009) estimate significant non-convex labor adjustment costs.

[11] A feature of this stochastic process is that the cross-sectional mean of z rises in periods of high uncertainty. As a result, uncertainty shocks will be expansionary when frictions are absent or weak. To avoid a time-varying cross-sectional mean, we would need to add a mean coefficient that varies in the history of uncertainty shocks. For the sake of parsimony, we therefore stick to the simple process above.

[12] We assume frictional *net* employment adjustment as in Cooper and Willis (2009). The alternative is to assume exogeneous labor attrition and frictional *gross* employment adjustment as in Bloom (2009). However, in standard models, the latter setup implies a negative mode of the cross-sectional net employment growth distribution, which contradicts the evidence in Davis and Haltiwanger (1992).

2.2 Capital adjustment frictions

Similar to labor adjustment, a large body of evidence supports non-convex capital adjustment frictions.[13] To study the job flow response under frictional capital adjustment, we propose a model similar to the previous one. Suppose again an industry populated by a unit mass of plants. Plants produce output according to $y = zk^{\alpha}\ell^{\nu}$, where k denotes capital and ℓ labor. The process of idiosyncratic productivity z is described by (1) and (2). The dynamic capital adjustment problem is

$$V(k; z, \sigma_z) = \max_{k'} \left\{ \max_{\ell} \{zk^{\alpha}\ell^{\nu} - w\ell\} - ac(k', k, z) + \beta \mathbb{E}\left[V(k'; z', \sigma_z') \mid z, \sigma_z\right] \right\}, \quad (4)$$
$$ac(k', k, z) = (k' - (1-\delta)k) + \theta^K \cdot zk^{\alpha}\ell^{*\nu} \cdot \mathbb{1}\{k' \neq (1-\delta)k\},$$

where parameter $\theta^K \geq 0$ governs the degree of capital adjustment frictions and ℓ^* denotes the profit-maximizing labor policy. When plants face non-convex capital adjustment frictions, plants freeze investment plans in response to uncertainty shocks. The capital stock of inactive plants decreases because of depreciation. This depresses labor demand, which lowers job creation. The effect on job destruction is ambiguous. The freezing of disinvestment plans lowers job destruction, while the freezing of investment plans increases job destruction. At the end of this section, we examine how the extent of capital adjustment costs shapes the job flow responses.

2.3 Financial frictions

If short-term credit is costly, higher uncertainty makes liquidity more valuable. Plants may decide to scale down operations in uncertain times to preserve liquidity. In this spirit, we propose a parsimonious version of the model in Arellano et al. (forthcoming) to study the transmission of uncertainty shocks under financial frictions.

Suppose again an industry populated by a unit mass of plants. Plants produce output according to $y = z\ell^{\nu}$, where ℓ denotes labor and z idiosyncratic productivity, which follows (1) and (2). Plants hire or fire workers before observing their productivity. Hence, a plant's revenue may fall short of its wage bill. The financial friction in this model is that plants have a limited capacity to borrow against expected future profits to finance such shortfalls. If the plant cannot raise enough funds to pay wages, it defaults. We assume plants face a short-term borrowing constraint, which we conveniently express

[13] For example, Bachmann and Bayer (2013) and Kehrig and Vincent (2016) show that gross investment rates exhibit excess kurtosis and negative skewness. In addition, Cooper and Haltiwanger (2006) and Bloom (2009) estimate significant non-convex capital adjustment costs.

in terms of the wage bill.[14] The plant's dynamic problem is

$$V(z, \sigma_z) = \max_{\ell} \mathbb{E}\left[z'\ell^{\nu} - w\ell + \beta V(z', \sigma_z') \,\middle|\, z, \sigma_z; z' > \hat{z}\right], \tag{5}$$
$$\text{s.t. } \hat{z}\ell^{\nu} - (1-\theta^F)w\ell = 0,$$

where parameter $0 \leq \theta^F \leq 1$ governs the degree of the short-term borrowing constraint. Under $\theta^F = 0$, the plant faces a zero borrowing limit. Whenever revenues $z'\ell^{\nu}$ realize lower than the predetermined wage bill $w\ell$, the plant defaults. To lower the risk of costly default, the plant produces at lower scale, i.e., it hires fewer workers, and thereby preserves a liquidity buffer. Conversely, under $\theta^F = 1$, the plant can borrow up to the total wage bill, hence default risk is zero. For sufficiently low θ^F, plants mitigate an increase in default risk that results from uncertainty shocks by further scaling down operations. Hence, job creation falls and job destruction increases.

2.4 Price rigidities

If prices are rigid, plants respond to higher uncertainty by precautionarily setting a higher price, see Fernandez-Villaverde et al. (2015). Important for the upward-pricing result is the asymmetry of the profit function in the price. If the plant's price is too low relative to aggregate prices, say, below marginal costs, profits turn negative. If the price is too high, demand goes toward zero and so do profits.

We study a plant problem subject to rigid prices á la Calvo (1983).[15] Plants produce output using $y = k^{\bar{\alpha}}\ell^{1-\bar{\alpha}}$. They face a demand curve $y = (p/P)^{-\xi}$, where p is their individual price, and P the aggregate price level. Macroeconomic uncertainty generates precautionary price-setting.[16] As a shortcut, we assume P is stochastic and follows the process described by (1) and (2), but parametrized by ρ_P, σ_P^L, σ_P^H. The dynamic plant problem is

$$V(p; P, \sigma_P) = \mathbb{E}\left[\theta^P \max_{p'}\left\{W(p'; P', \sigma_P')\right\} + (1-\theta^P)W(p; P', \sigma_P') \,\middle|\, P, \sigma_P\right], \tag{6}$$
$$W(p; P, \sigma_P) = \left[\frac{p}{P} - mc\right]\left(\frac{p}{P}\right)^{-\xi} + \beta V(p; P, \sigma_P),$$

where parameter $0 \leq \theta^P \leq 1$ governs the degree of price rigidity, and mc denotes

[14] We think of this constraint as a constraint on raising any funds, be it equity or credit.

[15] Similar upward-pricing emerges under Rotemberg price adjustment costs, see Fernandez-Villaverde et al. (2015) and Born and Pfeifer (2017).

[16] Since uncertainty about idiosyncratic productivity or demand does not generate precautionary price-setting, we do not model them.

marginal costs. Since we focus on the relative employment changes in an industry model, we set $mc = 1$ without loss of generality and compute employment as $\ell = (p/P)^{-\xi}$. If uncertainty increases, plants raise prices, and consequently, less jobs are created and more jobs destroyed.

2.5 Testable predictions

Finally, we investigate how the four frictions shape the response of job flows to uncertainty shocks. In particular, we study how the job flow responses change in the severity of the frictions, i.e., the *gradient* of the job flow responses in θ^L, θ^K, θ^F, and θ^P, repectively.

In all four models, we assume a period is a quarter. We follow Bloom et al. (2018) and set persistence $\rho_z = \rho_P = 0.95$, micro uncertainty $\sigma_z^L = 0.041$, $\sigma_z^H = 4.1 \cdot \sigma_z^H$, macro uncertainty $\sigma_P^L = 0.0067$, $\sigma_P^H = 1.6 \cdot \sigma_P^H$, and transition probabilities $\pi_{LL}^{\sigma} = 0.974$, $\pi_{HH}^{\sigma} = 0.943$. We assume $\beta = 0.99$ and $\delta = 0.025$. We set $\nu = 0.60$ and $\alpha = 0.24$, in line with the estimates in Cooper and Haltiwanger (2006) on plant-level LRD data, and close to the estimates in Gilchrist et al. (2014) and Winberry (2018) using Compustat and IRS data, respectively. For consistency, we set demand elasticity $\xi = 1/(1 - \alpha - \nu)$.

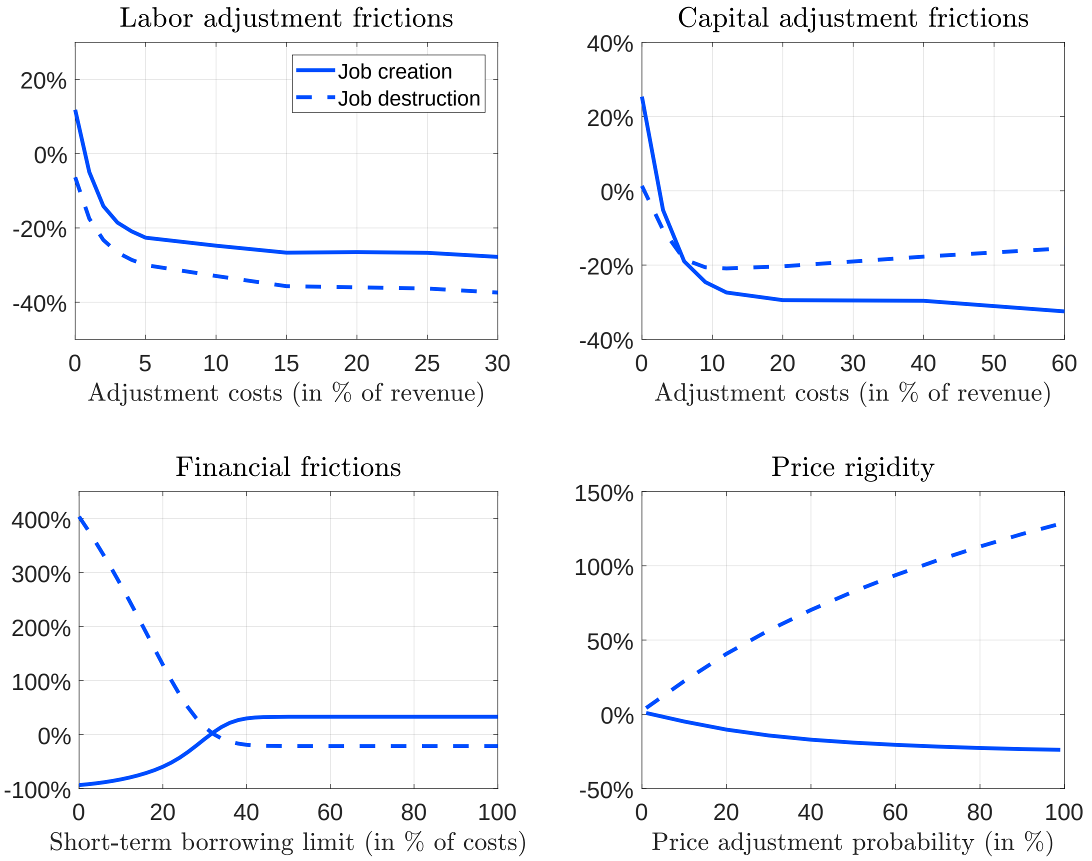
For the labor adjustment cost parameter θ^L, we consider an interval from 0 to 30%, which contains the estimates in Cooper and Willis (2009) and Bloom (2009). For the capital adjustment cost parameter θ^K, the interval ranges from 0 to 60%, which contains the estimates in Cooper and Haltiwanger (2006) and Bloom (2009).[17] The parameters of financial frictions, θ^F, and price rigidity, θ^P, are naturally bounded by the unit interval. For each model and each value of θ, we simulate 2,500 economies over 100 quarters, where each economy is hit with an uncertainty shock in the same quarter. The impulse response function of interest is the average percentage response of aggregate job flows in the period of the uncertainty shock.

Figure 1 shows the response of job flows to an uncertainty shock in the four models, varying the degree of the respective frictions (θ). The top-left panel shows the job flow responses under labor adjustment frictions. Two observations stand out. First, abstracting from adjustment costs below 2% of revenue, both job creation and job destruction fall after an uncertainty shock.[18] In other words, plants freeze. Second, the response of job flows is a falling function of labor adjustment costs. While it is well-known that average adjustment frequency falls in adjustment costs, we find that adjustment costs

[17]See Table 4 in Bachmann et al. (2013a) for an overview of capital adjustment costs.

[18]The increase in job creation for small adjustment costs is a result of the productivity process specified by (1) and (2), according to which mean productivity increases under higher uncertainty.

Figure 1: Job-flow responses to an uncertainty shock under various frictions



Notes: The solid (dashed) lines show the contemporaneous percentage change of job creation (job destruction) in response to an uncertainty shock. The x-axis in the subfigures displays the severity of various frictions, which corresponds to values of θ^L, θ^K, θ^F, and θ^P, respectively.

amplify the responses to uncertainty shocks. A necessary condition for amplification is that uncertainty shocks widen the employment adjustment triggers by more for higher adjustment costs. Under high adjustment costs, fewer plants adjust even in normal times. Hence, fewer plants are close to the adjustment triggers. If the triggers move by at least as much under high costs as under low costs, then the share of plants that adjust drops by more under high costs.[19]

The top-right panel of Figure 1 shows the job flow responses for various levels of capital adjustment costs. For adjustment costs above 3% of revenue, we find an un-

[19]In a related model framework, Abel and Eberly (1996) show analytically that the widening of the adjustment triggers increases in the cost of adjustment, see equation (20) in their paper.

ambiguous drop in job creation and job destruction. As discussed in 2.2, this means the freezing of *disinvestment* plans dominates the freezing of *investment* plans. Importantly, job creation is a falling function of capital adjustment costs, analogous to the case of labor adjustment frictions, while job destruction is an increasing function of capital adjustment costs.

The bottom-left panel of Figure 1 shows the job flow responses under various degrees of financial frictions. For short-term borrowing limits that cover less than 30% of total period costs, plants scale down operation when uncertainty increases. Job creation falls and job destruction increases. Above 30%, default risk is nil and the uncertainty shock becomes expansionary because employment policies respond to higher mean productivity. In the area below 30%, the response of job flows is amplified by tighter financial frictions. Job destruction increases the most and job creation falls the most under a zero borrowing limit.

Finally, the bottom-right panel of Figure 1 shows the job flow responses for different degrees of price rigidity. An uncertainty shock leads plants to upward adjust prices, which increases job destruction and decreases job creation. These responses are muted by more rigid prices. This is for two reasons. First, if fewer plants adjust their prices, fewer of them can raise them. Second, if prices are longer-lived, price setting will respond less to contemporaneous economic conditions such as high uncertainty.

We consider a transmission channel *empirically relevant* if four conditions are satisfied. The first two conditions are met if the empirically estimated job flow responses match the sign of the theoretically predicted responses. The other two conditions are met if the empirically estimated relations between the two job flow responses and the friction intensity, the job flow response *gradients*, match the theoretical prediction in sign. For this approach to be a valid one, we implicitly assume that the theoretical predictions obtained in models with a single friction, remain valid in the presence of further frictions. In other words, we assume the interaction between frictions is negligible.

Appendix A provides further results and robustness. In Figure 6, we show the response of employment to an uncertainty shock. As noted earlier, an uncertainty shock also raises mean productivity. Absent frictions the shock is hence expansionary. For the range for labor adjustment costs considered, we find that the shock is always expansionary even for sizable costs. Under capital adjustment costs, the shock is contractionary except for low adjustment costs. An important feature in which the capital adjustment model differs from the labor adjustment model is the presence of depreciation. When plants freeze their adjustment plans, the aggregate capital stock falls and so does employment because of complementarity. Under financial frictions, we obtain large employment declines if the borrowing limit is assumed tight. Similar to the job flow responses this highlights the potent role financial friction may play in amplifying the effects of uncertainty shocks. Under rigid prices, we find a small employment decline. The Appendix further shows that our baseline results in Figure 1 are robust when we study the job flow responses two quarters after an uncertainty shock, see Figure 7. Finally, we study the robustness of our results when changing parameter ν, which captures the decreasing returns to scale, or alternatively the steady state markup. Figures 8 and 9 show that our baseline results hold broadly robust.

3 Industry-level data on job flows and frictions

3.1 Job flows

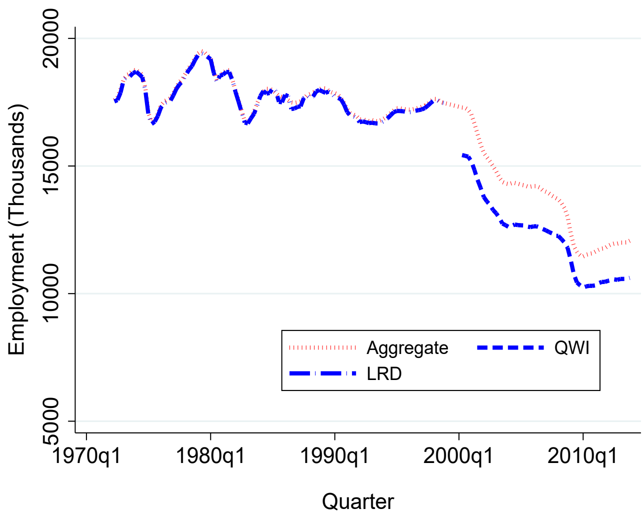
This paper constructs a new panel of quarterly industry-level job flows from 1972 to 2013. The panel has a relatively long time series dimension which helps to obtain precise estimates of the job flow responses to uncertainty shocks. To construct this panel we combine data from the Longitudinal Research Database (LRD) and the Quarterly Workforce Indicator (QWI). Davis et al. (1998) provide a publicly available panel of job flows from 1972 to 1998 based on the LRD. The data is disaggregated at the level of 4-digit SIC industries.[20] QWI data is publicly available and measures job flows disaggregated at the 4-digit NAICS level.[21] The underlying data is provided at the state level with some states initially missing from the sample. To obtain a fairly complete representation of US worker flows, we consider all states that provide information since 2000Q2. The selected sample constitutes 90% manufacturing employment in United States. We use the X-13 ARIMA to remove the seasonal component from the series. To create a common industry classification, we use a correspondence table from the NBER. Our final panel has a gap from 1999 to 2001. We refer the reader to Appendix B.1 for additional details about this data.

Figure 2 shows the aggregate time series of manufacturing employment based on our new panel compared to the official statistics published by the Bureau of Labor Statistics (BLS). While QWI-based employment is about 90% lower than the BLS series, the two series display strong comovement with the correlation being 98%.

[20]The LRD collects employment data from all US manufacturing plants with at least five employees. It accounts for more than 99% of total manufacturing employment.

[21]The QWI is based on the Longitudinal Employer-Household Dynamics (LEHD). It consists of linked employer-employee data covering over 95% of US private sector jobs.

Figure 2: Aggregate employment in US manufacturing



Notes: Manufacturing employment from the *aggregate*, offical BLS statistic is compared to manufacturing employment based on the *LRD* and *QWI* sample.

3.2 Friction indices

We propose industry-level indices to capture the strength of factor adjustment frictions, financial frictions, and price rigidities, respectively.

Labor adjustment frictions

The cost of hiring or firing workers may differ across industries. We consider three variables to capture these differences. Following Botero et al. (2004), we use the industry-level share of workers in full-time positions to measure the flexibility of employment contracts and the cost of firing workers. We further consider the industry-level share of workers affiliated to labor unions to capture union power.[22] Finally, we use the industry-level kurtosis of the cross-sectional net employment growth distribution computed from Compustat data. The presence of non-convex employment adjustment costs renders labor adjustment infrequent and lumpy, which implies excess kurtosis. Importantly, larger adjustment costs imply a larger kurtosis.[23]

[22]The share of full-time workers and union density are computed from the March Supplements of the Current Population Survey, see Table 1. To map the CPS industry classification into SIC, we use David Dorn's concordance table: http://www.dorn.net/data.htm.

[23]We compute the kurtosis of net employment growth for industries with at least ten observations. Given the low number of observations at the 4-digit industry level, we use the 3-digit level. For 10% of these industries, this leaves us without a kurtosis estimate, in which case we use the mean kurtosis

Capital adjustment frictions

Capital adjustment costs can be estimated through indirect inference using the distribution of cross-sectional gross investment rates, see, e.g., Cooper and Haltiwanger (2006) and Bachmann and Bayer (2014). A striking feature of the cross-sectional distribution is positive skewness and excess kurtosis. Non-convex capital adjustment costs lead to lumpy investment, which generates excess kurtosis. In combination with depreciation, it also generates positive skewness. Importantly, larger skewness and kurtosis can be explained by larger adjustment costs. Using Compustat data, we compute the within-industry skewness and kurtosis of the gross investment rate distribution to capture capital adjustment costs.[24] In addition, we consider the ratio of structures over equipment at the industry. Since structures are more costly to adjust than equipment capital, see, e.g., Caballero and Engel (1999), a large structure share implies larger capital adjustment costs for a given total stock of capital.

Financial frictions

Industries differ both in their liquidity and borrowing needs, as well as in their capacity to raise short-term funds. In other words, industries differ in the severity of the financial constraint they face. Following Raddatz (2006), we estimate liquidity needs by two ratios: the industry-level median ratios of inventories to sales and labor costs to sales.[25] Industries in which these ratios are larger have smaller liquidity buffers for bad times, and thereby may depend more on external finance. In principle, the constructed ratios may not be entirely technological. For example, businesses may opt to accumulate liquid assets to avoid financial dependence. To circumvent this problem, we follow the literature and construct the measures using information from publicly traded U.S. companies. The underlying assumption is that observed industry differences at these large publicly traded companies are not driven by the supply of credit.[26] We complement this information with the industry-level share of employment at firms younger than 5 years old. Ample evidence shows that young firms are more constraints in obtaining external funds, as they have a lower amount of collateral and shorter credit records.[27]

across all 3-digit industries in the same 2-digit industry group.

[24]We follow the procedure outlined for computing the industry-level employment growth kurtosis.

[25]We follow the procedure outlined for computing the industry-level employment growth kurtosis.

[26]Our results are robust when computing the inventory and labor ratio over sales from the NBER-CES manufacturing database.

[27]The literature has used firm size as alternative indicator for financial constraints. However, recent evidence suggests that financial frictions do not lead to different business dynamics across firm size, once controlling by the age of the firm, see Hurst and Pugsley (2011) and Fort et al. (2013).

Table 1: Variables (and sources) used to measure industry-level frictions

Labor adjustment frictions	
Share of full-time workers	March CPS: 1970-2011
Unionization rate of workers	March CPS: 1990-2011
Net employment growth kurtosis	Computstat: 1968-2006
Capital adjustment frictions	
Gross investment rate skewness	Compustat: 1968-2006
Gross investment rate kurtosis	Compustat: 1968-2006
Structure per equipment capital	NBER-CES: 1958-2011
Price rigidities	
Price adjustment frequency	BLS: 2005-2011
Financial frictions	
Inventory per sales	Compustat: 1968-2006
Labor cost per sales	Compustat: 1968-2006
Employment share young firms	QWI: 2000-2013

Price rigidity

To measure sectoral differences in price rigidity, we build on the microdata underlying the producer price index calculated by the BLS. In particular, we compute the frequency at which prices remain unchanged in a sector as measure of the sector's price rigidity. To do so, we use the four-digit sector-level price adjustment frequencies constructed in Pasten et al. (2018), which were generously provided to us by the authors.[28]

Indices

Table 1 summarizes the variables we use to capture cross-industry variation in the severity of various frictions. We aggregate the information by creating industry-level indices for the severity of each friction. Our baseline aggregation is to compute the unweighted arithmetic average after standardizing each variable to have mean zero and unit variance.[29] Our final panel includes 443 manufacturing industries. Table 2 presents the correlations between the (baseline) indexes. Industries with larger capital adjustment costs tend to have larger labor adjustment costs. At the same time, industries with

[28]As alternative measure of price rigidity, we have considered the price rigidity estimates in Petrella and Santoro (2012), estimated from a sector-specific New Keynesian Philips Curve, and generously shared with us by the authors. Our results are broadly unaffected when using this alternative.

[29]As alternative, we compute the first principal component over the set of standardized variables. Our main findings are robust to this specification, see Appendix B.2.

stronger factor adjustment frictions tend to be more financially constrained.

Table 2: Correlation between indexes

	Labor index	Capital index	Price index	Financial index
Labor index	1			
Capital index	.248***	1		
Price index	-.032	−.045	1	
Financial index	−.312***	−.063	0.099**	1

Notes: This table presents pairwise correlations between our indexes. See Table 1 for for a detail description of the industry indexes. Significance: 1% (***), 5% (**), 10% (*).

4 Empirical evidence

This section presents our main results. In particular, we find that the job flow responses to uncertainty shocks are stronger in more financially constrained industries. This supports financial frictions as important transmission channel of uncertainty shocks.

4.1 Empirical estimation strategy

To study the empirical relevance of various transmission channels, we proceed in two steps. First, we estimate industry-specific job flow responses. Second, we assess whether cross-industry variation in job flow responses is associated to cross-industry variation in the strength of frictions in line with the theoretical predictions in Section 2.

To estimate the industry-level response of job flows to uncertainty shocks, we use a quarterly structural vector autoregressive (VAR) model of lag order four with linear time trend. Estimating a single VAR model that includes the job flows of all industries is not feasible for the given sample size. Instead, we estimate separate VAR models for each industry. These models include the (log) S&P 500 stock market index, 3-month ahead uncertainty in Jurado et al. (2015), (log) aggregate manufacturing job creation and destruction, and (log) industry-specific job creation and destruction.[30] To identify uncertainty shocks, we follow Bloom (2009), and assume uncertainty is ordered second after the stock market level.

Without further restrictions, the estimated uncertainty shocks and their effects on aggregate variables will be different across the 443 industry-specific VAR models. In

[30] As robustness, we instead use the uncertainty measure in Ludvigson et al. (2019), see Appendix B.2.

contrast, our empirical strategy aims to exploit variation in the industry-level job flow responses to a shock that is uniform across industries. To identify such uniform shock, we restrict to zero the dynamic feedback from industry-specific job flows to aggregate variables. Formally, if $A_j^{k,l}$ denotes the slope coefficient that captures the effect of variable k on variable l at lag j, then the restrictions we impose are $A_j^{ijc,agg} = A_j^{ijd,agg} = 0$, $\forall\ j = 1, \ldots, 4$, and $\forall agg = s, u, jc, jd$, and where ijc and ijd denote industry-specific job creation and destruction, and s, u, jc, jd denote the stock market, uncertainty and aggregate job creation and destruction, respectively. This approach mimics Davis and Haltiwanger (2001), who identify the effect of oil price shocks on industry-level job flows.

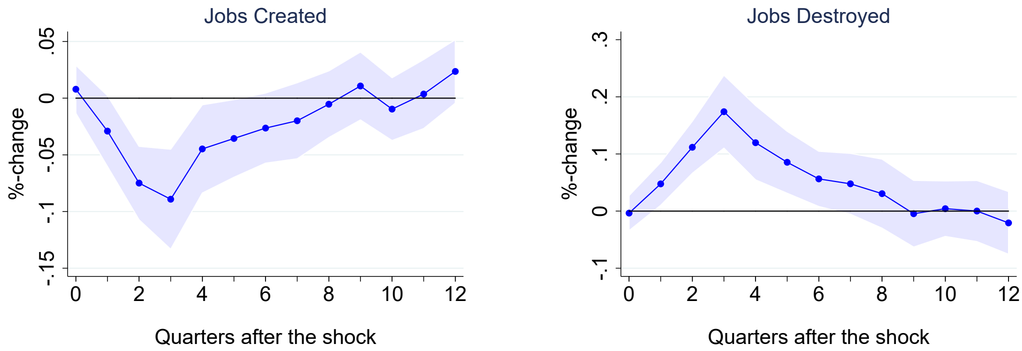
In practice, we directly estimate the impulse responses to uncertainty shocks using local projections, see Jorda (2005), while imposing the restrictions described above. Local projections are more robust to model misspecification and flexible in handling nonlinearities or the extra zero restrictions we impose on the reduced-form model. To account for the missing states in the QWI data used, we add a step dummy, which has value one from 2000Q2 onwards, and zero otherwise. We further allow for different time trends in the first part of the panel (1972-1998) and the second part (2000-2013).

4.2 Job flow responses to uncertainty shocks

Figure 3 shows the effects of an uncertainty shock on aggregate job creation and destruction. Job creation significantly falls while job destruction significantly increases. This finding is of interest by itself. It contradicts the labor adjustment model in Section 2, in which both job creation and job destruction fall, except for low adjustment costs, in which case the uncertainty shock is counterfactually expansionary. Hence, the sign of the aggregate job flow responses suggests that labor adjustment frictions are not central for the transmission of uncertainty shocks.

To compress the information contained in 443 industry-level impulse response functions, we focus on the average response within the first year after the uncertainty shock hits. We restrict attention to the short-term responses because in models with factor adjustment frictions the real options effect has predominantly short-term effects. This restriction is further justified by the fact that the estimated responses in Figure 3 are insignificant 4-6 quarter after the shock. Figure 4 shows the cross-sectoral variation in job flow responses to uncertainty shock. Reconfirming the result in Figure 3, in 80% of industries we estimate a decline in job creation and an increase in job destruction. While the average response of job creation is about -0.1% and +0.1% for job destruction, close to the responses of aggregate job flows, we observe substantial heterogeneity in the responses across industries.

Figure 3: Response of aggregate job flows to uncertainty shock



Notes: The blue lines show the responses of aggregate manufacturing job flows to a positive, three-standard deviation uncertainty shock. The shaded area is the 90% confidence interval using block bootstraps as in Kilian and Kim (2009).

4.3 Transmission channels

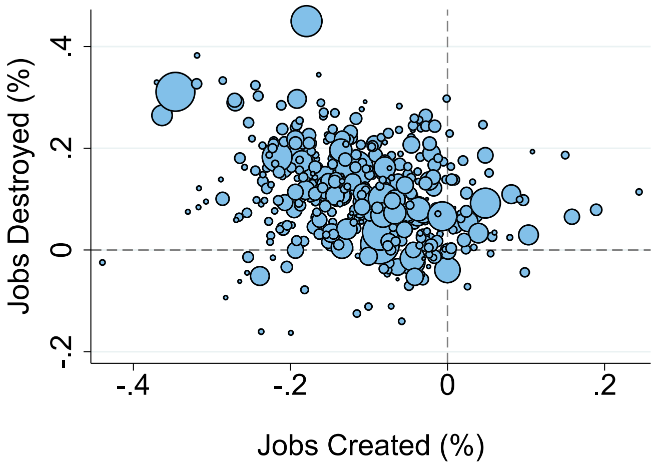
To assess the relevance of different transmission channels of uncertainty shocks, we regress the industry-level responses on the labor frictions index, capital frictions index, price rigidity index, and financial friction index.

We start with a simple sample split exercise. In Table 3, we rank industries according to the friction indices and provide mean and standard error of the job flow response of industries in the bottom and top quartiles of each friction, respectively.[31] For example, the top left number, -0.094, is the average job creation response for sectors in the bottom 25% of labor frictions, and 0.01 is the associated standard error. For industries subject to larger labor adjustment frictions, the job creation response is insignificantly smaller while the job creation response is significantly larger (at 10% significance level). The negative gradient for the job creation response fits the theoretical prediction of labor adjustment frictions in Section 2. However, the positive gradient for the job destruction response contradicts the prediction. Further, the positive sign of the job destruction response goes counter Section 2. This leads us to conclude that labor adjustment frictions are likely not of central importance for the transmission of uncertainty shocks.

The second row of Table 3 shows that the job creation response is insignificantly different across industries that differ in the degree of capital adjustment frictions, while the

[31] To account for outliers, we discard industries, for which any friction index is more than three standard deviations away from mean. The results barely change when we include all industries instead. In addition, the main results are robust to splitting the sample by tertiles or quintiles.

Figure 4: Cross-industry variation in job flow responses to uncertainty shock



Notes: Response of job flows averaged over the first year horizon to a three-standard deviation uncertainty shock. Marker size is proportional to employment of an industry.

job destruction response is significantly lower for industries with stronger capital adjustment frictions. Compared against the theoretical predictions, the insignificant difference in the job creation responses fails to support an important role of capital adjustment frictions as transmission channel. The price rigidity model in Section 2 perfectly explains the sign of the empirically estimated job flow responses to an uncertainty shocks. However, comparing industries that differ in the degree of price rigidity, we fail to detect any significant interaction with the job flow response, which contradicts the theoretical prediction.

Finally, we find that for sectors in the upper quartile of the financial frictions index, which face tighter short-term borrowing constraints, job creation significantly falls by more and job destruction significantly rises by more in response to uncertainty shocks. Both the sign of the responses and the sign of their gradient in financial frictions align well with the theoretical predictions.[32] To summarize, the evidence does supports financial frictions as important transmission channel of uncertainty shocks, while it does not support any of the other three channels.

While delivering sharp conclusions, the previous analysis in Table 3, may fail to

[32]To be clear, the results in Section 2 show that for loose borrowing limits, the signs of the job flow responses flip. Since this region also implies that uncertainty shocks are expansionary, which contradicts the vast empirical evidence suggesting the opposite, we assume the average sector is not in this region.

Table 3: Job flow responses and quartiles of friction indices

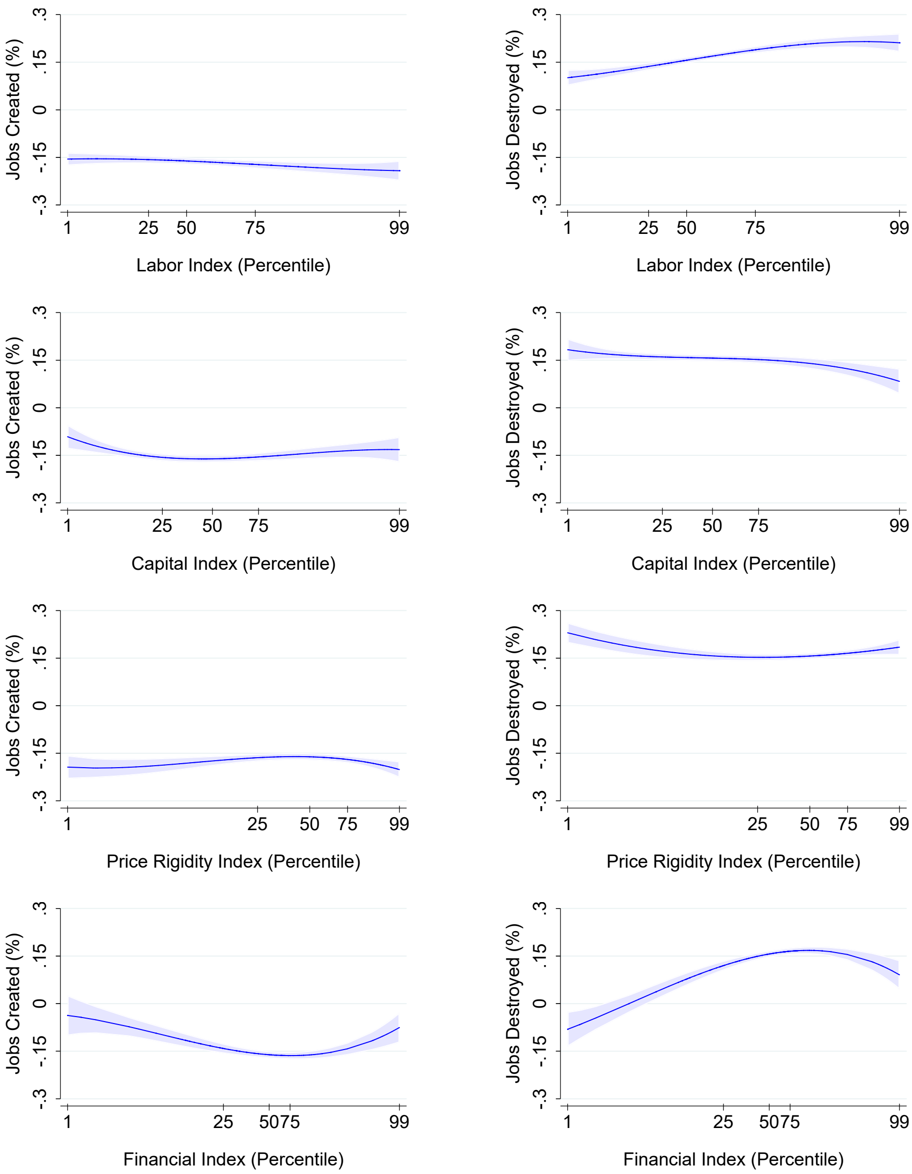
	Job creation		Job destruction	
	Bottom 25%	Top 25%	Bottom 25%	Top 25%
Labor frictions index	-0.094	-0.117	**0.061**	**0.124**
	(0.010)	(0.009)	(0.007)	(0.010)
Capital frictions index	-0.101	-0.110	**0.117**	**0.095**
	(0.010)	(0.009)	(0.009)	(0.009)
Price rigidity index	-0.104	-0.100	0.108	0.089
	(0.009)	(0.010)	(0.009)	(0.009)
Financial frictions index	**-0.077**	**-0.108**	**0.064**	**0.114**
	(0.008)	(0.009)	(0.008)	(0.008)

Bottom (Top) 25%: First-year average job flow response of industries in the first (last) quartile of the cross-industry distribution of a given index. Standard errors of the group means are in parenthesis. Bold-printed numbers indicate that group differences are significant at the 10% level.

isolate the effect of a single friction by not controlling for other frictions. In addition, we only compare subsets of the cross-sectional distribution. To address these shortcomings, we estimate a single regression of the job flow response on cubic polynomials of *all* four friction indices. Figure 5 shows the fitted relationships between the job flow responses and each individual friction index. The results broadly reconfirm and strengthen the findings in Table 3.

While job creation falls in labor adjustments frictions, so does job creation, which contradicts the theoretical prediction. Job creation does not appear to systematically comove with the capital index, while job destruction declines, in line with the previous results. The overall relation between job flows and price rigidity is characterized by U-shapes. When zooming into the range that describes the bulk of industries between the 10th and 90th percentiles the relation between rigidity and job creation is insignificant and job destruction increases in rigidity. The latter relationship was not detected in the simpler analysis of Table 3. Nonetheless, it contradicts the theoretical prediction, and thereby does not lend support to the price rigidity channel. Finally, for financial frictions, we again observe some U-shapes. However, between the 10th and 90th percentiles, we detect a monotone relation between financial frictions and job flow responses which qualitatively reconfirms the previous finding. The more severe the financial frictions in an industry, the stronger is the response of job flows to an uncertainty shock. The role of financial frictions is also quantitatively important: In response to a three-standard

Figure 5: Nonlinear relation between job flow responses and friction indices



Notes: Blue lines show the estimated (non-linear) relation between job flow responses and one friction index when keeping the other friction indices at their median levels, respectively. Shaded areas denote 90% confidence interval. We weight industry-level responses by the estimated absolute effect relative to its standard error.

deviation uncertainty shock, job creation barely falls for industries with weak frictions, while it falls by up to 0.15% under strong frictions. Similarly, job destruction does not increase in industries with mild frictions, while it increases by up to 0.15% in industries with strong frictions.

4.4 Robustness of empirical findings

Our main empirical findings, in particular the empirical support of financial frictions as transmission mechanism for uncertainty shocks, is robust along various dimensions. In Appendix B.2, we show that the results are robust against an alternative uncertainty measure, notably financial uncertainty based on Ludvigson et al. (2019). Moreover, we construct an alternative friction index by computing the first principal components of the series in Table 1. To address concerns about the construction of our job flow panel, we separately consider the LRD-based panel from 1972 to 1998 and the QWI-based panel from 2000 to 2013. The former panel reconfirms our baseline findings. This also shows that our results are not exclusively driven by the extraordinary uncertainty spike during the Great Recession. For the second sample, we receive the same qualitative results, with the only exception that the job creation response varies insignificantly across quartiles of the financial frictions index.

In addition, we assess whether our findings are robust in a richer VAR system which explicitly controls for monetary and fiscal shocks. We augment our baseline specification with monetary and fiscal shocks identified through narrative approaches. In particular, we include the shocks by Coibion et al. (2012) and Mertens and Ravn (2014). Data availability limits this analysis until 2006Q4. We place the tax and monetary shocks first in the recursive ordering. We find that in more than 60% of the industries, an uncertainty shock leads to a joint increase in job destruction and a decrease in job creation. Figure 13 shows that the relation between job flow responses and financial vulnerability remains significant and of similar quantitative magnitude compared to our baseline.

5 Conclusion

This paper reviews a number of transmission channels for uncertainty shocks studied in the literature, in particular labor adjustment frictions, capital adjustment frictions, price rigidities, and financial frictions. We provide new empirical evidence on the aggregate and industry-level response of job flows to uncertainty shocks. The key contribution of this paper is to exploit the cross-industry variation in job flow responses to assess the empirical relevance of various transmission channels. We create industry-level data on job flows for 1972-2013 in the US and find that a positive uncertainty shock jointly raises job destruction and lowers job creation in 80% of the industries. These responses are significantly stronger in industries that face tighter financial constraints, which supports financial frictions as transmission channel of uncertainty shocks. On the contrary, we do not find evidence in support of factor adjustment frictions or price rigidities as transmission channels of uncertainty shocks.

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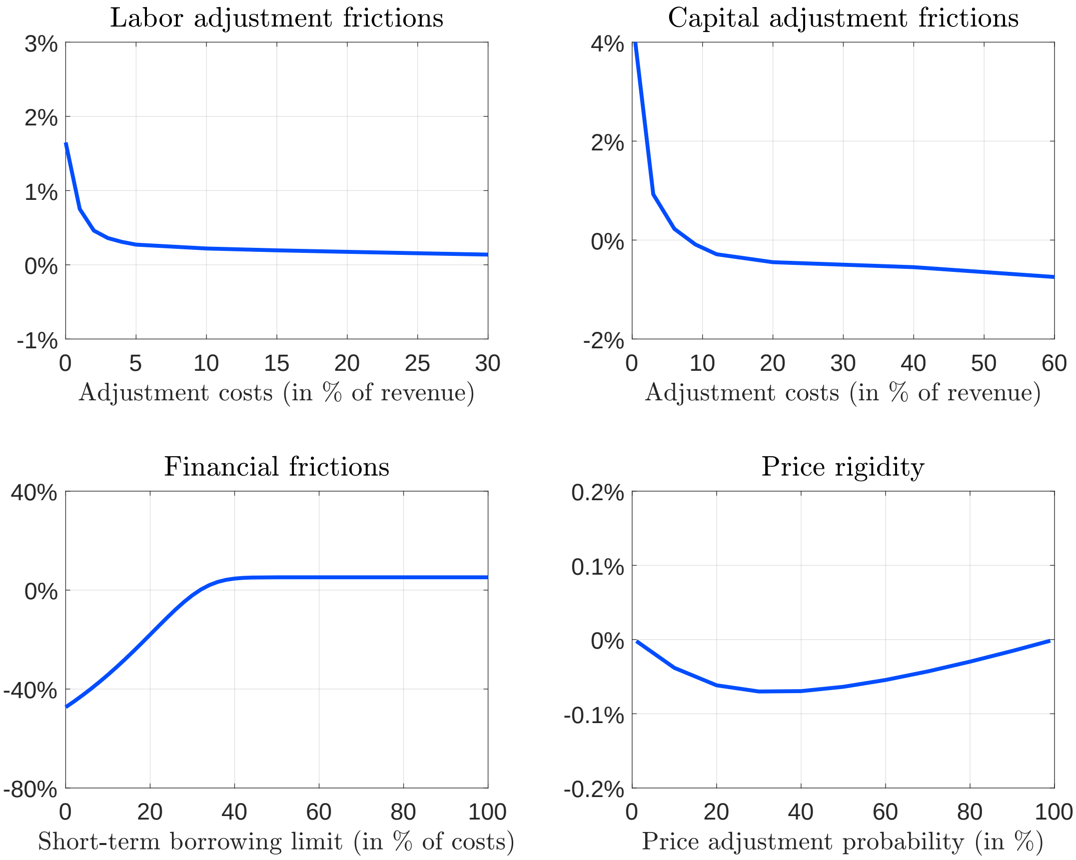
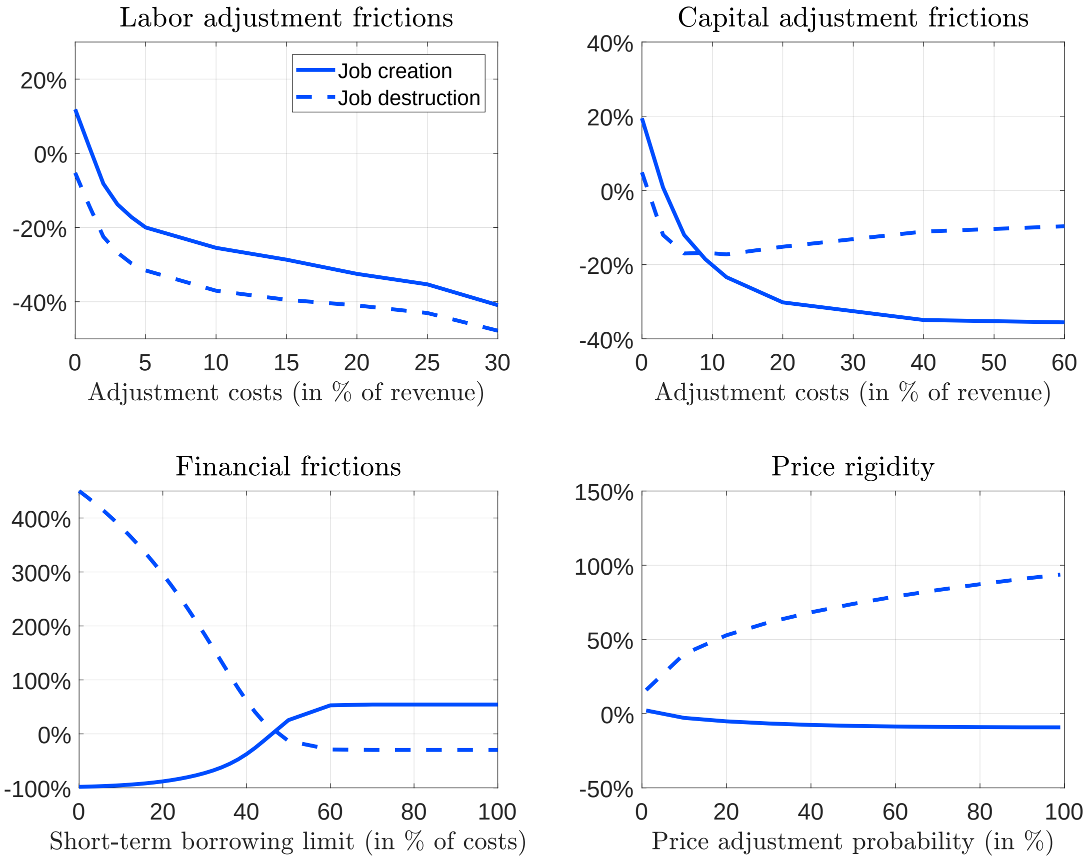
A Appendix: Models

Figure 6: Employment response to an uncertainty shock under various frictions



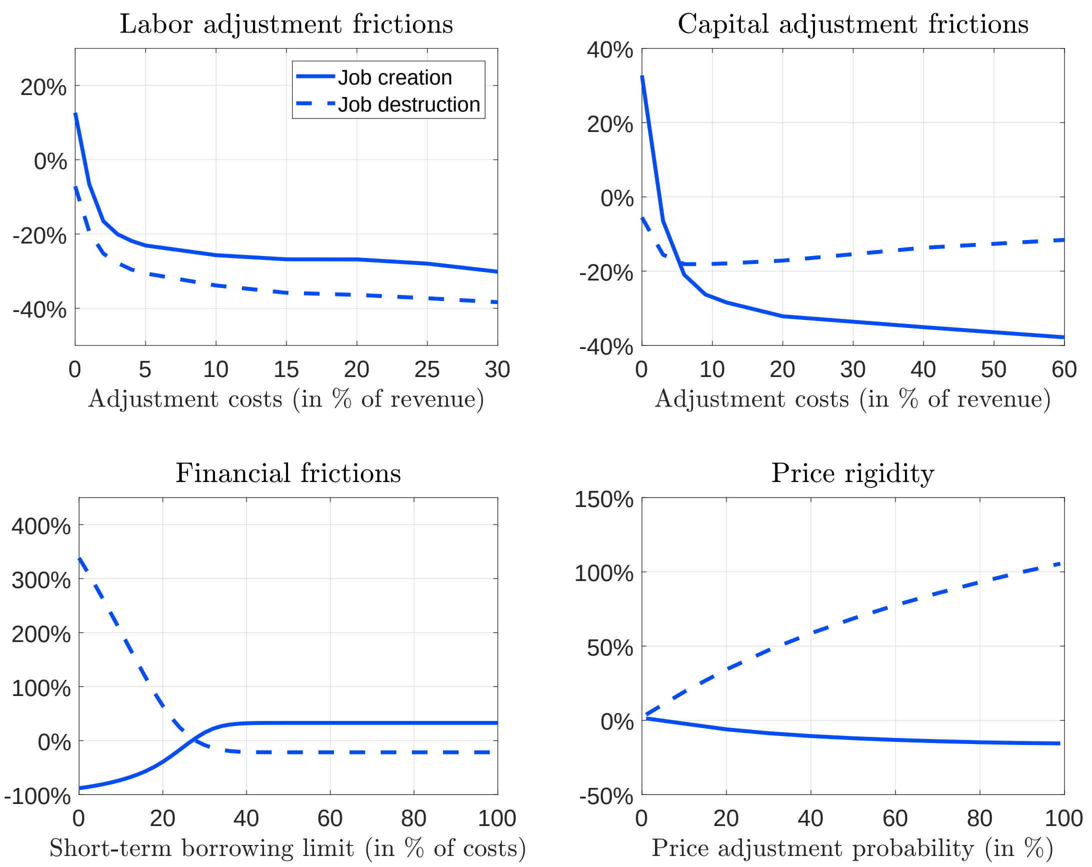
Notes: The solid lines show the contemporaneous percentage change of employment in response to an uncertainty shock. The x-axis in the subfigures displays the severity of various frictions, which corresponds to values of θ^L, θ^K, θ^F, and θ^P, respectively.

Figure 7: Robustness: job-flow responses two quarters after the shock



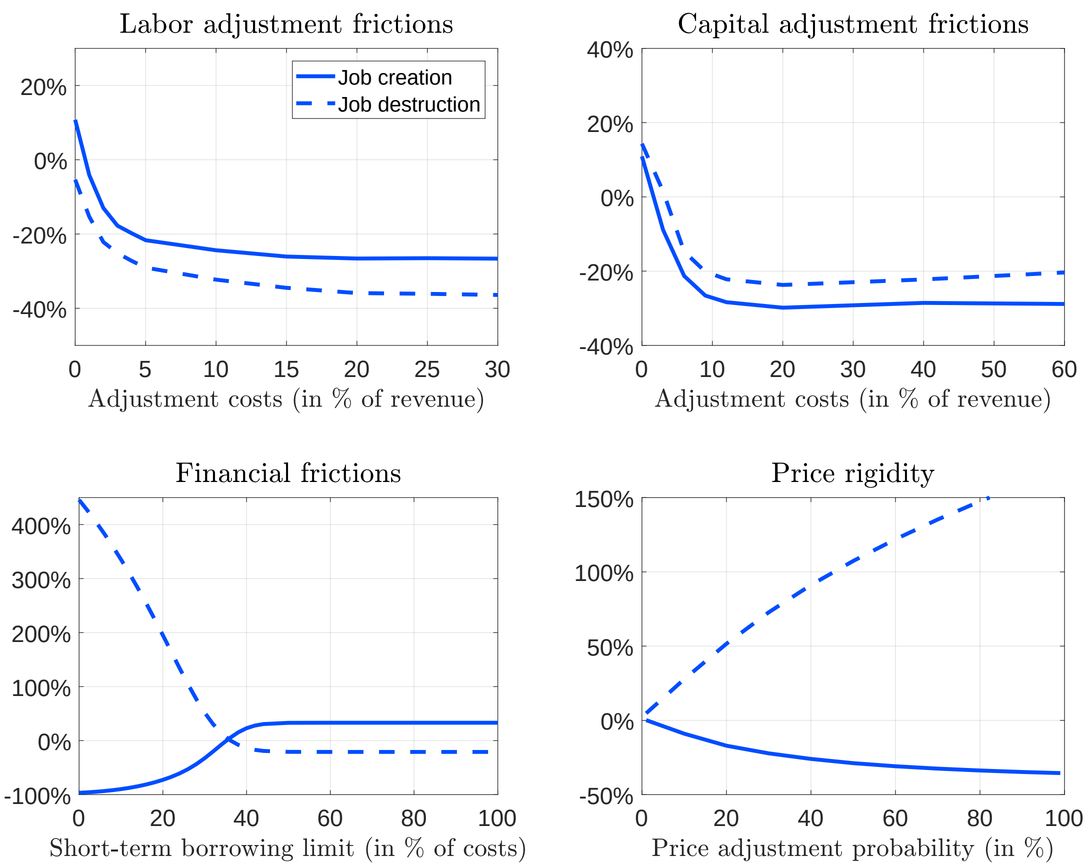
Notes: The solid (dashed) lines show the percentage change of job creation (job destruction) in response to an uncertainty shock two quarters before. The x-axis in the subfigures displays the severity of various frictions, which corresponds to values of θ^L, θ^K, θ^F, and θ^P, respectively.

Figure 8: Robustness: job-flow responses when $\nu = 0.56$



Notes: The solid (dashed) lines show the contemporaneous percentage change of job creation (job destruction) in response to an uncertainty shock. The x-axis in the subfigures displays the severity of various frictions, which corresponds to values of θ^L, θ^K, θ^F, and θ^P, respectively.

Figure 9: Robustness: job-flow responses when $\nu = 0.64$



Notes: The solid (dashed) lines show the contemporaneous percentage change of job creation (job destruction) in response to an uncertainty shock. The x-axis in the subfigures displays the severity of various frictions, which corresponds to values of θ^L, θ^K, θ^F, and θ^P, respectively.

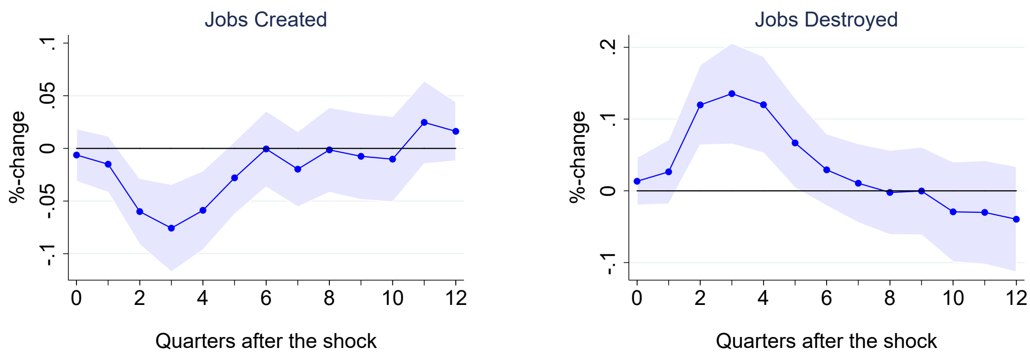
B Appendix: Empirical evidence

B.1 Data description

We use a concordance table provided by the National Bureau of Economic Research (NBER) to connect the LRD-based information at the 4-digit 1987 SIC level with the data series from QWI, disaggregated at the 4-digit 2007 NAICS level, see http://www.nber.org/nberprod/. We create consistent a consistent industry classification using this concordance table together with weights that reflect the share of employment at the SIC level which corresponds to an industry in NAICS. Before proceeding with this concordance, we need to conduct some adjustments. First, the available concordance between SIC and NAICS is based on the 1997 NAICS. Therefore, we translate 6-digit 2007 NAICS into 6-digit 1997 NAICS using the table given by US Census Bureau at http://www.census.gov/eos/www/naics/concordances/concordances.html. Second, we adjust the concordance table from the 6-digit NAICS level to the 4-digit NAICS level, and re-compute the weights from SIC into NAICS based on the share of employment of the 6-digit NAICS industry at the 4-digit NAICS level. At the end, we are able to map all industry-level job flows from NAICS with the LRD-based data from Davis et al. (1998).

B.2 Robustness exercises

Figure 10: Response of aggregate job flows to uncertainty shocks using financial uncertainty from Ludvigson et al. (2019)



Notes: The blue lines show the responses of aggregate manufacturing job flows to a positive, three-standard deviation uncertainty shock. The shaded area is the 90% confidence interval using block bootstraps as in Kilian and Kim (2009).

Table 4: Job flow responses and quartiles of friction indices using financial uncertainty from Ludvigson et al. (2019)

	Job creation		Job destruction	
	Bottom 25%	Top 25%	Bottom 25%	Top 25%
Labor frictions index	-0.104	-0.110	0.049	0.101
	(0.008)	(0.010)	(0.008)	(0.010)
Capital frictions index	-0.111	-0.110	0.102	0.073
	(0.009)	(0.010)	(0.009)	(0.009)
Price rigidity index	-0.107	-0.102	0.083	0.081
	(0.010)	(0.009)	(0.009)	(0.009)
Financial frictions index	-0.082	-0.114	0.057	0.087
	(0.008)	(0.008)	(0.008)	(0.009)

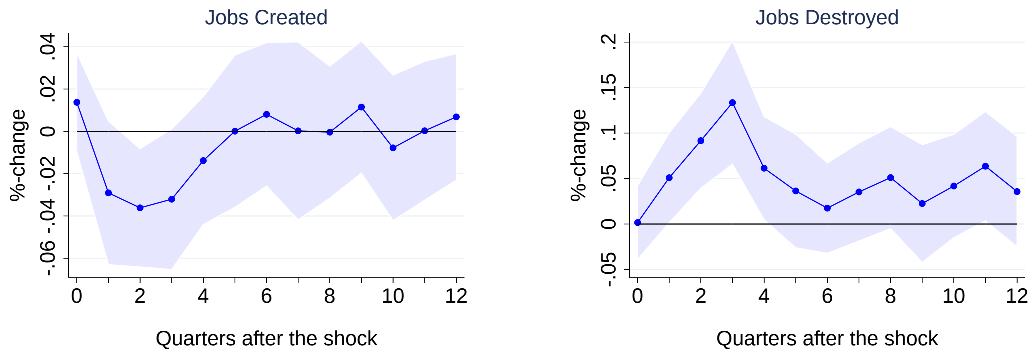
Notes: Bottom (Top) 25%: First-year average job flow response of industries in the first (last) quartile of the cross-industry distribution of a given index. Standard errors are in parenthesis.

Table 5: Job flow responses and quartiles of friction indices using the first principal components to construct friction indices

	Job creation		Job destruction	
	Bottom 25%	Top 25%	Bottom 25%	Top 25%
Labor frictions index	-0.098	-0.118	0.067	0.133
	(0.010)	(0.009)	(0.007)	(0.010)
Capital frictions index	-0.083	-0.108	0.107	0.102
	(0.010)	(0.009)	(0.009)	(0.009)
Price rigidity index	-0.102	-0.102	0.104	0.089
	(0.009)	(0.009)	(0.009)	(0.009)
Financial frictions index	-0.080	-0.090	0.046	0.122
	(0.008)	(0.009)	(0.007)	(0.008)

Notes: Bottom (Top) 25%: First-year average job flow response of industries in the first (last) quartile of the cross-industry distribution of a given index. Standard errors are in parenthesis.

Figure 11: Response of aggregate job flows to uncertainty shock: sample 1972-1998



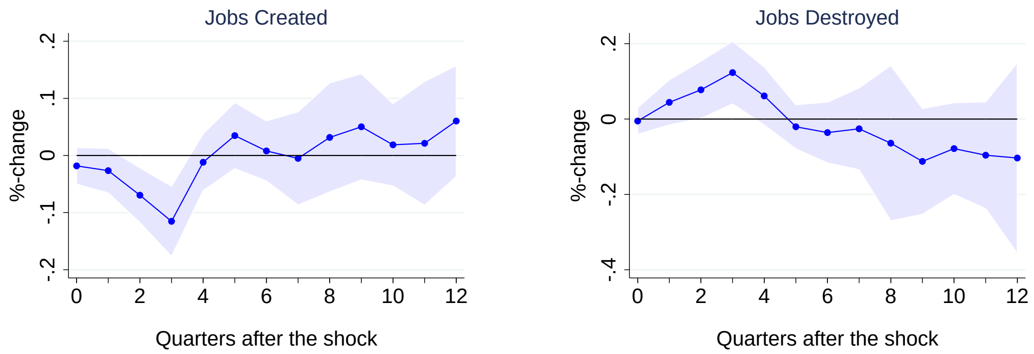
Notes: The blue lines show the responses of aggregate manufacturing job flows to a positive, three-standard deviation uncertainty shock. The shaded area is the 90% confidence interval using block bootstraps as in Kilian and Kim (2009).

Table 6: Job flow responses and quartiles of friction indices: sample 1972-1998

	Job creation		Job destruction	
	Bottom 25%	Top 25%	Bottom 25%	Top 25%
Labor frictions index	-0.074	-0.105	0.022	0.116
	(0.012)	(0.012)	(0.010)	(0.012)
Capital frictions index	-0.078	-0.098	0.082	0.084
	(0.009)	(0.013)	(0.012)	(0.011)
Price rigidity index	-0.090	-0.083	0.090	0.056
	(0.012)	(0.013)	(0.011)	(0.011)
Financial frictions index	-0.052	-0.094	0.063	0.084
	(0.011)	(0.011)	(0.010)	(0.013)

Notes: Bottom (Top) 25%: First-year average job flow response of industries in the first (last) quartile of the cross-industry distribution of a given index. Standard errors are in parenthesis.

Figure 12: Response of aggregate job flows to uncertainty shock: sample 2000-2013



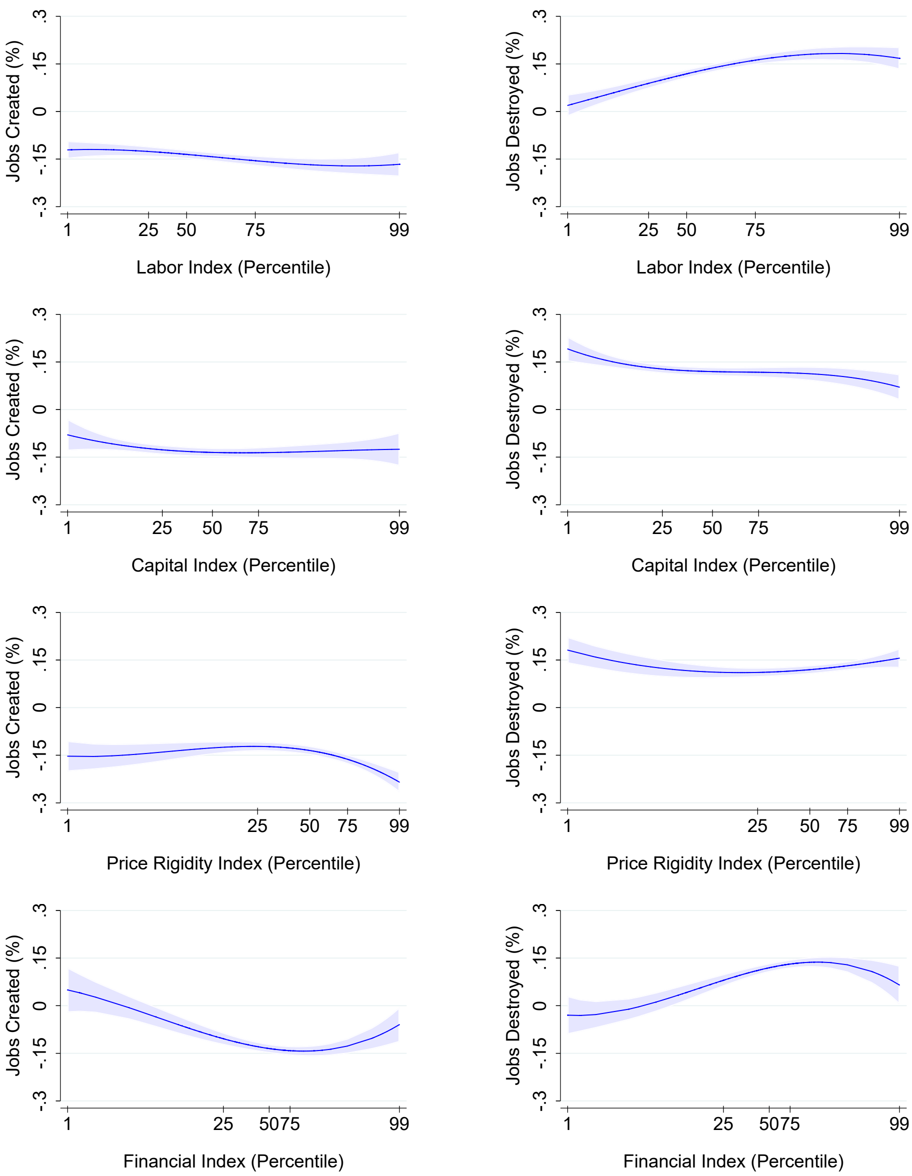
Notes: The blue lines show the responses of aggregate manufacturing job flows to a positive, three-standard deviation uncertainty shock. The shaded area is the 90% confidence interval using block bootstraps as in Kilian and Kim (2009).

Table 7: Job flow responses and quartiles of friction indices: sample 2000-2013

	Job creation		Job destruction	
	Bottom 25%	Top 25%	Bottom 25%	Top 25%
Labor frictions index	-0.049	-0.084	0.061	0.072
	(0.005)	(0.006)	(0.004)	(0.006)
Capital frictions index	-0.068	-0.063	0.088	0.056
	(0.007)	(0.004)	(0.006)	(0.005)
Price rigidity index	-0.062	-0.055	0.067	0.067
	(0.006)	(0.006)	(0.006)	(0.005)
Financial frictions index	-0.056	-0.064	0.042	0.082
	(0.005)	(0.004)	(0.005)	(0.004)

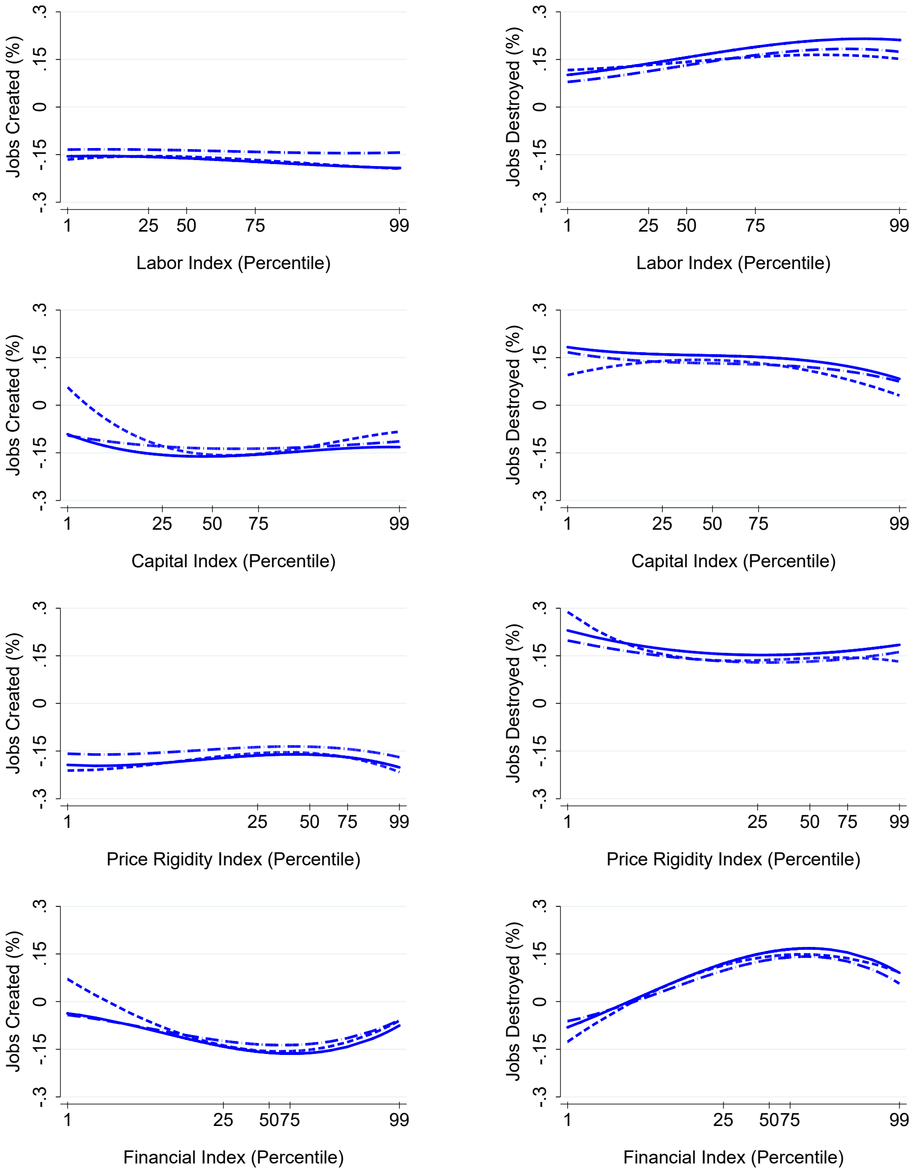
Notes: Bottom (Top) 25%: First-year average job flow response of industries in the first (last) quartile of the cross-industry distribution of a given index. Standard errors are in parenthesis.

Figure 13: Nonlinear relation between job flow responses and friction indices when explicitly controlling for monetary and fiscal shocks



Notes: Blue lines show the estimated (non-linear) relation between job flow responses and one friction index when keeping the other friction indices at their median levels, respectively. Shaded areas denote 90% confidence interval. We weight industry-level responses by the estimated absolute effect relative to its standard error.

Figure 14: Nonlinear relation between job flow responses and friction indices when using different horizons of job flow responses



Notes: Dashed/solid/dash-dotted lines show the estimated relation between first-two-quarters/first-year/first-six-quarters average job flow responses and one friction index when keeping the other friction indices at their medians, respectively.