

# Creative Destruction and Uncertainty over the Business Cycle\*

Petr Sedláček  
University of Bonn<sup>†</sup>

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## Abstract

Recessions are associated with increases in uncertainty. This paper shows that a simple model of creative destruction, in which new productive businesses push out old obsolete ones, produces increases in measured uncertainty during recessionary periods even without time-variation in second moments of exogenous shocks. Moreover, the suggested channel is also borne out by the data. Using an established identification strategy within a structural vector autoregression, this paper documents that several popular measures of uncertainty increase significantly in response to creative destruction shocks. This suggests that variation in measured uncertainty is (at least partly) and endogenous response of the economy to “standard” first-moment shocks.

## 1 Introduction

Are recessions fueled by increases in uncertainty, or is uncertainty an epiphenomenon of economic downturns? Triggered by the seminal paper of Bloom (2009), there is by now a vast set of studies documenting that economic downturns, including the most recent recession, are accompanied by increases in uncertainty. However, which way the causality runs is not entirely clear. Bloom argued that causality runs from uncertainty to economic

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<sup>†</sup>Address: Department of Economics, University of Bonn, Adenauerallee 24-42, 53113 Bonn, Germany.  
Email: [sedlacek@uni-bonn.de](mailto:sedlacek@uni-bonn.de)

activity, because higher uncertainty makes it more attractive to wait for more information. Investment and hiring freeze and aggregate economic activity falls.

Instead, this paper shows that a simple model of creative destruction, in which new productive businesses push out old obsolete ones gives rise to increases in measured uncertainty without reverting to time-variation in second moments of exogenous shocks. Moreover, using structural vector autoregressions and an established identification strategy of creative destruction shocks, the paper also documents that this channel is borne out in the data.

First, this paper builds a relatively standard model of creative destruction and a frictional labor market. The economy is characterized by a technological frontier which grows along a stochastic trend. While newly created firms possess this frontier technology, older businesses keep the technological level from the time of their birth unless they managed to innovate. The process of innovation happens with an exogenous probability and leads firms to jump to the technological frontier.

When firms are repeatedly unsuccessful in innovation they fall behind the technological frontier and become relatively more and more unproductive. At the same time, all firms obtain idiosyncratic productivity shocks at the beginning of each period. Firms with particularly bad realizations of these shocks become unprofitable and they shut down. Therefore, an increase in the technological frontier leads to not only greater incentives for creating new productive jobs, but also to an rise in the mass of exiting firms. Workers coming from exiting firms reallocate to new jobs, but the frictional labor market makes this adjustment sluggish resulting in a temporary economic downturn (a rise in unemployment and a drop in output).

Within the model it is possible to construct measures of uncertainty typically used in the empirical literature. In particular, this paper uses the same empirical strategy as in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) to quantify changes in uncertainty by estimating firm-specific productivity regressions controlling for firm and time fixed effects and investigating time-variation in the cross-sectional variance of residuals from such regressions. As in the data, also in the model the cross-sectional variance of residuals moves countercyclically. Moreover, the magnitude of these movements accounts for about three quarters of that estimated in the data.

The intuition for this result is one of regression misspecification. The true model of productivity evolution in the model includes an indicator function accounting for the possibility of innovation (and a jump to the technological frontier). When this possibility is

not considered, productivity changes among innovating firms are captured by the residual term of the regression (even when accounting for firm and time fixed effects). The magnitude of this regression “error” then rises when the frontier expands (which is associated with a recessionary response as explained above).

Second, this paper documents that the channel suggested in the model is also borne out by the data. Specifically, using structural vector autoregressions (SVARs) to identify creative destruction shocks as in Gali (1999) and Fisher (2006) this paper shows that several popular measures of uncertainty increase significantly following a positive creative destruction shock. Therefore, this paper shows that movements in measured uncertainty are (at least partly) driven by endogenous responses of the economy to “standard” first-moment shocks rather than the result of shocks to second moments.

The rest of the paper is organized as follows. The next section summarizes the related literature. Section 3 builds the structural model of creative destruction and describes the calibration and solution method. Section 4 then presents the model-results with a focus on endogenous uncertainty movements. Next, Section 5 identifies creative destruction shocks in the data using SVARs and documents that uncertainty measures respond to them. Finally, Section 6 provides some concluding remarks.

## 2 Related literature

This section briefly summarizes existing papers studying uncertainty (its measures, its impact on the economy and reasons for why it may be varying over time) as well as papers investigating “Schumpeterian” creative destruction shocks and their effect on the economy.

### 2.1 Uncertainty measures

In an influential paper Bloom (2009) presented new evidence on the counter-cyclicity of measures of uncertainty. In particular, Bloom shows that the VXO index of stock market volatility covaries negatively with industrial production and positively with cross-sectional dispersion in profits and stock returns. Moreover, he finds that positive innovations to the VXO index cause a drop in industrial production in a VAR, where the innovations are identified using a Choleski-ordering approach. Based on this evidence, Bloom offers an interpretation in which causation runs from “uncertainty shocks” to real activity.

The above-mentioned paper sparked a large research effort attempting to measure changes in uncertainty. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012)

document that the dispersion of growth rates or sales across listed companies and across all industries are strongly counter-cyclical. Bachmann and Bayer (2014) find that in a long panel of German firms the cross-sectional dispersion of productivity, output and employment growth is counter-cyclical, but that the dispersion of firm-level investment rates is pro-cyclical. Vavra (2014) uses micro-data underlying the Consumer Price Index and finds that the cross-sectional standard deviation of price changes is strongly counter-cyclical. Bachmann, Elstner, and Hristov (2014) use survey data for German manufacturing firms to directly quantify firm-level investment innovation shocks (a difference between firms' investment expectations and realizations). They find that the cross-sectional dispersion in these innovations is strongly counter-cyclical and that measures of firm-level risk have sizeable fluctuations.

Recently the focus of many researchers has moved towards uncertainty in macroeconomic policies. Baker, Bloom, and Davis (2012) measure uncertainty in macroeconomic policies using news from the media. Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez, and Uribe (2011) document time-variation in the volatility of the real interest rate faced by a sample of emerging small open economies and Fernandez-Villaverde, Guerron-Quintana, Kuester, and Rubio-Ramirez (2012) estimate tax and spending processes for the U.S. and find time-varying volatility.

Finally, Jurado, Ludvigson, and Ng (forthcoming) take a data-rich econometric approach in obtaining "direct" measures of uncertainty. In particular, they define uncertainty as the common volatility in the unforecastable component of a large number of economic indicators. They group these indicators into aggregate variables and firm-level variables and thus refer to macro- and micro-uncertainty. They find that while uncertainty remains counter-cyclical, quantitatively important uncertainty episodes appear less frequently than indicated by other popular proxies.

## **2.2 Effects of uncertainty shocks**

As was mentioned earlier, Bloom (2009) presents a model in which positive shocks to uncertainty (of an empirically plausible magnitude) cause substantial and sharp declines in real activity. Arellano, Bai, and Kehoe (2012) study how financial frictions and uncertainty shocks help explain the drop in output as well as the large movements in the labor wedge. Bachmann and Bayer (2014) find that in a neoclassical model which is calibrated to match the observed pro-cyclicality of investment rates shocks to the dispersion of firm-level TFP

cannot be too large and as such cannot cause serious business cycles. Christiano, Motto, and Rostagno (2010) fit a DSGE model with a banking sector and financial markets to US and Euro-Area data and find that shocks to the perception of market risk are one of the prime determinants of economic fluctuations. Chugh (2014) uses a micro-estimated process for the dispersion of firm-level productivity as an input in a DSGE financial accelerator model and finds that these shocks explain only a small fraction of GDP fluctuations. ? analyze how uncertainty shocks and financial frictions can give rise to business cycle fluctuations which are observationally equivalent to TFP-driven fluctuations. Finally, Schaal (2012) builds a labor market model with idiosyncratic volatility shocks to explain the large and persistent increase in unemployment and a rise in labor-productivity observed during the Great Recession in the U.S. economy.

### **2.3 Endogenous fluctuations in uncertainty**

The group of papers which tries to investigate the opposite direction of causality, i.e. from first-moment shocks to uncertainty, is much smaller. Bachmann and Moscarini (2012) propose a model with imperfect information about demand in an otherwise standard monopolistically competitive setup. When a firm deviates from competitors' average prices, it faces a potential profit loss, but learns more about its elasticity (market power). Dispersion in prices then endogenously increases in bad economic times because these are well suited for price experimentation as the opportunity costs of price mistakes are lower.

Boedo, Decker, and D'Erasmus (2014) use the U.S. Census Bureau's Longitudinal Business Database to show that measures of market reach are pro-cyclical and that the counter-cyclicality of firm-level volatility is driven mainly by those firms that adjust the number of markets to which they are exposed. Further, they show that these findings are consistent with a model in which firm endogenously choose the degree of market exposure and which is driven by only shocks to total factor productivity.

Cui (2014) shows that reallocation activity is slowed down in a general equilibrium model in which firms face idiosyncratic productivity risks, are subject to partial irreversibility and financing constraints. The reason is that partial irreversibility generates selling delays and these are exacerbated in bad times when financing constraints are tighter.

## 2.4 Schumpeterian technology shocks

The empirical results in this paper are related to Gali (1999), Christiano, Eichenbaum, and Vigfusson (2003), Francis and Ramey (2005), Fisher (2006), Lopez-Salido and Michelacci (2007) and Canova, Lopez-Salido, and Michelacci (2013), who study the effects of neutral (and investment specific) technology shocks within a structural VAR framework on hours worked, unemployment and labor market flows, respectively. The empirical evidence on the effects of neutral technology shocks on hours is mixed and Fernald (2007) and Canova, Lopez-Salido, and Michelacci (2013) attribute this, at least in part, to the influence of low-frequency movements. A consensus view does, however, appear for the effect of technology shocks on unemployment and labor market flows. In particular, neutral technology (Schumpeterian) shocks have been found to increase (decrease) unemployment and separations (the probability of finding a job) temporarily.

The role of creative destruction shocks for driving economic fluctuations or growth has been analyzed in several papers. For instance, Aghion and Howitt (1994) analyze the link between growth (driven by the introduction of new technologies) and unemployment (arising from labor reallocation). Caballero and Hammour (1996) study the timing and efficiency of creative destruction and Mortensen and Pissarides (1998) investigate the link between productivity growth and unemployment depending on the extent of costs of technological updating. Lopez-Salido and Michelacci (2007) provide a search and matching model explaining observed patterns of unemployment and worker flows in response to neutral and investment specific technological shocks.

## 3 Model

This section presents a search and matching model with vintage technologies. The “leading” technology evolves according to an exogenous stochastic process (random walk with drift) and new jobs are created with the latest leading technology. Jobs keep their initial technology level, but each period they “upgrade” to the newest leading technology with a certain probability. It will be shown that in this setup technology shocks (i.e. innovations to the leading technology) lead to not only an increase in unemployment, but also to a widening of the cross-sectional dispersion of firm level TFP innovations. In other words, this model features endogenous movements in measured uncertainty which are driven by a first-moment productivity shock.

### 3.1 Technology and production

The “leading” technology in the economy (the technological frontier)  $z_t$  evolves according to

$$z_t = \bar{z} + z_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma_z^2), \quad (1)$$

where  $\bar{z} > 0$  is a constant drift component. At any point in time, an individual firm’s productivity  $z_{i,t}$  is “updated” to the frontier with probability  $p$  and it is “downgraded” with probability  $1 - p$  (i.e.  $P(z_{0,t+1}|z_{i,t}) = p$ ).<sup>1</sup>

Let  $\gamma_{i,t} = z_t - z_{i,t}$  be the technological gap of an individual firm. Given that the technological frontier has a positive drift, remaining at a given productivity level means that the technological gap increases. Without loss of generality, let  $i$  denote the number of periods an individual firm did not update its technology. Let  $K$  be the maximum number of periods a given firm is allowed not to upgrade its technology before it exits the economy.

The stochastic aggregate trend is given by  $e^{z_t}$  around which the economy fluctuates. To stationarize the economy, I scale quantities by  $e^{z_t}$ , unless stated otherwise. Production happens in firms which employ (one) worker as the only input in production.

### 3.2 Household

The representative household maximizes the following preferences

$$\sum_{t=0}^{\infty} \beta^t (\ln C_t - \zeta N_t)$$

subject to its budget constraint

$$C_t = N_t W_t + \Pi_t, \quad (2)$$

where  $C_t$  is aggregate consumption,  $N_t$  is aggregate employment,  $W_t$  is the aggregate wage and  $\Pi_t$  are aggregate profits coming from the ownership of firms. The above gives rise to the familiar first order condition

$$W_t = C_t \zeta. \quad (3)$$

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<sup>1</sup>Note that the “leading technology” need not be the most productive one in the economy. A sequence of negative shocks  $\epsilon_t$  can push the leading technology below previous levels making some firms which are not at the frontier more productive.

### 3.3 Firms and aggregates

In this model I consider only one-worker firms. Existing firms produce output and pay a wage to their worker. Conditional on not shutting down in the next period, they then continue to produce in the future. The value of existing firms can be written as

$$V_{i,j,t} = y_{i,j,t} - W_t - \phi_{i,t} + \beta\Lambda_t \left[ p(1 - \delta_{0,t+1})\widehat{V}_{0,t+1} + (1-p)(1 - \delta_{i+1,t+1})\widehat{V}_{i+1,t+1} \right], \quad (4)$$

where  $y_{i,j,t} = \exp(\gamma_{i,t})\chi_{j,t}$  is output which depends on the productivity gap from the frontier and on an idiosyncratic productivity shock  $\chi_{j,t}$ . It is assumed that these idiosyncratic shocks are iid shocks from a distribution  $H$ . The aggregate wage is given by  $W_t$  and the household's stochastic discount factor by  $\Lambda_t$ .  $\phi_{i,t} = \phi \exp(\gamma_{i,t})$  is an operational cost which is assumed to be proportional to expected output.  $\delta_{i,t} = \delta + (1 - \delta)H(\widetilde{\chi}_{i,t})$  is the probability of shutting down, where  $\delta$  is an exogenous parameter and  $\widetilde{\chi}_{i,t}$  is a cutoff for firm-specific productivity below which it is optimal for a firm to shut down.  $H(\widetilde{\chi}_{i,t})$  then gives the endogenous probability of shutting down. Finally, hatted variables denote expectations conditional on survival, i.e.  $\widehat{x} = \mathbb{E}[x|\chi > \widetilde{\chi}]$ .

The idiosyncratic productivity cutoff is defined implicitly by firm value being equal to zero. This results in the following expression:

$$\widetilde{\chi}_{i,t} = \frac{1}{\exp(\gamma_{i,t})} \left\{ W_t + \phi_{i,t} - \beta\Lambda_t \left[ p(1 - \delta_{0,t+1})\widehat{V}_{0,t+1} + (1-p)(1 - \delta_{i+1,t+1})\widehat{V}_{i+1,t+1} \right] \right\}. \quad (5)$$

It is assumed that entry of new firms into the economy is free subject to a payment of a startup cost  $\kappa$ . Moreover, new firms enter with the frontier technology. Under these assumptions, entry will occur until the costs are equal to the expected benefits:

$$\kappa = \beta(1 - \delta_{0,t+1})V_{0,t+1}. \quad (6)$$

The evolution of the (active) number of firms is given by

$$\begin{aligned} \omega_{0,t} &= (1 - \widetilde{\delta}_{0,t})(S_t + p\Omega_{t-1}), \\ \omega_{i,t} &= (1 - \widetilde{\delta}_{i,t})(1 - p)\omega_{i-1,t-1}, \quad \text{for } i = 1, 2, \dots, K, \end{aligned} \quad (7)$$

where again  $\Omega_t = \sum_i \omega_{i,t}$  and  $S_t$  is the number of startups. Finally, the aggregates must take into account that at the beginning of the period not all firms survive:

$$Y_t = \sum_i \omega_{i,t} \widehat{y}_{i,t}, \quad (8)$$



Total employment is simply given by the number of firms  $N_t = \Omega_t$  and aggregate consumption is given by

$$C_t = Y_t - \kappa S_t. \quad (9)$$

### 3.4 Equilibrium

To be written.

### 3.5 Calibration

The parameters of the exogenous neutral technology process include the constant drift term  $\bar{z}$ , its standard deviation  $\sigma_z$  and at this point also the probability of a given firm transitioning to the frontier technology  $p$ . The drift term is set to 0.0054 such that the annual growth in output per worker is the observed 2.2 percent (for output per hour in the non-farm business sector). The standard deviation of  $\sigma_z$  is set such that in simulated data the fraction of firms with productivity higher than the current frontier technology is 40% (following Michelacci and Lopez-Salido). Finally, notice that  $1 - p$  is the autocorrelation coefficient in the firm-level productivity. Therefore,  $p$  is set to 0.08 such that the annual autocorrelation coefficient is 0.7 as estimated by Imrohoroglu (2013) (note that Christian finds a much higher autocorrelation coefficient in German data - about 0.95 at the annual frequency).

Parameters pertaining to the labor market include the vacancy posting cost  $\kappa$ , match efficiency  $m$ , matching elasticity  $\mu$ , the bargaining power of workers  $\eta$ , the outside option  $b$ , an exogenous separation rate  $\rho$ , the size of the labor force  $L$  and the mean and standard deviation of the idiosyncratic productivity shocks  $\mu_H$  and  $\sigma_H$ .

The matching elasticity and the bargaining power are both set to 0.5 following much of the literature and adhering to the Hosios condition. The standard deviation of the idiosyncratic productivity shocks is such that the relative volatility of separations (w.r.t. output volatility) matches the data. The outside option is set such that the replacement rate is 40% as in ?. The exogenous separation rate is set such that total separations are equal to 4.3 percent on a quarterly basis as is the case in the CPS. Finally, the vacancy posting cost  $\kappa$  is then implied by the vacancy posting condition.

### 3.6 Solution method

To be written.

## 4 Model results

### 4.1 Model performance

To be written.

- calibration targets and model predictions
- business cycle properties of model

### 4.2 Endogenous fluctuations in measured uncertainty

The focus of this paper is on the cross-sectional dispersion of firm-level TFP shocks as measured in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012). It is possible to replicate the estimations done in the afore-mentioned paper within the model. In particular, using the policy functions obtained from the solution, one can simulate a cross-section of firms to obtain a panel dataset of firm-level productivity observations. Using this panel dataset, I run the following regression

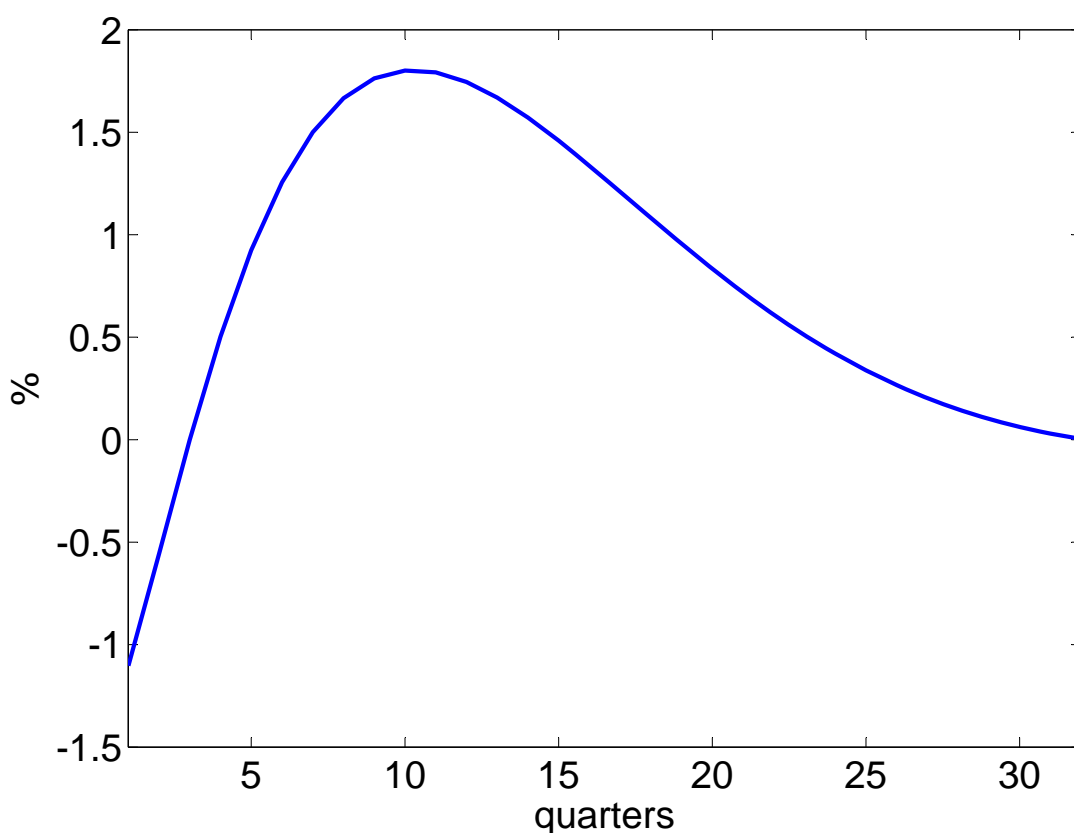
$$\ln z_{i,t} = \bar{z}_i + \lambda_t + \alpha \ln z_{i,t-1} + \epsilon_{i,t}, \quad (10)$$

where  $z_{i,t}$  is firm-level productivity,  $\bar{z}_i$  is a firm-specific fixed effect,  $\lambda_t$  is a year fixed effect, and  $\epsilon_{i,t}$  are firm specific innovations to productivity. Regression (10) is identical to equation (4) in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012). The measure of dispersion is then the cross-sectional variation in  $\epsilon_{i,t}$ .

Before moving on to the results, let us first discuss the intuition as to why the model delivers counter-cyclical variation in the above measure of uncertainty. From the model we know that firm-level productivity either remains constant at  $z_{i,t-1}$  if the firm does not innovate, or it changes to the latest value of the leading technology  $z_t$  if the firm innovates. Therefore, the “mistake” made by the regression model in (10) relates to firms which innovate and move to the frontier. This makes clear that in the period of a positive technology shock (i.e. when unemployment increases) the dispersion of the  $\epsilon_{i,t}$  shocks increases because the distance to the frontier increases for all firms.

Quantitatively, the estimated dispersion in firm-level productivity innovations moves closely with the business cycle. In particular, the correlation coefficient between the dispersion measure and output growth is  $-0.37$  in the model and  $-0.45$  in the data. The size of the fluctuations in the dispersion of firm-level shocks is, however, almost twice as

Figure 1: Impulse response functions - productivity dispersion



Notes: Impulse response functions (in percent) of firm-level productivity to a positive one-standard-deviation shock to neutral technology.

large in the model compared to the data. While in the data the relative volatility of the dispersion measure with respect to output fluctuations is about 6.5, in the model this statistic is about 4.9. However, this is also accompanied by a much lower level of the interquartile range in the model.

An alternative measure of uncertainty is the dispersion of firm-level productivity. Figure 1 depicts the impulse response function of the dispersion of productivity to a positive one-standard-deviation creative destruction shock. Clearly, the uncertainty measure increases in a hump-shaped fashion, but only after a few periods of a decline. The decline comes from the fact that initially, the destruction of existing firms which are close to being obsolete is faster than the subsequent building of new productive businesses. This means that initially productivity dispersion decreases because the lower tail of the distribution

disappears quickly.

## 5 Empirical evidence

This section provides empirical evidence on the response of several uncertainty measures to neutral technology shocks identified with long-run restrictions within a structural VAR.

### 5.1 Structural VAR with long-run restrictions

Let  $Y_t$  be a vector of variables with a moving average representation  $Y_t = C(L)\epsilon_t$ , where  $C(L)$  is a matrix of lag polynomials and  $\epsilon_t$  is a vector of (reduced-form) innovations with a variance-covariance matrix  $\Sigma$ . Furthermore, assume that the vector of variables also has a moving average representation linked to “structural” innovations  $v_t$  given by  $Y_t = A(L)v_t$ , where the variance-covariance matrix of the structural innovations is normalized to the identity matrix. The structural and reduced form innovations are then related according to the following relation

$$v_t = A_0^{-1}\epsilon_t, \quad (11)$$

where  $A_0$  is the coefficient matrix on the current values of  $v_t$ . The variance-covariance matrix of the reduced-form innovations can then be expressed as

$$A_0 A_0' = \Sigma \quad (12)$$

Finally, let the first element of  $Y_t$  be the growth rate of productivity and assume, without loss of generality, that the first element of  $v_t$  is a neutral technology shock. Following Gali (1999) the neutral technology shock can be identified using a long-run restriction. In particular, it is assumed that only a neutral technology shock can impact labor productivity in the long-run. This implies that only the first element in the first row of the matrix  $\bar{A} = \sum_{i=0}^{\infty} A_i$  is non-zero and the rest are restricted to zero.<sup>2</sup>

### 5.2 Data

Let  $Y_t = (\Delta a_t, u_t, q_t)'$ , where  $a_t$  is (the log of) labor productivity,  $\Delta$  is the first-difference operator,  $u_t$  is the log of the unemployment rate and  $q_t$  is the log of a measure of economic uncertainty. Labor productivity is taken as the non-farm business output per hour, the

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<sup>2</sup>A detailed description of the identification procedure is provided in the Appendix.

unemployment rate is taken from the Bureau of Labor Statistics and I consider several uncertainty measures.

The benchmark measure is the cross-sectional dispersion (inter-quartile range) of establishment -level total factor productivity (TFP) of estimated in Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) using the Census of manufacturing establishments.<sup>3</sup> The reason for choosing this variable as our benchmark is that it is closest to the notion of measured uncertainty considered in the model. However, this measure is only available on an annual basis from 1972. Therefore, I also consider three other uncertainty measures. These measures include the VXO index of stock market volatility used in Bloom (2009), firm-level and macro uncertainty estimated by Jurado, Ludvigson, and Ng (forthcoming). The advantage of the latter three measures is that they are available at a higher than annual frequency.

The sample period is governed by the availability of the uncertainty measure. For our benchmark, the sample period is thus annual and runs from 1972 to 2009. In the case of the VXO index, the sample period runs from 1962Q3-2011Q2, for firm-level uncertainty it is 1970Q3-2011Q2 and for macro uncertainty it is 1960Q3-2011Q2. Following Fernald (2007), sub-sample means are removed prior to estimation, where the breaks are set at 1973Q1 and 1997Q1.

### 5.3 Empirical results

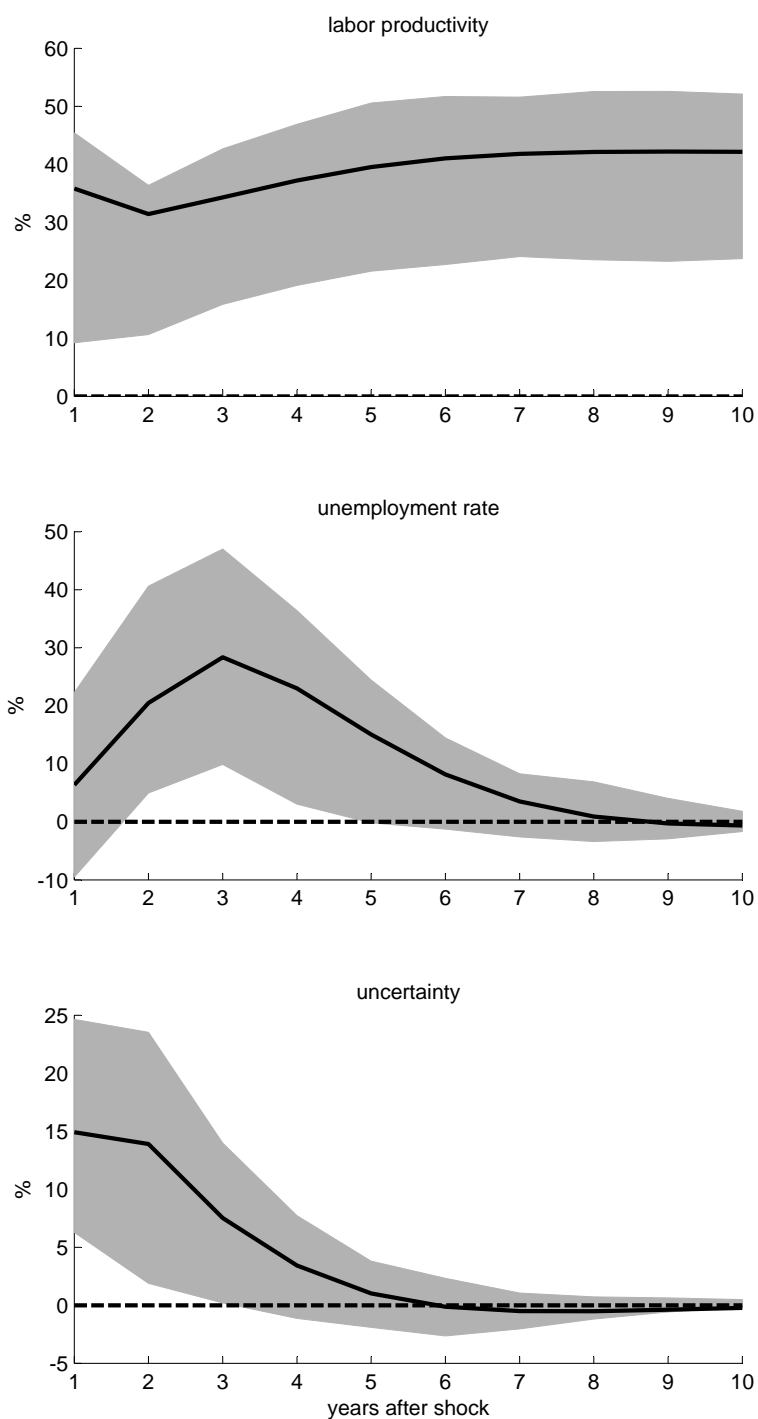
This subsection presents the empirical results of the structural VAR analysis. The bottom line is that measures of uncertainty respond to technology shocks. In particular, positive technology shocks lead to increases in measured uncertainty.

Figure 2 shows the impulse responses to a positive one-standard-deviation shock to technology with shaded areas representing 66% confidence bands. The top panel shows the response of productivity, which (by assumption) increases and remains at a new, higher long-run level. The middle panel shows the response of the unemployment rate which, as confirmed by several previous studies, increases temporarily in response to a technology shock. The bottom panel presents new evidence on the response of uncertainty (measures) to technology shocks. There is a statistically significant increase in measured uncertainty following a technology shock. This by itself already suggests that at least

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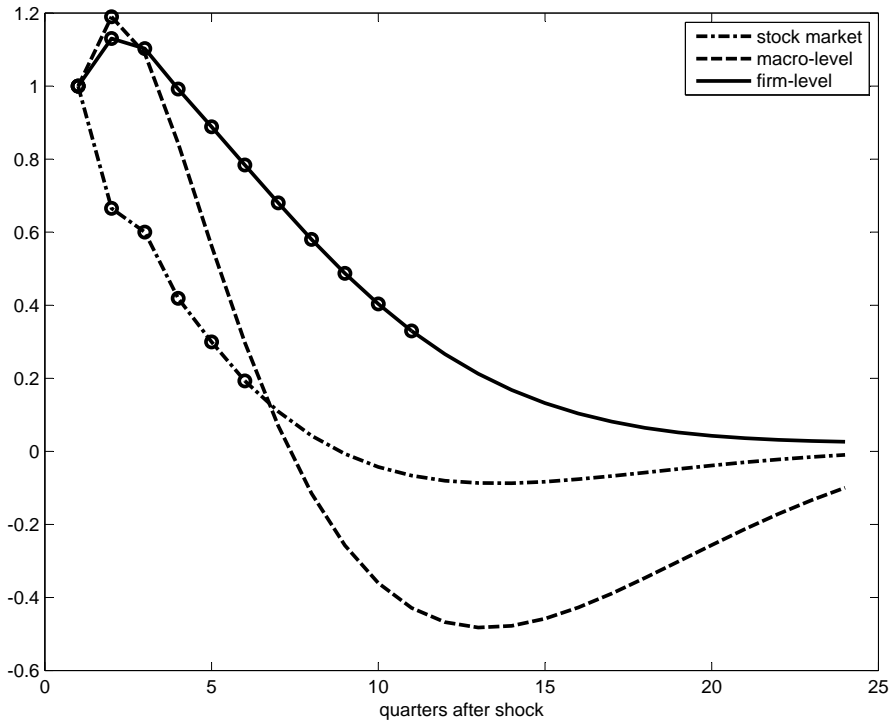
<sup>3</sup>In particular, the authors regress log establishment TFP on its lag an establishment-level fixed effect and a year fixed effect. The uncertainty measure is then the cross-sectional interquartile range of the residuals resulting from the afore-mentioned regression.

Figure 2: Impulse response functions - benchmark uncertainty measure



Notes: Impulse response functions (in percent) to a positive one-standard-deviation shock to neutral technology. Shaded areas are 66% confidence bands.

Figure 3: Impulse response functions - other uncertainty measures



Notes: Impulse response functions (in percent) to a positive one-standard-deviation shock to neutral technology scaled such that the impact response is 1. “Stock market” refers to the VXO index, “macro-level” and “firm-level” refer to the macro and firm-level uncertainty measures estimated by Jurado, Ludvigson, and Ng (forthcoming). Circles indicate values at which the 66% confidence band is different from zero.

part of measured uncertainty represents an endogenous reaction of the economy to other structural disturbances.

Figure 3 plots the responses of other uncertainty measures to a positive one-standard-deviation shock to technology all scaled such that the impact response is equal to 1. All considered measures of uncertainty increase in response to a positive technology shock (circles indicate values at which the 66% confidence band is different from zero).<sup>4</sup>

A fundamental question is whether technology shocks cause changes in uncertainty or the other way around. Empirically, Granger-causality tests can give an indication of which way the causation runs. The next section provides a model, in which technology shocks lead to endogenous changes in measured uncertainty.

<sup>4</sup>In all specifications the unemployment rate increases significantly following a positive technology shock.

While a Granger-causality test cannot reject the null hypothesis that uncertainty does not cause the identified neutral technology shocks, the opposite is not true. In particular, the test rejects the null hypothesis that neutral technology shocks do not cause uncertainty at the 5 percent level for two of the four measures (the VXO index and firm-level uncertainty).<sup>5</sup> For the cross-sectional dispersion of TFP shocks and for macro uncertainty, the null hypothesis cannot be rejected in either direction.

## 6 Conclusion

To be written.

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<sup>5</sup>The lag length is selected using the Bayesian information criterion.



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