Quantitative Economics 12 (2021), 587–623 1759-7331/20210587

Uncertainty-driven business cycles: Assessing the markup channel

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Precautionary pricing and increasing markups in representative-agent DSGE models with nominal rigidities are commonly used to generate negative output effects of uncertainty shocks. We assess whether this theoretical model channel is consistent with the data. Three things stand out. First, consistent with precautionary wage setting, we find that wage markups increase after uncertainty shocks. Second, the impulse responses of price markups are largely inconsistent with the standard model, both at the aggregate as well as the industry level. Finally, and in contrast to times-series evidence, our theoretical model robustly predicts that uncertainty shocks have a quantitatively small impact on the economy.

Keywords. Uncertainty shocks, precautionary pricing, markup channel, price markup, wage markup.

JEL classification. E01, E24, E32.

1. Introduction

Since the seminal paper by Bloom (2009), many studies have focused on the effects of uncertainty shocks on economic fluctuations (see Castelnuovo (2019), for a survey). While time-series approaches regularly find negative effects of uncertainty shocks on output (Baker, Bloom, and Davis (2016), Jurado, Ludvigson, and Ng (2015), Bachmann, Elstner, and Sims (2013), and numerous others),[1] it has proven surprisingly difficult to

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We would like to thank three anonymous referees, as well as Angela Abbate, Klaus Adam, Lukas Freund, Matthias Hartmann, Alex Kriwoluzky, Keith Kuester, Ariel Mecikovsky, Gernot Müller, Morten Ravn, Mirko Wiederholt, and audiences at the Universities of Aarhus, Barcelona, Frankfurt, Göttingen, Halle, Heidelberg, Cologne, Lüneburg, Southampton, Toulouse, and Tübingen, as well as at University College London, the CESifo Survey Conference 2016, the CIRET/KOF/RIED WSE Workshop 2015, the Dynare Conference 2016, the ECB, ESSIM 2016, the Frankfurt-Mannheim Workshop 2015, the EU Joint Research Council at Ispra, T2M 2016, the Annual Meeting of the Verein für Socialpolitik 2016, and the Meeting of the Macroeconomic Council of the Verein für Socialpolitik 2017 for helpful comments and suggestions. Special thanks go to Randy A. Becker and Wayne Gray for important clarifications regarding the NBER-CES Manufacturing Industry Database.

[1] See Berger, Dew-Becker, and Giglio (2020) for a countervailing viewpoint that it is only realized volatility and not future uncertainty that matters.

Available at http://qeconomics.org. https://doi.org/10.3982/QE1297

generate negative output effects after uncertainty shocks in representative-agent models as uncertainty shocks are expansionary in the standard RBC model.[2] As shown by Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Born and Pfeifer (2014a), Basu and Bundick (2017) and used in various papers, countercyclical aggregate markups of the form present in standard New Keynesian (NK) models are key to match the empirical evidence. Many recent representative-agent DSGE studies rely on this countercyclical movement of price and/or wage markups conditional on uncertainty shocks.[3] However, direct empirical evidence on the presence of this transmission channel is limited.

We therefore assess whether this so-called "markup channel" is consistent with the data. To this end, we build and (partially) estimate an NK DSGE model with time-varying price and wage markups that serves two purposes. First, the dynamic dimension of the model is used to generate predictions on the effects of uncertainty shocks on price and wage markups that can be empirically tested. Second, the intratemporal first-order conditions can be used as a Chari, Kehoe, and McGrattan (2007)-type business cycle accounting framework to construct aggregate price and wage markups from the data.

As predicted by the previous literature, in the model an increase in uncertainty leads to an increase in both price and wage markups and a decline in output, whereas without nominal rigidities the precautionary labor supply motive dominates and output increases. However, overall, the model-implied effects of uncertainty shocks on output are quantitatively small. This is due to two things. First, we employ a microestimate-based, conservative model parameterization not specifically tailored to generate large effects. Second and most importantly, our driving processes estimated using full information techniques do not feature large and persistent increases in uncertainty.

Time-series techniques are then used to identify uncertainty shocks in the data and to study whether the conditional comovement between markups and output is consistent with the one implied by the model. Overall, we find that in the data, wage markups consistently increase after identified uncertainty shocks as the model predicts. This finding is robust across different identification schemes as well as uncertainty and wage markup measures. In contrast, the impulse responses of price markups are largely inconsistent with the standard model. We do not find robust evidence for a strong increase in price markups, neither at the aggregate nor at the industry level, regardless of whether markups are measured along the intensive labor or the intermediate input margin. The only exception is the extensive labor margin, where price markups tend to increase. This latter finding suggests that recent modeling efforts combining search-and-matching models with uncertainty shocks are particularly promising for obtain-

[2]The present paper is not concerned with heterogeneous agent models with nonconvex adjustment costs and idiosyncratic uncertainty like Bloom (2009), Bachmann and Bayer (2013), where real options effects are responsible for the negative effects of uncertainty.

[3]For example, Başkaya, Hülagü, and Küşük (2013), Mumtaz and Zanetti (2013), Cesa-Bianchi and Fernandez-Corugedo (2018), Carriero, Mumtaz, Theodoridis, and Theophilopoulou (2015), Alessandri and Mumtaz (2019), Castelnuovo and Pellegrino (2018), and Leduc and Liu (2016). Notable exceptions are Christiano, Motto, and Rostagno (2014) and Chugh (2016), who embed uncertainty in a financial accelerator mechanism.

ing data-consistent responses (Leduc and Liu (2016), den Haan, Freund, and Rendahl (2020)).

Our findings come with obvious caveats. There is no consensus on how to measure markups, neither at the aggregate nor the individual level.[4] The same applies to measuring uncertainty and identifying uncertainty shocks. To alleviate these concerns, we show that our results are robust to employing various uncertainty measures, identification schemes, and assumptions for measuring markups. Nevertheless, results will always rely on modeling assumptions. Despite this drawback, we consider theory-driven studies of markups useful as they may inform us on both the likely validity of the underlying model's assumptions and the measurement approach itself.

Our investigation of price markups is most closely related to Nekarda and Ramey (2013), who argue that aggregate price markups are pro- to acyclical unconditionally and also regularly do not show the conditional movement after shocks predicted by standard NK models. However, they do not consider uncertainty shocks and only focus on the price markup, while the main effect might work through wage markups. This is important as, for example, Karabarbounis (2014) argues that about 90% of the cyclical movement in the total markup derives from movements in the wage component of this markup. Fernández-Villaverde et al. (2015) provided some tentative evidence of an increase in the price markup following an uncertainty shock. But this critically relies on estimating uncertainty shocks based on an exogenous process, but subsequently treating these exogenous shocks as endogenous variables in an unrestricted VAR. Recently, Basu and House (2016) and Bils, Klenow, and Malin (2018) (BKM in the following) have argued that measured average hourly earnings often are not allocative due to the presence of implicit contracts and composition effects and, as BKM argue, this distorts the cyclicality of the resulting price markups. BKM, therefore, proposed to rather measure price markups for the self-employed and along the intermediate input margin. Our paper is also related to earlier papers studying the (unconditional) cyclical movement of (price) markups, surveyed in Rotemberg and Woodford (1999), as well as "business cycle accounting" studies like Chari, Kehoe, and McGrattan (2007), Hall (1997). Galí, Gertler, and López-Salido (2007) is an influential study that decomposes the labor wedge into a firm and a household component to study the welfare implications of labor-wedge fluctuations.

Section 2 provides a detailed exposition on the mechanism embedded in NK models that gives rise to contractionary uncertainty effects. Section 3 presents a baseline NK DSGE with time-varying wage and price markups and documents the predicted conditional comovement of output and markups following uncertainty shocks. The intratemporal first-order conditions of the model also provide an accounting framework, which is used to construct markups from the data. Section 4 then identifies uncertainty shocks from the data, studies whether the conditional comovement between markups and output is consistent with the one implied by the model, and provides robustness checks. Section 5 investigates the price markup response at the industry level. Section 6 concludes.

[4]See, for example, the discussions in Nekarda and Ramey (2013), Anderson, Rebelo, and Wong (2018), and De Loecker, Eeckhout, and Unger (2020).

2. Precautionary pricing: A stylized model

As shown by Basu and Bundick (2017), the reason that uncertainty is expansionary in the standard RBC model is the presence of a “precautionary labor supply” motive. When faced by higher uncertainty, the household does not only self-insure by consuming less and investing more, but also by working more. From the neoclassical production function, where TFP is unaffected by uncertainty and capital is predetermined, it follows that this increase in labor results in an output expansion that fuels higher savings. The solution to generate contractionary effects of uncertainty is to break this tight link between labor supply and production. This can be achieved by introducing monopolistic competition in labor and goods markets, which gives rise to time-varying markups (see also Fernández-Villaverde et al. (2015), Born and Pfeifer (2014a)). In the presence of sticky prices and wages, firms and households in their price- and wage-setting decisions face a convex marginal revenue product. This gives rise to inverse Oi–Hartman–Abel-effects and precautionary pricing when faced with uncertainty about future economic variables. Price-setters face the following choice: If prices are set too low, more units need to be sold at too low a price, which is bad for the firm. In contrast, if prices are set too high, the higher price compensates for being able to sell fewer units. Due to this asymmetric, nonlinear effect, price setters prefer to err on the side of too high prices and increase their markups. It is instructive to consider the case of perfect competition. If the price is just an epsilon below marginal costs, the firm will have to satisfy all demand at a loss, leading to (potentially) unbounded losses. In contrast, if the price is just an epsilon too high, the firm will face zero demand. Hence, the worst case if the price is too high is zero profits. If this increase in markups after uncertainty shocks is strong enough, it dampens demand and decreases output.

To see this more clearly, consider the following stylized partial equilibrium example. A firm i of a continuum of identical, monopolistically competitive firms chooses its optimal price $p_{i,t-1}$ subject to a Dixit–Stiglitz-type demand function $y_{i,t} = (\frac{p_{i,t-1}}{p_t})^{-\theta_p} y_t$, where y_t is aggregate demand, θ_p is the demand elasticity, and p_t the aggregate price level. For the mechanism to be as transparent as possible, we assume the firm is subject to a Taylor-type pricing friction in that it has to set its price one period in advance.[5] Its output is produced using a constant returns to scale production function that is linear in labor: $y_{i,t} = l_{i,t}$. The labor market is assumed to be competitive, with the economy-wide wage being denoted by w_t. Real firm profits are then given by

$$\pi = \left[\frac{p_{i,t-1}}{p_t} - \frac{w_t}{p_t}\right]\left(\frac{p_{i,t-1}}{p_t}\right)^{-\theta_p} y_t. \tag{2.1}$$

[5]A similar mechanism is also present in the Rotemberg price adjustment cost framework used in the medium-scale NK model below as well as in Calvo- and Menu Cost-models. In these settings, marginal profits are still convex in the price (see, e.g., Fernández-Villaverde et al. (2015), Balleer, Hristov, and Menno (2017)). While the logic in a symmetric Rotemberg equilibrium is a bit more involved (see Oh (2020)), the underlying upward pressure on markups resulting from the nonlinear Phillips Curve is still crucial.

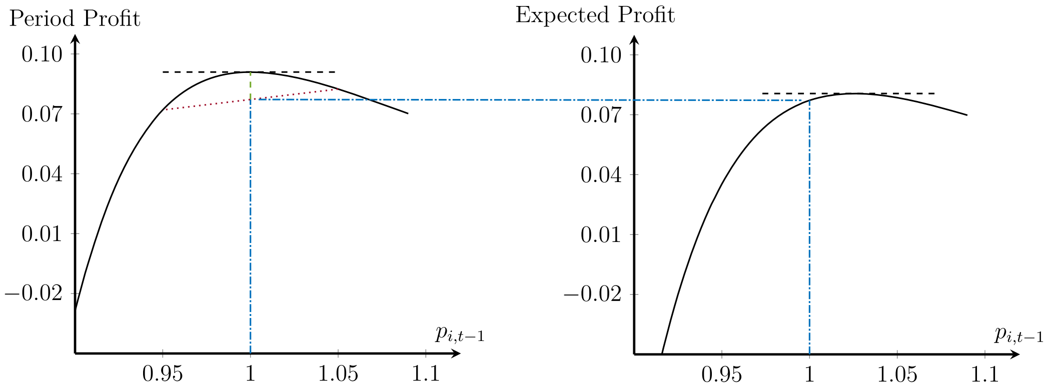


FIGURE 1. Stylized pricing example. *Notes*: period profit (left panel) and expected profit of the firm (right panel) as function of the price $p_{i,t-1}$. The dashed horizontal line indicates the maximum of the respective function. Dotted line: mean preserving spread to the optimal price that the firm faces. Dash–dotted line: profits when choosing the mean optimal price of 1.

Without loss of generality, assuming for the aggregate variables that $y_t = 1$ and $\frac{w_t}{p_t} = (\theta_p - 1)/\theta_p$, this simplifies to

$$\pi = \left[\frac{p_{i,t-1}}{p_t} - \frac{\theta_p - 1}{\theta_p}\right]\left(\frac{p_{i,t-1}}{p_t}\right)^{-\theta_p}. \tag{2.2}$$

Expression (2.2) shows that there are two different channels through which prices affect profits. First, a higher price $p_{i,t-1}$ has an immediate price impact on the revenue, while leaving the marginal costs unaffected. But second, there is an additional impact on the quantity sold. The left panel of Figure 1 shows the profit function for $\theta_p = 11$. As is well known, in the absence of uncertainty the firm will optimally charge a gross markup $\frac{\theta_p}{\theta_p - 1}$ over marginal costs, resulting in a profit-maximizing price of $p_{i,t-1} = 1$.

Assume now that the firm faces uncertainty about the optimal price, because the aggregate price level is with probability 1/2 either $p_t = 1/1.05$ or $p_t = 1/0.95$, so that in the absence of pricing frictions, either $p_{i,t} = 0.95$ or $p_{i,t} = 1.05$ is optimal. Thus, compared to the previous situation, the optimal price is subject to a mean-preserving spread.[6] Setting the price at the expected optimal $p_{i,t-1} = 1$ is suboptimal, because it would lead to lower expected profits due to the marginal profit being convex in the price. Rather, the optimal price in this case is slightly higher at $p_{i,t-1} = 1.02$. This can be seen in the expected profit schedule as a function of $p_{i,t-1}$ shown in the right panel of Figure 1. A formal proof can be found in Appendix E (Born and Pfeifer (2021)).

[6]For ease of exposition, we consider a mean-preserving spread to the endogenous variable. The same effect would arise following a mean-preserving spread to aggregate price p_t, but in this case an additional Jensen's inequality effect would complicate matters due to the price level entering in the denominator.

The same mechanism is at work in the household sector where the households have to maximize utility by setting a nominal wage subject to an equivalent demand function for their labor services.[7]

We close this section by pointing out that the empirical test of the markup channel has implications beyond the precautionary pricing mechanism outlined above. Even in models where precautionary pricing is shut off by linearizing the New Keynesian Phillips Curves, countercyclical markups due to nominal rigidities are key because they are instrumental in amplifying "run-of-the-mill" demand effects (see the excellent discussion in den Haan, Freund, and Rendahl (2020)). A case in point is the work of Leduc and Liu (2016), whose search-and-matching framework generates negative output effects even in a flex-price model via nonlinearities in the wage setting equation. However, even in their setting, price rigidities and the associated countercyclical price markup are used in the final model to provide key amplification (up to a factor of 20).

3. Model

In this section, we construct a prototypical New Keynesian DSGE model that embeds the previously outlined mechanism on the firm and household side. The model serves two purposes. First, the dynamic dimension of the model can be used to generate predictions on the effects of uncertainty shocks on price and wage markups. Second, the intratemporal first-order conditions can be used as a Chari, Kehoe, and McGrattan (2007)-type business cycle accounting framework to construct aggregate price and wage markups from the data.

The model economy is populated by a continuum of intermediate good firms producing differentiated intermediate goods using bundled labor services and capital, and a final good firm bundling intermediate goods to a final good. A continuum of households $j \in [0, 1]$ sells differentiated labor services to a labor bundler. In addition, the model features a government sector that finances government spending with distortionary taxation and transfers, and a monetary authority, which sets the nominal interest rate according to an interest rate rule. The full set of model equations is relegated to Appendix A.1.

3.1 *Firms*

The final good Y_t is assembled from a continuum of differentiated intermediate inputs $Y_t(i)$, $i \in [0, 1]$, using the constant returns to scale Dixit–Stiglitz-technology

$$Y_t = \left[\int_0^1 Y_t(i)^{\frac{\theta_p - 1}{\theta_p}} \, di\right]^{\frac{\theta_p}{\theta_p - 1}},$$

[7]The asymmetry of the profit function comes from the isoelastic Dixit–Stiglitz demand function paired with the assumption that demand always has to be satisfied. For small to moderate shocks, the latter assumption can be justified by contractual obligations and reputational concerns. Firms tend to not close shop if their posted price turns out to be too low, while workers cannot stay at home when asked to work overtime, even if their marginal rate of substitution turns out to be high. However, these considerations also suggest that firms can more easily avoid having to satisfy demand by "being out of stock." This potential violation of a crucial model assumption may be one reason why we find less evidence of a precautionary pricing for firms.

where $\theta_p > 0$ is the elasticity of substitution between intermediate goods. Standard cost minimization yields the demand for good i:

$$Y_t(i) = \left[\frac{P_t(i)}{P_t}\right]^{-\theta_p} Y_t,$$

where P_t is the aggregate price level.

The monopolistically competitive intermediate good firms produce $Y_t(i)$ using capital $K_t(i)$ and a hired composite labor bundle $N_t(i)$ according to a CES production function

$$Y_t(i) = Y^{\text{norm}}\left\{\alpha\left[K_t(i)\right]^{\frac{\psi-1}{\psi}} + (1-\alpha)\left[Z_t\left(N_t(i) - N^o\right)\right]^{\frac{\psi-1}{\psi}}\right\}^{\frac{\psi}{\psi-1}} - \Phi. \tag{3.1}$$

Here, $0 \leq \alpha \leq 1$ parameterizes the labor share and Y^{norm} is a normalization factor that makes output equal to one in steady state. ψ is the elasticity of substitution between capital and labor, with $\psi = 1$ being the Cobb–Douglas case. The fixed cost of production Φ reduces economic profits to zero in steady state, thereby ruling out entry or exit (see, e.g., Christiano, Eichenbaum, and Evans (2005)). $N^o = \phi_o N$, where N denotes steady-state labor, is overhead labor used in the production of goods.[8] Z_t denotes a stationary, labor-augmenting technology process specified below. Each intermediate good firm owns its capital stock, whose law of motion is given by

$$K_{t+1}(i) = (1-\delta)K_t(i) + \left(1 - \frac{\phi_K}{2}\left(\frac{I_t(i)}{I_{t-1}(i)} - 1\right)^2\right) I_t(i), \quad \phi_K \geq 0, \tag{3.2}$$

where δ denotes the quarterly depreciation rate of the capital stock. Equation (3.2) includes investment adjustment costs at the firm level of the form popularized by Christiano, Eichenbaum, and Evans (2005).

Intermediate good producers are owned by households and, therefore, use the households' stochastic discount factor for discounting. They maximize the present discounted value of per period profits subject to the law of motion for capital and the demand from the final good producer:

$$\left[\frac{P_t(i)}{P_t}\right]^{1-\theta_p} Y_t - \frac{W_t}{P_t} N_t(i) - I_t(i) - \frac{\phi_P}{2}\left(\frac{P_t(i)}{P_{t-1}(i)} - \Pi\right)^2 Y_t(i),$$

where $N_t(i)$ is hired in a competitive rental market at given wage rate W_t. The last term denotes Rotemberg price adjustment costs as in Fernández-Villaverde et al. (2015), where Π is steady-state inflation. From the firms' cost minimization problem follows the first-order condition for labor inputs as

$$\Xi_{p,t}\frac{W_t}{P_t} = MPL_t,$$

[8]Overhead labor, apart from being an empirically realistic feature, allows the marginal wage in the economy to differ from the average wage. This is important, because it makes the price markup more countercyclical than would be inferred from the rather a-cyclical total labor share alone (see, e.g., Rotemberg and Woodford (1999)).

where $\Xi_{p,t}$ is the gross price markup over marginal costs. Due to monopolistic competition, $\Xi_{p,t}$ will generally not be equal to 1 as firms set a markup over marginal costs. Time-variation in this markup is a central element of shock transmission in the NK model.

3.2 *Households*

Following Erceg, Henderson, and Levin (2000), we assume that the economy is populated by a continuum of monopolistically competitive households, supplying differentiated labor $N_t(j)$ at wage $W_t(j)$ to a labor bundler who then supplies the composite labor input to the intermediate good producers. Formally, the aggregation technology follows a Dixit–Stiglitz form

$$N_t = \left[\int_0^1 N_t(j)^{\frac{\theta_w - 1}{\theta_w}}\, dj\right]^{\frac{\theta_w}{\theta_w - 1}}, \quad \theta_w > 0.$$

Expenditure minimization yields the optimal demand for household j's labor as

$$N_t(j) = \left[\frac{W_t(j)}{W_t}\right]^{-\theta_w} N_t \quad \forall j. \tag{3.3}$$

Household j has preferences

$$V_t = \sum_{h=0}^{\infty} \beta^h \frac{\left[\left(C_{t+h}(j)\right)^\eta \left(1 - N_{t+h}(j)\right)^{1-\eta}\right]^{1-\sigma} - 1}{1-\sigma}, \tag{3.4}$$

where the parameter $\sigma \geq 0$ measures the risk aversion, $0 < \beta < 1$ is the discount rate, and $0 < \eta < 1$ denotes the share of the consumption good in the consumption-leisure Cobb–Douglas bundle.

The household faces the budget constraint

$$\begin{aligned}\left(1 + \tau_t^c\right) C_t(j) + \frac{B_t(j)}{P_t} \leq{}& \left(1 - \tau_t^n\right) \frac{W_t(j)}{P_t} N_t(j) + R_{t-1} \frac{B_{t-1}(j)}{P_t} + D_t(j) \\ &- \frac{\phi_w}{2}\left(\Pi^{-1} \frac{W_t(j)}{W_{t-1}(j)} - 1\right)^2 Y_t + T_t,\end{aligned} \tag{3.5}$$

where the household earns income from supplying differentiated labor, which is taxed at rate τ_t^n. In addition, it receives real dividends $D_t(j)$ from owning a share of the firms in the economy and a real gross return $R_{t-1}(B_{t-1}(j)/P_t)$ from investing in a zero net supply riskless nominal bond. The household spends its income on consumption $C_t(j)$, taxed at rate τ_t^c, real savings in the private bond $B_t(j)/P_t$, and to cover the costs of adjusting its wage (the second to last term on the right-hand side). Finally, T_t denotes transfers/lump-sum taxes.

The optimization problem of the household involves maximizing (3.4) subject to the budget constraint (3.5) and the demand for the household's differentiated labor input

(3.3). The first-order condition for labor supply implies that a gross markup over the after-tax marginal rate of substitution $\Xi_{w,t}$ is chosen such that

$$\frac{W_t}{P_t} = \Xi_{w,t} \frac{1+\tau_t^c}{1-\tau_t^n} \frac{(-1)V_{N,t}}{V_{C,t}},$$

where V_N and V_C are the partial derivatives of the utility function with respect to labor and consumption, respectively.

3.3 *Government sector*

The government's budget constraint is given by

$$\tau_t^c C_t + \tau_t^n \frac{W_t}{P_t} N_t = G_t + T_t,$$

where G_t is exogenous government consumption and where we have suppressed aggregation over households j for notational convenience.

The model is closed by assuming that the central bank follows a Taylor rule that reacts to inflation and output:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_R} \left(\left(\frac{\Pi_t}{\Pi}\right)^{\phi_{R\pi}} \left(\frac{Y_t}{Y_t^{\mathrm{HP}}}\right)^{\phi_{Ry}}\right)^{1-\rho_R}.$$

Here, $0 \leq \rho_R \leq 1$ is a smoothing parameter introduced to capture the empirical evidence of gradual movements in interest rates, Π is the target inflation rate set by the central bank, and the parameters $\phi_{R\pi}$ and ϕ_{Ry} capture the responsiveness of the nominal interest rate to deviations of inflation from its steady-state value and output from its model-consistent Hodrick and Prescott (HP) filter trend Y_t^{HP}, respectively.[9]

3.4 *Exogenous shock processes*

The two exogenous processes for government spending and TFP follow AR(1)-processes with stochastic volatility:

$$\begin{aligned}
\hat{Z}_t &= \rho_z \hat{Z}_{t-1} + \sigma_t^z \varepsilon_t^z, \\
\hat{G}_t &= \rho_g \hat{G}_{t-1} + \phi_{gy} \hat{Y}_{t-1} + \sigma_t^g \varepsilon_t^g, \\
\sigma_t^z &= (1-\rho_{\sigma^z})\bar{\sigma}^z + \rho_{\sigma^z} \sigma_{t-1}^z + \eta_{\sigma^z} \varepsilon_t^{\sigma^z}, \\
\sigma_t^g &= (1-\rho_{\sigma^g})\bar{\sigma}^g + \rho_{\sigma^g} \sigma_{t-1}^g + \eta_{\sigma^g} \varepsilon_t^{\sigma^g},
\end{aligned}$$

where the ε_t^i, $i \in \{z, g, \sigma^z, \sigma^g\}$ are standard normally distributed i.i.d. shock processes, hats denote percentage deviations from trend, and ϕ_{gy} governs the output feedback to government spending. σ_t^z and σ_t^g are our proxies for supply and demand uncertainty, respectively, with $\varepsilon_t^{\sigma^z}$ and $\varepsilon_t^{\sigma^z}$ being the corresponding uncertainty shocks.

[9]This specification follows Born and Pfeifer (2014a). The HP filtered output gap is embedded into the dynamic rational expectations model following the approach of Cúrdia, Ferrero, Ng, and Tambalotti (2015).

3.5 *Equilibrium*

The use of Rotemberg price and wage adjustment costs implies the existence of a representative firm and a representative household. We consider a symmetric equilibrium in which all intermediate good firms charge the same price and choose the same labor input and capital stock. Similarly, all households set the same wage, supply the same amount of labor, and will choose the same consumption and savings.

The resource constraint then implies that output is used for consumption, investment, government spending, and to pay for price and wage adjustment costs:

$$Y_t = C_t + I_t + G_t + \frac{\phi_w}{2}\left(\Pi^{-1}\frac{W_t}{W_{t-1}} - 1\right)^2 Y_t + \frac{\phi_p}{2}\left(\Pi^{-1}\frac{P_t}{P_{t-1}} - 1\right)^2 Y_t.$$

3.6 *Parametrization*

Table 1 displays the parametrization of our quarterly model for the US economy from 1964Q1 to 2015Q4. The capital share α is set to one third and the depreciation rate δ to imply an annual depreciation rate of 10%. The discount factor $\beta = 0.995$ implies an annualized interest rate of 2% in steady state. The investment adjustment cost parameter ϕ_k is set to 2.5, the value estimated in Christiano, Eichenbaum, and Evans (2005).

The price adjustment cost parameter ϕ_p is chosen to imply the same slope of the linear New Keynesian Phillips Curve as a Calvo model with an average price duration of 3 quarters. While this value is in the range of typical estimates based on microdata (e.g.,

TABLE 1. Model parametrization.

Parameter	Description	Value	Target
α	Capital share	0.094	Capital share of 1/3
β	Discount factor	0.995	2% annualized interest rate
δ	Depreciation rate	0.025	10% per year
σ	Risk aversion	2	standard value
ϕ_k	Inv. adj. costs	2.5	Christiano, Eichenbaum, and Evans (2005)
ϕ_p	Price adj. costs	59	Implied average duration of 3 quarters
ϕ_w	Wage adj. costs	371	Implied average duration of 3 quarters
θ_w	Labor subst. ela.	11	10% steady-state markup
θ_p	Goods subst. ela.	11	10% steady-state markup
η	Leisure share	0.468	Frisch elasticity of 1
ϕ^o	Overh. lab. share	0.11	Nekarda and Ramey (2013)
ψ	Subst. ela. CES	0.5	Chirinko (2008)
Φ	Fixed costs	0.019	0 Steady-state profits
Π	Ss gross inflation	1	Zero inflation
ρ_r	Interest smoothing	0.75	Standard value
$\phi_{R\pi}$	Inflation feedback	1.35	Standard value
ϕ_{Ry}	Output feedback	0.125	Standard value
τ^c	Cons. tax rate	0.094	Sample mean
τ^n	Labor tax rate	0.220	Sample mean
G/Y	G/Y share	0.206	Sample mean
Y^{norm}	Output normalization	1.351	Output of 1

Nakamura and Steinsson (2008)), it is slightly lower than the typical value of 4 quarters used in the uncertainty literature (e.g., Leduc and Liu (2016), Basu and Bundick (2017), Fernández-Villaverde et al. (2015)). Similarly, the wage adjustment cost parameter is chosen to imply an average wage contract duration of 3 quarters (see Born and Pfeifer (2020)). We will explore the robustness to these choices below. The two substitution elasticity parameters θ_p and θ_w are set to 11, which implies a steady-state markup of 10%.

We consider a zero-inflation steady state, that is, $\Pi = 1$. The Taylor rule parameters are standard values in the literature with a moderate degree of interest smoothing and output feedback.[10] The risk aversion parameter is set to $\sigma = 2$. The leisure share in the Cobb–Douglas utility bundle η is set to imply a Frisch elasticity of 1.[11] We set the share of overhead labor to 11%, following the evidence of Levitt, List, and Syverson (2013) that adding a second shift in car manufacturing plants increases labor by 80%. Given that automobile plants run two shifts most of the time, this means overhead labor accounts for $20/180 = 0.11$ (see Nekarda and Ramey (2013)). The fixed costs Φ are set to imply 0 profits in steady state, thereby ruling out entry and exit.[12] The substitution elasticity between capital and labor is set to $\psi = 0.5$, the midpoint of the estimates surveyed in Chirinko (2008) and in line with Chirinko and Mallick (2017) and Oberfield and Raval (forthcoming).[13] The fiscal parameters are set to their mean over the sample 1964Q1 to 2015Q4. The tax rates are computed as average effective tax rates following Jones (2002).[14]

Finally, the exogenous processes are estimated via Bayesian techniques using sequential Monte Carlo Methods on a quarterly US sample from 1964Q1 to 2015Q4.[15] To construct output, government spending, and TFP deviations from trend, a one-sided HP-filter ($\lambda = 1600$) is used. For TFP, we cumulate the utilization-adjusted TFP series constructed by Fernald (2012).[16] Table 2 displays the prior and posterior distributions, while Figure A.1 shows the smoothed volatilities.

3.7 *Dynamic effects of uncertainty shocks*

As outlined in Section 2, precautionary price and wage setting in response to an increase in uncertainty lead to an increase in both price and wage markups. Thinking

[10] It should be noted that the choice of monetary policy is not completely innocuous. If the central bank puts relatively little weight on current inflation, it will tolerate large deviations of sticky prices from their optimal target. Firms will anticipate this and react with strong precautionary pricing. For the parameter ranges typically found in the literature, we experienced quantitative differences, but the qualitative effect we are investigating in this paper remained unaffected.

[11] See Appendix A.2.1.

[12] Note that in contrast to, for example, Smets and Wouters (2007), these fixed costs are nonlabor related fixed costs as the latter are captured in the overhead labor share.

[13] We verified that our results are robust to variations in the substitution elasticity; see Section 4.5 below.

[14] While we allow tax rates to vary in the empirical analysis, we keep them fixed at their steady-state value for the model analysis. See Appendix C for details on the construction of tax rates.

[15] Our approach is described in Section A.5 of the Appendix, which also provides convergence diagnostics.

[16] See Appendix C.1 for details on the data construction.

Table 2. Prior and posterior distributions of the shock processes.

	Prior Distribution			Posterior Distribution		
Parameter	Distribution	Mean	Std. Dev.	Mean	5%	95%
			G process			
ρ_{σ^g}	Beta*	0.90	0.100	0.513	0.313	0.708
ρ_g	Beta*	0.90	0.100	0.945	0.883	0.999
η_{σ^g}	Gamma	0.50	0.100	0.003	0.002	0.004
$\overline{\sigma}^g$	Uniform	0.05	0.014	0.008	0.007	0.009
ϕ_{gy}	Normal	0.00	1.000	0.028	−0.026	0.083
			TFP process			
ρ_{σ^z}	Beta*	0.90	0.100	0.517	0.312	0.722
ρ_z	Beta*	0.90	0.100	0.773	0.692	0.855
η_{σ^z}	Gamma	0.50	0.100	0.002	0.002	0.003
$\overline{\sigma}^z$	Uniform	0.05	0.014	0.007	0.006	0.008

Note: Beta* indicates that the parameter divided by 0.999 follows a beta distribution. The sample ranges from 1964Q1 to 2015Q4 ($N = 208$).

about a stylized labor market as depicted in the schematic diagram shown in Figure 2, this should cause both the labor demand and supply curves to shift to the left, resulting in an overall decrease in hours worked and a reduction in aggregate output.

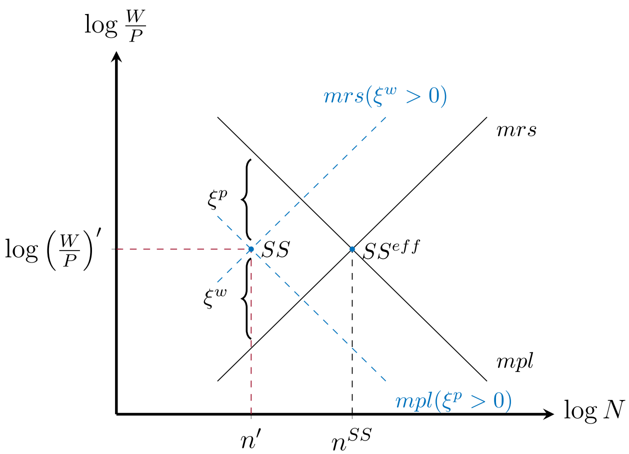
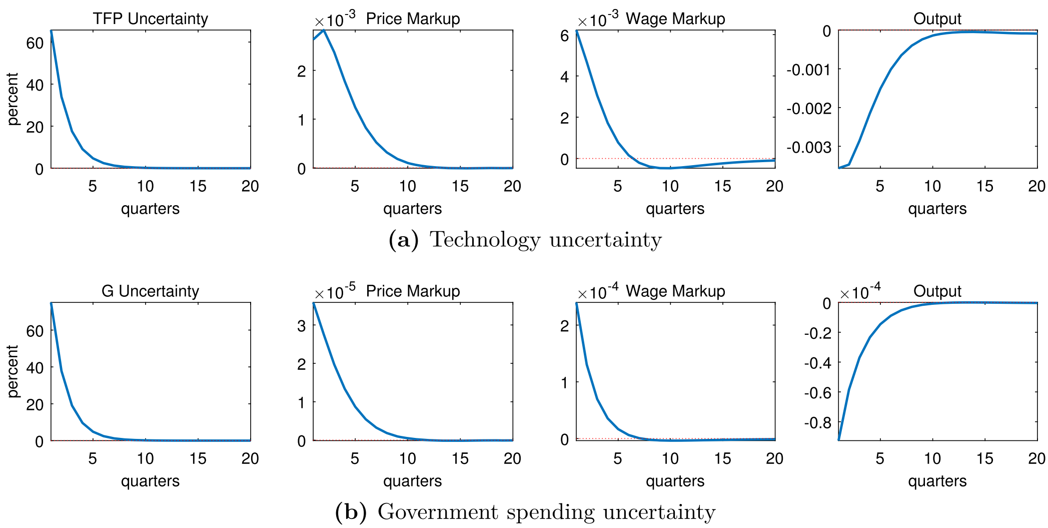


Figure 2. Uncertainty shocks ins a stylized labor market. *Notes*: Labor supply is characterized by the condition that the log marginal rate of substitution (*mrs*) is equal to the log real wage, while the labor supply curve is characterized by the log marginal product of labor (*mpl*) being equal to the log real wage. The point SS^{eff} denotes the efficient steady state where *mrs* and *mpl* are equal. The presence of a wage and price markup (ξ^w and ξ^p) drives a wedge between the two curves and the real wage.

We can now feed uncertainty shocks into our general-equilibrium model to study the effects on markups and real activity in a richer model environment.[17] We solve the model using third-order approximation around the deterministic steady state, using Dynare 4.6.1 (Adjemian et al. (2011)) with the pruning algorithm of Andreasen, Fernández-Villaverde, and Rubio-Ramírez (2018). IRFs are generalized impulse response functions, shown as percentage deviations from the stochastic steady state (for details, see the Appendix to Born and Pfeifer (2014b)). We use two-standard deviation uncertainty shocks.[18]

Figure 3 displays the impulse responses to a two-standard deviation technology (i.e., supply) uncertainty shock (top panel) and to a two-standard deviation government spending (i.e., demand) uncertainty shock (bottom panel). We see that, indeed, an increase in uncertainty leads to an increase in both price and wage markups and a decline in output.[19] When the shock dies out, the markups converge back to their pre-shock values as does output. The output response is quantitatively small, an issue we will investigate further in the next subsection. We do not show here the response of the real wage, which increases. As the labor market diagram in Figure 2 makes clear, its theoretical response is ambiguous, depending on whether the wage or price markup response is stronger, increasing for the former and falling for the latter.



(a) Technology uncertainty

(b) Government spending uncertainty

Figure 3. Model IRFs to two-standard deviation technology uncertainty (Panel a) and government spending uncertainty (Panel b) shocks. *Notes:* IRFs measured in percentage deviations from the stochastic steady state.

[17] Figure A.5 displays the IRFs to *level* shocks. They look as expected and square well with the empirical literature.

[18] The empirical literature (see, e.g., Bloom (2009), Jurado, Ludvigson, and Ng (2015)) often uses four-standard deviations because it this is roughly the increase in uncertainty proxies during the Great Recession. As the size of the model IRFs scales roughly linearly in the size of uncertainty shocks, this would imply a doubling of the effects.

[19] Output is plotted net of price and wage adjustment costs.

A necessary ingredient for the negative response of output to an uncertainty shock is the presence of at least one type of nominal rigidity. Figures A.2 and A.3 in the Appendix show the IRFs with only price and wage rigidity, respectively. In both cases, there is a drop in output, which is even more pronounced in the case of price stickiness only. That indicates a significant interaction effect between both types of rigidity as wage stickiness limits the firms' cost risk. Finally, Figure A.4 shows the IRFs in the model without nominal rigidities. In this case, the precautionary labor supply motive dominates and output increases.

3.8 *Dissecting the quantitative output response*

While the previous subsection discussed the qualitative effects of uncertainty shocks on markups and output, in this subsection we will investigate the quantitatively small output response after an uncertainty shock. We will focus on TFP uncertainty here, but all results also hold for the government spending uncertainty shock.

In our baseline parameterization, output falls by about 0.0035% on impact after a two-standard deviation uncertainty shock. As Figure 4 demonstrates (dashed line), this number can be almost doubled by introducing an additional precautionary motive for firms. Specifically, we allow for a higher risk aversion of $\sigma = 20$ in the stochastic discount factor the firm uses in its price setting decision and which strengthens their precaution-

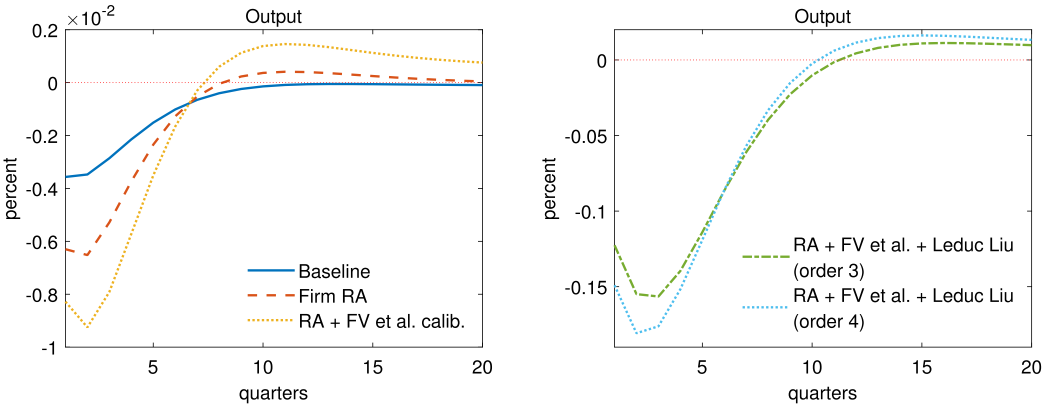


FIGURE 4. Model IRFs to a two-standard deviation technology uncertainty shock using our estimated TFP process (left panel) and the TFP process estimated in Leduc and Liu (2016) (right panel). The left panel displays the output response for the baseline calibration (solid line), the baseline calibration with higher firm risk aversion (dashed line), and the latter calibration with lower real and higher nominal rigidities as in Fernández-Villaverde et al. (2015) (dotted line). The right panel combines the last calibration with the Leduc and Liu (2016) TFP process, with the model solved at order 3 as in the baseline (dash–dotted line) and at order 4 (dotted line). See the main text for details. *Notes:* IRFs measured in percentage deviations from the stochastic steady state.

ary pricing motive. This higher risk aversion choice may reflect the preferences of owners of closely held firms that are not diversified.[20]

To increase the output response further, we (on top of the first change) decrease real and increase nominal rigidities. In particular, we set the costs of adjusting investment to $\phi_k = 0.75$, the implied average price and wage duration to four quarters, and the price and wage demand elasticities to imply steady-state markups of 5%.[21] These parameter values are used in Fernández-Villaverde et al. (2015). As we discuss in more detail in Born and Pfeifer (2014a), especially the higher demand elasticities lead to larger output effects due to them increasing the convexity of the marginal profit function, and hence the precautionary pricing effect. Overall, we get another 40% increase in the impact output response (dotted line).

Our last experiment keeps the Fernández-Villaverde et al. (2015) parameter values fixed and feeds in different processes for the level and the volatility of TFP. We take those from Leduc and Liu (2016), who parameterize the level process to standard values in the RBC literature ($\rho_z = 0.95$, $\bar{\sigma}^z = 0.01$) and the volatility process to match the VAR response of uncertainty to an uncertainty shock ($\rho_{\sigma^z} = 0.76$, $\eta_{\sigma^z} = 0.005$). The right panel of Figure 4 shows that this more volatile and persistent TFP process generates much larger output effects of the uncertainty shock.

Recently, Diercks, Hsu, and Tamoni (2019) have argued that the standard third-order perturbation solution employed in most of the aggregate uncertainty literature including the present paper is insufficient to capture the full quantitative effect of uncertainty shocks. When we employ their suggested unpruned fourth-order perturbation solution, we also find that the peak responses become quantitatively larger. However, the amplification through the additional fourth-order polynomial is far less than the almost doubling found for the model in their paper. The dotted line in the right panel of Figure 4 displays the output response at order 4. Its peak is only 17% bigger than the one at order 3 (dash–dotted line). Thus, a more accurate solution technique is not sufficient to generate more sizeable effects of uncertainty shocks.[22]

Overall, this investigation shows that the small effects of uncertainty shocks in our baseline model are the result of two things. First, we employed a microestimate-based, conservative model parameterization not specifically tailored to generate large effects. Second and most importantly, our driving processes estimated using full information techniques do not feature large and persistent increases in uncertainty. This contrasts with studies like Leduc and Liu (2016) or Bianchi, Kung, and Tirskikh (2019) that generate rather large effects of TFP uncertainty shocks by, among other things, employing

[20]We thank the editor for this idea.

[21]Larger steady state markups as in the baseline are more consistent with micro studies, while the 5% steady state markup is consistent with macroestimates in Kuester (2010) and Altig, Christiano, Eichenbaum, and Lindé (2011). Similarly, micropricing studies find average price durations closer to 2–3 quarters (e.g., Nakamura and Steinsson (2013)), while macroestimates like Richter and Throckmorton (2016) and Fernández-Villaverde et al. (2015) find values around four quarters.

[22]Figure A.6 displays the output response at order 4 for the other model variants in Figure 4. The same small quantitative changes hold true there. Figure A.7 shows that the amplification is also muted for the case of large shocks as well as cascading uncertainty shocks.

exogenous TFP driving processes that were not restricted by actual TFP realizations.[23] These processes can be rather interpreted as subjective uncertainty about TFP as opposed to objective uncertainty used in rational expectations modeling.

4. Aggregate evidence

In this section, we investigate the responses of aggregate price and wage markups to exogenous uncertainty shocks. We first construct aggregate markups from the data. To measure aggregate uncertainty, we use a variety of measures and approaches. The first uncertainty proxy is a model-consistent measure derived from the particle smoother used to parameterize the model. We also employ the general macroeconomic uncertainty measure of Jurado, Ludvigson, and Ng (2015) (JLN) and identify exogenous shocks via a recursive ordering. Given that many uncertainty measures are available at monthly frequency while we only have quarterly or annual markup data, we will employ two different approaches to deal with this mixed-frequency problem: a two-step frequentist procedure using local projections (Òscar Jordà (2005)), and a Bayesian mixed-frequency VAR (Eraker, Chiu, Foerster, Kim, and Seoane (2015)). The section concludes with a number of robustness checks concerning the ordering of variables in the VAR, the assumptions made to construct markups, and the chosen uncertainty proxy.

4.1 *Constructing aggregate markups*

Our ultimate goal is to compare the theoretical model IRFs with their empirical counterparts. To this end, we need to construct aggregate markups from the data.

Using the intratemporal first-order conditions of the model, empirical measures of both price and wage markups can be constructed in a business cycle accounting-style exercise. Using the Cobb–Douglas felicity function from Section 3, the wage markup over the marginal rate of substitution satisfies

$$\Xi_{w,t}\frac{1-\eta}{\eta}\frac{C_t}{1-N_t}=\frac{1-\tau_t^n}{1+\tau_t^c}\frac{W_t}{P_t}.$$

Expanding this fraction and taking logs, $\xi_t^w\equiv\log(\Xi_{w,t})$ can be computed from

$$\xi_t^w=\log\left(\frac{1-\tau_t^n}{1+\tau_t^c}\right)+\log\left(\frac{W_tN_t}{P_tY_t}\right)+\log\left(\frac{Y_t}{C_t}\right)-\log\left(\frac{1-\eta}{\eta}\right)+\log\left(\frac{1-N_t}{N_t}\right),$$

where the second term on the right is the labor share.

The firm-side price markup $\xi_t^p\equiv\log(\Xi_{p,t})$ can be constructed using the CES-production function (3.1) as (see Appendix B for details)

$$\xi_t^p=\log\big((1-\alpha)\big(Y^{\text{norm}}\big)^{\frac{\psi-1}{\psi}}\big)+\frac{\psi-1}{\psi}Z_t+\frac{1}{\psi}\log\left(\frac{Y_t+\Phi}{N_t-N^o}\right)-\log\left(\frac{W_t}{P_t}\right).$$

[23] Bianchi, Kung, and Tirskikh (2019) estimate their full model using full information techniques and find TFP uncertainty to contribute a large share to business cycle volatility. But they do not use TFP as an observable and estimate a first-order autocorrelation of 0.67 for TFP *growth*, while it is close to iid in Fernald (2012)'s data. Moreover, their uncertainty shock roughly increases TFP volatility by 50% and has an autocorrelation above 0.9.

To compute both price and wage markups, all that is needed are aggregate time series on output, consumption, taxes, labor-augmenting technology, and various labor market variables like hours worked and wages. Again, we use quarterly US data from 1964Q1 to 2015Q4.[24] On the household side, we follow Karabarbounis (2014) and rely on broad, encompassing measure of hours, employment, and population that takes the substantial U.S. military employment into account (see Cociuba, Prescott, and Ueberfeldt (2018)) when measuring the marginal rate of substitution. On the firm side, it is crucial to correctly measure the marginal product of labor. For this purpose, we follow Nekarda and Ramey (2013) and rely on data from the private business sector, which distinguishes production from overhead workers. We use Fernald (2012)'s utilization-adjusted TFP measure to back out labor-augmenting technology.

Figure 5 shows the HP-filtered ($\lambda = 1600$) markups over time. As already documented in Nekarda and Ramey (2013), the price markup tends to have its trough during or shortly after recessions, while its peak happens in the middle of expansions. In contrast, the wage markup tends to peak during recessions. This finding is consistent with evidence presented by Karabarbounis (2014) and Galí, Gertler, and López-Salido (2007). The cyclical behavior of the markups is confirmed by the cross-correlograms depicted in Figure 6. While the baseline price markup (solid line) is acyclical, the correlation becomes negative for leads: a drop in GDP today signals an increase in the price markup in the future. In contrast, the wage markup shows a pronounced countercyclicality. The only exception is the price markup when not adjusting TFP for variable factor utilization

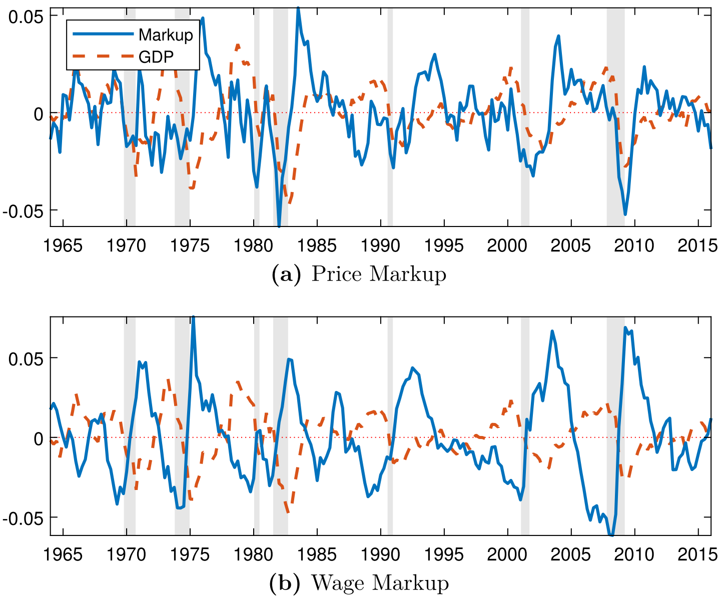


Figure 5. Cyclical component of the price markup ξ_t^p (top panel) and of the wage markup ξ_t^w (bottom panel) over time. *Notes:* Solid line: respective markup; dashed line: GDP. Grey shaded areas denote NBER recessions.

[24] Appendix C describes the respective data sources used in detail.

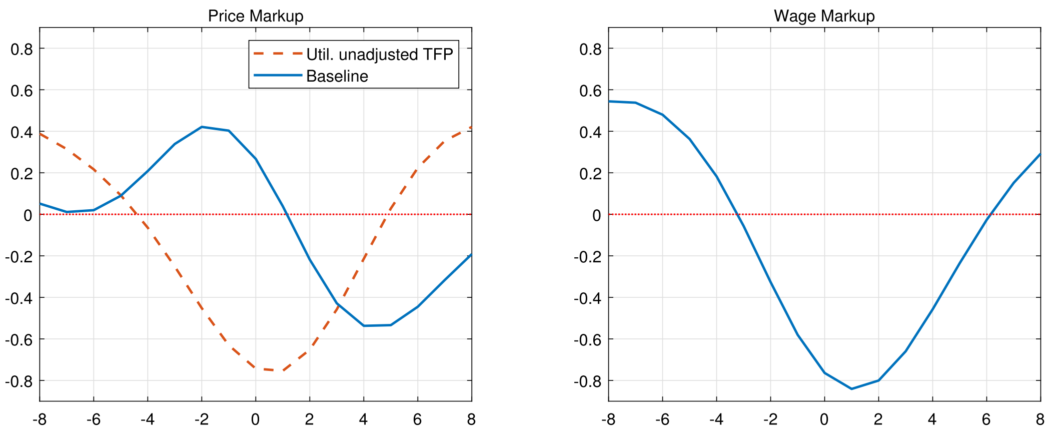


FIGURE 6. Correlation of the cyclical components of the price markup ξ^p_{t+j} and the wage markup ξ^w_{t+j} with output y_t. *Notes:* Price markup is shown for both utilization-adjusted (solid line) and unadjusted (dashed line) TFP measures.

(dashed line). In that case, the price markup shows a pronounced counter-cyclicality that comes from ascribing differences in factor utilization to technology. While this is not our preferred price markup measure, we will show in Section 4.5 below that despite its unconditionally more "favorable" cyclicality, there still is no evidence for an increase conditional on an identified uncertainty shock.

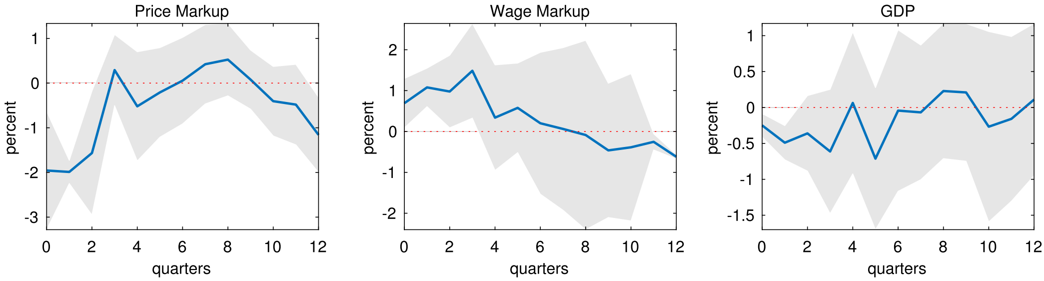
4.2 *Model-consistent uncertainty measures*

For our first approach, we use the median quarterly smoothed uncertainty shocks $e_t \in \{\hat{\varepsilon}_t^{\sigma_z}, \hat{\varepsilon}_t^{\sigma_g}\}$ (where hats denote estimates from the smoother) from the estimated TFP and government spending processes that drive our DSGE model (see Section 3.4). These shocks are included in a local projection model (Òscar Jordà (2005)) of the form

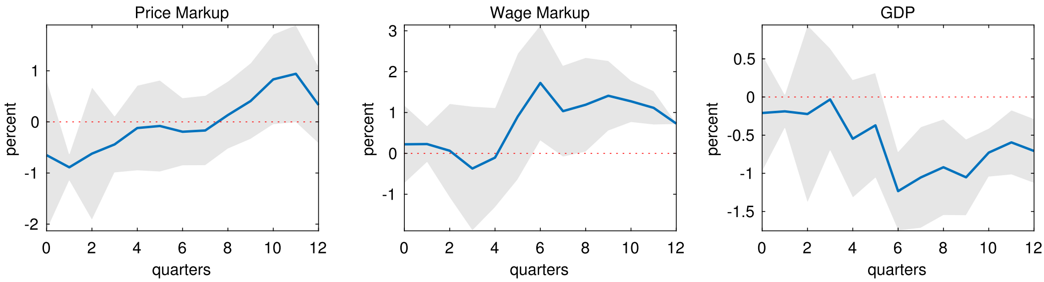
$$x_{t+h} = \alpha_h + \beta_h t + \gamma_h e_t + \eta_{t,h}. \tag{4.1}$$

Here, γ_h denotes the response of a particular variable x_{t+h} at horizon h to an exogenous variation in uncertainty at time t, e_t. In our baseline x_{t+h} stands for either price or wage markup or GDP. α_h and $\beta_h t$ are a constant and a linear time trend, respectively. The error term $\eta_{t,h}$ is assumed to have a zero mean and strictly positive variance. We estimate model (4.1) using OLS where, in order to improve the efficiency of the estimates, we include the residual of the local projection at $t+h-1$ as an additional regressor in the regression for $t+h$ (see Òscar Jordà (2005)).[25] We view these local projections as first tentative evidence. The uncertainty shocks are derived under the assumption that all heteroskedasticity in the residuals is the result of exogenous uncertainty shocks. Insofar as there is endogenous uncertainty in these objects (see, e.g., Caldara, Fuentes-Albero,

[25]The estimated shocks are generated regressors in the second stage. However, the standard errors on the generated regressors are asymptotically valid under the null hypothesis that the coefficient is zero.



(a) Technology uncertainty.



(b) Government spending uncertainty.

FIGURE 7. Local projection responses to model-consistent two-standard deviation uncertainty shocks. *Notes:* Shaded areas denote 90% confidence intervals based on Newey–West standard errors.

Gilchrist, and Zakrajšek (2016), Plante, Richter, and Throckmorton (2018)), we would be mis-measuring the shocks. We will turn to more sophisticated identification schemes below.

Figure 7 presents the IRFs to our model-consistent uncertainty shocks. As expected, an increase in technological uncertainty is associated with a drop in GDP. However, the conditional markup response in the data partially differs from the one predicted by the model.[26] On impact, the price markup falls. In contrast, the DSGE model implies that the price markup quickly peaks and then declines back to its stochastic steady state as the effect of price stickiness subsides over time. The movement of the wage markup squares better with the model: it increases after an uncertainty shock and then slowly declines back to steady state. The evidence after a government spending uncertainty shock is not as conclusive, but also does not lend strong support to the model mechanism.

4.3 *Two-step approach using broad macro uncertainty measure*

The first set of impulse responses from the model-consistent uncertainty measures tentatively suggests that the conditional behavior of the price markup is not consistent with the model prediction. However, the bands were relatively wide. This is not entirely surprising as TFP measures are notoriously noisy and government spending shocks are

[26]This conditional markup response is consistent with the conditional comovement Nekarda and Ramey (2013) found after other types of shocks, which also contradicted the sticky price model.

hard to identify. Thus, we would like to rely on an uncertainty proxy that is still closely linked to the model concept of uncertainty, but at the same time has a better signal-to-noise ratio. A measure satisfying this criterion has recently been proposed by (Jurado, Ludvigson, and Ng, 2015, JLN henceforth). Their measure is closely linked to the concept of forecast error uncertainty employed in business cycle models, but relies on a broad information set to extract the signal.[27] We think that this is currently the broadest and at the same time cleanest uncertainty measure available.[28]

We are ultimately interested in the dynamic response of markups to innovations, or "shocks," to uncertainty. Given that the JLN uncertainty measure is available at monthly frequency while we only have quarterly markup data, we will employ a two-step procedure following Kilian (2009) and Born, Breuer, and Elstner (2018). In the first step, to identify structural uncertainty shocks, we follow Bloom (2009) and Jurado, Ludvigson, and Ng (2015) and employ a Cholesky-ordering within a *monthly* VAR framework. The structural shocks are then aggregated to *quarterly* frequency by averaging the monthly shocks and, in the second step, fed into a local projection as in (4.1).[29] We pursue this approach, because the monthly time horizon of the VAR makes the recursive timing assumption underlying the identification scheme more plausible than in a quarterly VAR.

Our sample ranges from 1964M1 to 2015M12. The variable vector X_t in our VAR contains (1) real industrial production, (2) total nonfarm employment, (3) real personal consumption expenditures, (4) the personal consumption expenditure deflator, (5) real new orders, (6) the manufacturing real wage, (7) hours worked in manufacturing, (8) the Wu and Xia (2016) shadow federal funds rate,[30] (9) the S&P 500 Index, (10) M2 money growth, and (11) the 1-step ahead JLN uncertainty proxy.[31] Formally, we estimate the following VAR using OLS

$$X_t = \mu + \alpha t + A(L)X_{t-1} + \nu_t, \tag{4.2}$$

where and μ and αt are a constant and time trend, respectively, $A(L)$ is a lag polynomial of degree $p = 6$, and $\nu_t \overset{\text{iid}}{\sim} (0, \Sigma)$. In terms of identification, we assume a lower-triangular

[27]JLN stress that in order to measure uncertainty, it is important to purge the predictable component of volatility. They estimate a factor-based forecasting model on 279 monthly economic and financial time series. Given their estimated factors, they then compute forecast errors for 132 of these variables and subsequently use the forecast errors to construct an uncertainty time series for each variable based on the assumption that these follow a stochastic volatility process. Their macroeconomic uncertainty measure is the common factor of the uncertainty connected to the individual variables. We use their one-period ahead forecast measure (i.e. $h = 1$, not to be confused with the forecast horizon in the local projection).

[28]Measures like the economic policy uncertainty index by Baker, Bloom, and Davis (2016) have a very narrow focus, while financial market-based measures like the VIX or realized (return) volatility are likely to be contaminated by changes in risk aversion and financial market conditions (see, e.g., Bekaert, Hoerova, and Duca (2013), Caldara et al. (2016)). We will employ these alternative measures in the robustness section.

[29]Using the average follows Kilian (2009). Readers worried about time aggregation are referred to the mixed-frequency VAR below.

[30]We use this measure to alleviate concerns about the effective zero lower bound introducing a nonlinearity the VAR is not being able to capture. Using the effective federal funds rate instead yields very similar results.

[31]See Appendix D.2 for a detailed description of the macro dataset and the transformations used for the respective variables.

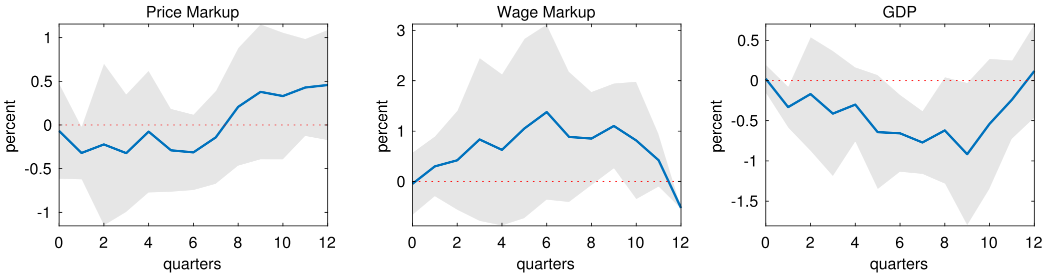


FIGURE 8. Local projection responses to a JLN-based two-standard deviation uncertainty shock in the two-step model. *Notes:* Shaded areas denote 90% confidence intervals based on Newey–West standard errors.

matrix B, which maps reduced-form innovations ν_t into structural shocks $\varepsilon_t = B\nu_t$. The employed ordering follows JLN and relies on economic aggregates not reacting within the month to an increase in macroeconomic uncertainty, while uncertainty itself may react to other shocks. In Section 4.5, we confirm that our results are robust to ordering uncertainty before macroeconomic aggregates.

After averaging the monthly shocks and feeding them into the local projection model, the resulting IRFs are plotted in Figure 8. They corroborate our previous finding. After an uncertainty shock, the wage markup increases significantly, consistent with a precautionary wage setting motive as in the model. The same does not apply to the price markup, which tends to decline.

4.4 *Mixed-frequency VAR*

The two-step approach comes at the disadvantage of not making full use of (relatively) high-frequency information. As mentioned before, the constructed markups are only available at quarterly frequency. To use all available monthly information on the other variables, we assume that we cannot observe the monthly realizations of the markup measure and treat these data as missing values. Following the Bayesian VAR framework outlined in Eraker et al. (2015), we can then employ a Gibbs sampler to deal with these missing observations by sampling the missing data from their conditional distribution.

Our sample again ranges from 1964M1 to 2015M12, on which we estimate the 11-variable VAR in equation (4.2) with $p = 6$, but where we add our quarterly markup measures as an additional twelfth variable observed every third month. Consistent with the model, we order the markups after the respective uncertainty measure so that markups can react on impact. We use a shrinking prior of the Independent Normal–Wishart type, where the mean and precision are derived from a Minnesota-type prior.[32] We use 90% highest posterior density intervals (HPDIs) based on 1000 random posterior draws after burn-in.

We estimate three separate mixed-frequency VARs, one including the price markup, one including the wage markup, and one including the total markup or "labor wedge,"

[32] See Appendix D.1 for details.

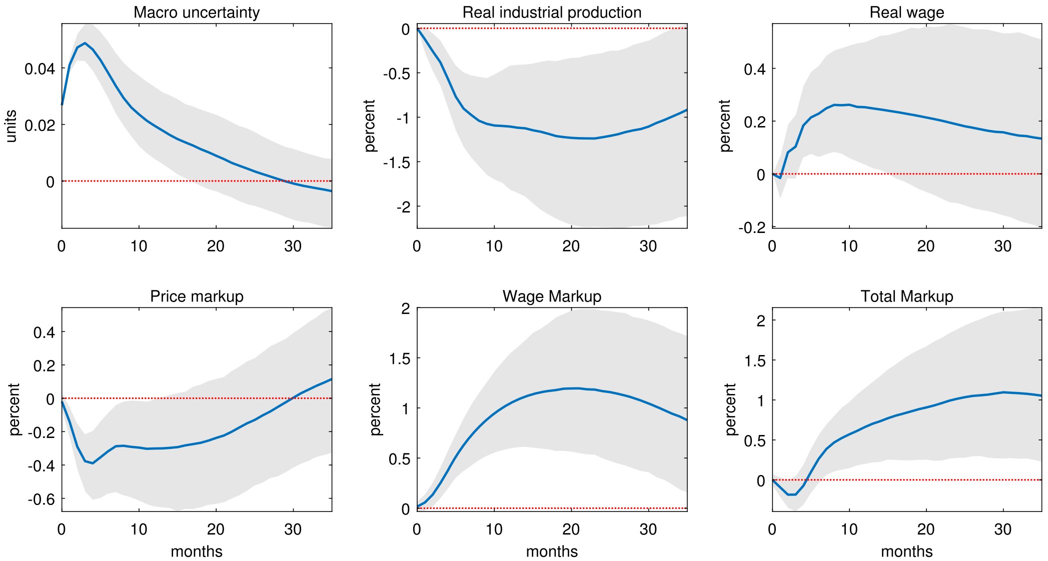


FIGURE 9. IRFs to JLN-based two-standard deviation uncertainty shock in the mixed-frequency VAR. *Notes:* Bands are pointwise 90% HPDIs. The respective markups are rotated into the VAR as the 12th variable. The macroeconomic uncertainty index is measured in arbitrary units and has a mean of 0.65. The first row and the price markup response are from a VAR including the price markup. The responses of wage and total markup are from separate VARs (see text).

that is, the sum of the price and wage markup. Figure 9 presents the key impulse responses following a two-standard deviation shock to macroeconomic uncertainty based on the three models.[33] As with the model-consistent measure and the two-step approach, wage markups increase after an uncertainty shock but price markups fall.

The bottom right panel of Figure 9 displays the total markup or "labor wedge," that is, the sum of the price and wage markup. During the first few months, it is dominated by the price markup response and slightly falls, before it becomes dominated by the wage markup and increases subsequently. As the figure shows, after an uncertainty shock the real wage increases. This response, together with a fall in hours worked shown in the Appendix, is perfectly consistent with a situation where the wage markup increases while the price markup stays flat (see the stylized labor market diagram in Figure 2).[34] While the model does not predict the same hump-shaped movement, it predicts the same countercyclical movement of the wage markup. At least in that regard, the data is consistent with the markup channel in NK models and the role of uncertainty shocks more generally. Empirically, most of the movement in the labor wedge seems to come from this margin. However, from the vantage point of the basic NK model with only sticky prices, the price markup response presents a challenge.

We also compute the posterior unconditional forecast error variance share explained by the identified uncertainty shock. Uncertainty shocks account for about 13% of output

[33] Appendix D.2 includes a full set of impulse responses of all three VARs.

[34] The model with only rigid wages also delivers an increase in the real wage and a drop in hours worked.

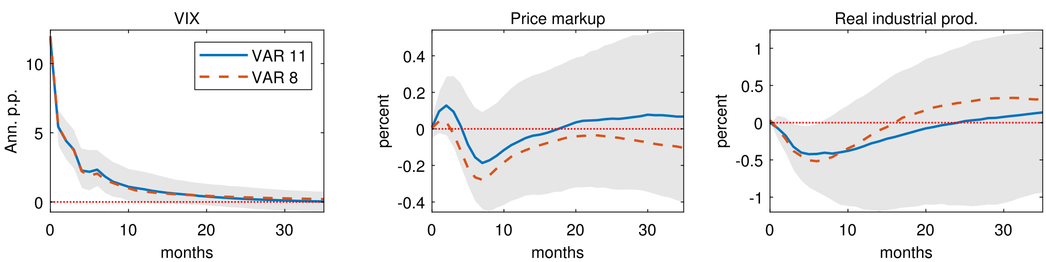
fluctuations, 15% of the wage markup, but only 8% of the price markup. Taken together, uncertainty shocks account for 11% of total labor wedge fluctuations (see Table D.5 in the Appendix).

4.5 *VAR-based robustness checks*

While our results are robust across different time-series approaches, one might wonder whether they depend on the ordering of variables in the VAR, the assumptions made to construct markups, or the chosen uncertainty proxy. We will address these concerns in the following.

Bloom (2009) VAR Bloom (2009) considers a different, 8-variable VAR where uncertainty is ordered second and measured by stock market volatility via the VIX. The reasoning behind this ordering is that uncertainty shocks instantaneously influence stock market volatility and other prices and quantities, but that first moment shocks to stock-market levels are already controlled for when investigating the response to uncertainty shocks. In a first step, we check whether using the VIX instead of the JLN measure makes a difference in our VAR 11+1. The solid lines in Figure 10 confirm that the results are robust to this change.

Next, we investigate the original Bloom 8-variable VAR with uncertainty, measured by the VIX, ordered second. We add our markup measure as the ninth variable.[35] Results



(a) Price Markup

(b) Wage Markup

FIGURE 10. IRFs to two-standard deviation uncertainty shocks measured via the VIX. *Notes:* Solid line: mixed-frequency 11+1-VAR with VIX ordered second-to-last; dashed line: 8+1-Bloom (2009)-VAR with VIX ordered second (see text for details). Bands are pointwise 90% HPDIs computed for the 11+1-VAR.

[35]See Appendix D.3 for a detailed variable listing and Figure D.10 for a full set of IRFs.

from the mixed-frequency estimation are included as dashed lines in Figure 10. They are very similar to the baseline results, indicating that the ordering of the uncertainty measure is not crucial for our results.[36]

Alternative markup measurements In our baseline price markup measure, we employ the utilization-adjusted TFP measure of Fernald (2012), which results in an acyclical price markup. As a robustness check, we also use Fernald's utilization-*un*adjusted TFP measure. This results in a strongly countercyclical price markup (see the dashed line in the left panel of Figure 6), which, as Nekarda and Ramey (2013) note, is very similar to the countercyclical markup measure constructed in Galí, Gertler, and López-Salido (2007). Estimating our mixed-frequency VAR including this alternative price markup measure yields the IRFs reported in the upper left panel of Figure 11. The drop in the price markup is less pronounced than in the baseline, but there is still no robust evidence for an increase.

With respect to the price markup, one might also worry that the correction for overhead labor, fixed costs, and a CES production function might be overdoing things. Figure 11 therefore also reports the responses of three "conventional" markup measures based on a setup with no fixed costs and a Cobb–Douglas production function. In this case, the aggregate price markup corresponds to the inverse labor share. The upper right panel of Figure 11 displays the response of the price markup for the labor share based on total compensation in the nonfinancial business sector (available from the NIPA tables).

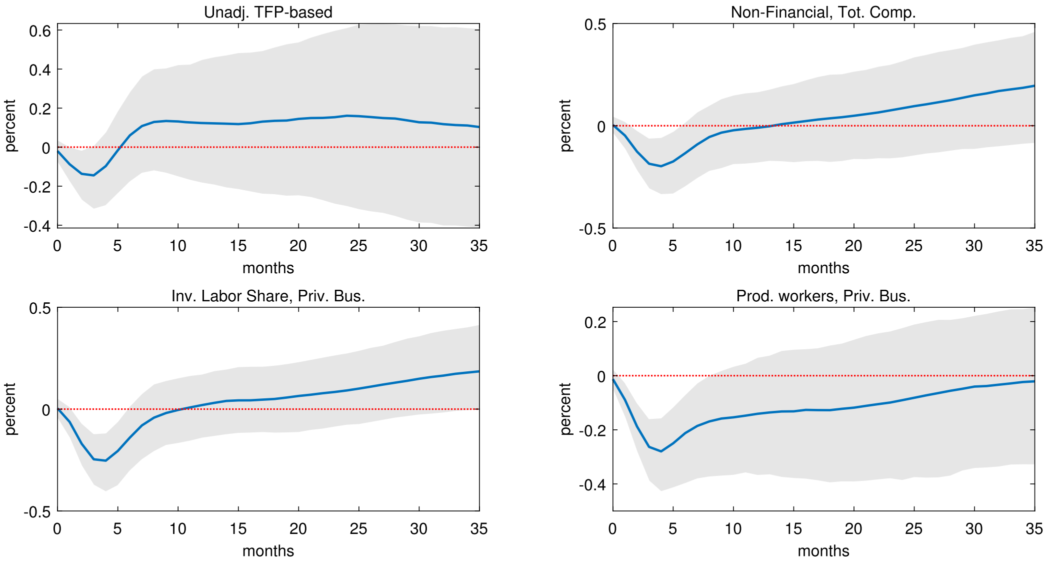


FIGURE 11. Alternative price markup-IRFs to JLN-based two-standard deviation uncertainty shocks in the mixed-frequency 11+1-VAR. *Notes:* See text for description of measures. Bands are pointwise 90% HPDIs.

[36]Figure D.11 shows that the IRFs when using the JLN-measure ordered second in the VAR are also similar. Appendix D.4 provides the IRFs for various other measures of uncertainty.

The lower left panel uses the labor share of production and supervisory workers in the private business sector, while the lower right panel is based on production workers only in the private business sector, that is, excludes overhead workers (both available from the BLS). In all three cases, the price markup significantly drops after an uncertainty shock. The first two measures, which are based on all workers, tend to recover somewhat more quickly than the third measure, which accounts for the presence of overhead labor as in the baseline. But even for the first two measures, we do not find a significant increase of the price markup within the first three years.

We also check whether our choice of the elasticity of substitution (EOS) between capital and labor influences the dynamic response of the price markup. Unfortunately, the EOS is difficult to measure in the data and estimates range from 0.5–0.7 (e.g., Chirinko (2008), Oberfield and Raval (forthcoming)) to 1.25 and higher (e.g., Karabarbounis and Neiman (2014)). We therefore compute price markups for parameterizations of the EOS ranging from 0.5 to 1.5 and report the resulting IRFs to a two-standard-deviation uncertainty shock in the left panel of Figure 12. While larger values of the EOS correlate with smaller drops in the price markup, the general pattern of a fall in the price markup following an uncertainty shock stands.

We also check the robustness of the wage markup response with respect to the preference specification used (right panel of Figure 12). It first varies the functional form, keeping the Frisch elasticity at its baseline value of 1. The solid line shows separable isoelastic preferences of the type $U = \log C_t - \psi N_t^{1+1/\eta}$, while the dashed line at the bottom displays (Greenwood, Hercowitz, and Huffman, 1988, GHH) preferences of the form $U = \log(C_t - \psi N_t^{1+1/\eta})$.[37] Isoelastic preferences result in a wage markup that is more volatile over the business cycle (see also Karabarbounis (2014)), but that is otherwise

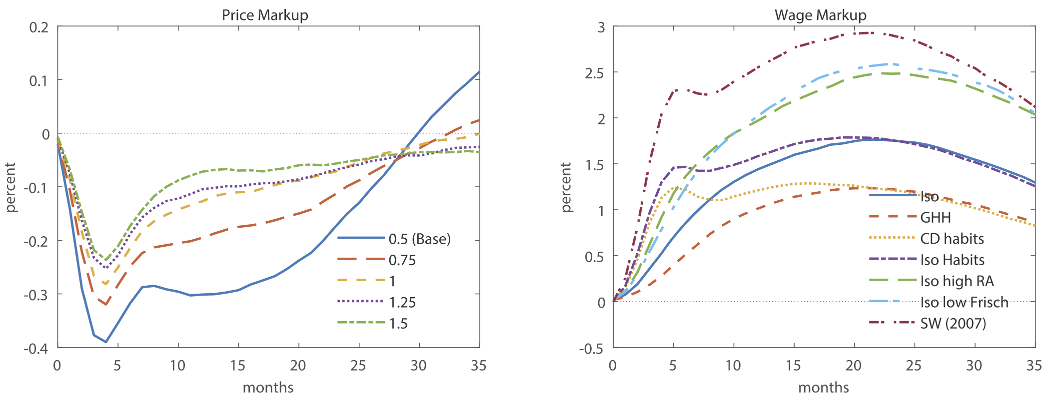


FIGURE 12. IRFs to JLN-based two-standard deviation uncertainty shocks in the mixed-frequency 11+1-VAR using a variety of measured markups. *Notes:* Left panel: price markups for range of EOS between capital and labor; right panel: wage markup for different preference specifications (see text for details).

[37]The labor disutility parameter ψ only affects the constant in our markup measure and, therefore, can be set to 1 without loss of generality.

similar to the baseline. The wage markup response with GHH preferences is also very similar to the baseline. The dotted and the dash-dotted lines display the Cobb–Douglas and the isoelastic preferences with external habits of 0.7, a common value in the literature. Habits cause a quicker and more persistent increase in the wage markup. The next two lines display the effect of parameter variations for the case of isoelastic preferences. The long-dashed line uses a higher risk aversion parameter of $\sigma = 2.5$, while the long/short-dashed line lowers the Frisch elasticity to 0.5. In both cases, the response of the wage markup almost doubles, but is qualitatively still the same. Finally, the dot-dash–dotted line at the top combines a higher risk aversion of 1.4, a lower Frisch elasticity of 0.5, and external habits of 0.71 as estimated for the US in Smets and Wouters (2007). The response of the wage markup in this case combines the quick and drawn out increase of the external habit case with the higher peak response of the high risk aversion/low Frisch elasticity cases.

4.6 *Price markup based on self-employed and new jobs formed*

The previous analyses have relied on a measure of average hourly earnings, which would be the appropriate measure of firms' marginal cost of labor if transactions took place in perfectly competitive spot markets. But due to implicit long-term contracts between firms and workers this measure of earnings may not play an allocative role. For this reason, (Bils, Klenow, and Malin, 2018, BKM) have recently investigated the labor wedge of self-employed people along the intensive margin. Arguably, no wage rigidities and labor market distortions affect their decision to supply labor to their own business. In this case the wage markup is zero and the labor wedge coincides with the price markup. The share of self-employed in nonagricultural industries is roughly 10%. The BKM data is based on the Annual Social and Economic Supplements to the CPS from 1987 to 2012 with a gap in 1994 and 1995 due to a CPS sample redesign. The wedge construction assumes separable isoelastic preferences with a Frisch elasticity of unity and an intertemporal elasticity of substitution of 0.5.

In Table 3, we investigate the effect of uncertainty shocks on the BKM annual intensive margin labor wedges during the first two years after the shock. The aggregate uncertainty shock is constructed as the annual average of the monthly uncertainty shocks estimated using the VAR (4.2). The first column displays the results based on hours, labor productivity, and consumption of all workers, not just the self-employed.[38] The response therefore needs to be interpreted as the total markup. Consistent with our previous findings based mostly on quarterly NIPA data, it shows a delayed increase. The next columns subsequently replace the aggregate components of the wedge computation by measures specific to the self-employed. Most importantly, starting with the second column the total hours measure is replaced by the one for the self-employed. The resulting wedge can therefore be interpreted as the price markup. As the second column shows, we find a significant increase of the price markup after one year, consistent with the markup channel. The third column then replaces the aggregate labor

[38] For details on the construction of the respective wedges, we refer the reader to BKM.

TABLE 3. Short-run response of BKM annual price markup to aggregate macroeconomic uncertainty shock.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$h = 0$	0.340	0.198	0.288	0.490	−0.003	−0.241	−0.145
	(0.482)	(0.672)	(0.393)	(0.017)	(0.314)	(0.575)	(0.310)
$h = 1$	1.616	1.787	1.561	0.377	1.081	1.220	0.818
	(0.561)	(0.737)	(1.015)	(1.889)	(0.651)	(0.675)	(1.394)
Hours	All workers	SE	SE	SE	SE	SE	SE
MPN	Agg.	Agg.	SE	SE	Uninc	SE	SE
Cons.	PCE	PCE	PCE	+CE Adj.	PCE	PCE	PCE
Weight.	Equal	SE in CPS	SE in CPS	SE in CPS	SE in CPS	All in CPS	Emp.

Note: Responses are in percent. Regressions based on years 1987–1993 and 1996–2012. Newey–West standard errors are in parentheses. Hours are weekly. MPN refers to how the marginal product is measured: “Agg.” denotes the NIPA labor productivity measure, “SE” denotes self-employed income per hour, “Uninc” denotes unincorporated self-employed income per hour. “Cons.” denotes the respective consumption measure. PCE: NIPA aggregate real expenditures on nondurables and services. CE adjustment incorporates consumption for the self-employed versus all persons from the Consumer Expenditure Surveys. Weighting schemes: “SE in CPS” weights all self-employed in the CPS equal, “All in CPS” weights self-employed to achieve mirror industry structure of all workers in the CPS, and “Emp.” reweights with the share of self-employed with employees (see BKM for details).

productivity measure by one for the self-employed, that is business income divided by hours. This change causes the price markup increase to become insignificant. The reason may be that, as argued in BKM, this measure tends to understate the cyclicality of the labor wedge. The fourth column adjusts the previously used aggregate consumption measure by a measure of consumption for the self-employed derived from the CPS. Self-employed consumption is more cyclical, which causes the estimated price markup to increase significantly on impact, but revert more quickly. The fifth column again uses aggregate consumption, but considers only nonincorporated businesses to avoid issues with reporting of business income as corporate profits. We find a marginally significant increase in the price markup after one year. Finally, columns (6) and (7) use a different weighting scheme. Column (6) reweights observations by industry in order to achieve a weighting of self-employed by industry that mirrors the one of all employees.[39] This assures a similar aggregate cyclical exposure of the self-employed wedge measure as for the whole worker population. This reweighting hardly makes a difference. We still only find a marginally significant increase in the wedge after one year. Finally, column (7) reweights observations by the share of self-employed with employees. The goal is to give less weight to self-employed people that might just contract with one employer and are thus quasi-employees with all associated rigidities. In this case, the price markup increase after one year becomes insignificant.

Summarizing, estimating the response of the price markup based on an annual dataset of self-employed persons yields some tentative evidence for the presence of the markup channel. One year after the shock, the point estimate is consistently positive. However, the significance of this increase in the price markup depends on the exact specification used.

[39]For example, if self-employment is twice as likely in construction than overall, self-employed in construction only receive a weight of one-half.

Finally, we turn to the extensive labor margin. Most representative agent models investigating the effect of uncertainty shocks only feature an intensive margin of labor adjustment and rely on a measure of average hourly earnings to represent the opportunity cost of firms (e.g., the estimations in Born and Pfeifer (2014a), Fernández-Villaverde et al. (2015)). In theory, if this wage measure were allocative, for example, if all workers were hired in spot markets, markups based on it should return the same result as any other margin of adjustment available to the firm. However, there are well-documented reasons like implicit long-term contract concerns that may prevent wages of existing jobs from adjusting in a frictionless way (see, e.g., Basu and House (2016)). We investigate whether our findings change if we consider the extensive margin adjustment and analyze a firm's decisions when forming new jobs.

For this purpose, we rely on two quarterly extensive margin price markups constructed in BKM for the period from 1987 to 2012.[40] Instead of relying on average hourly earnings of all workers, the two measures follow Kudlyak (2014) and employ the wage of new hires and the user cost of labor, respectively.[41] Both cost measures are arguably more relevant for the firm's hiring decisions than average wages. BKM obtain these two measures based on their respective semi-elasticities and the one of average hourly earnings with respect to the unemployment rate. While average wages fall by 1.5% for each percentage point increase in unemployment, wages of newly hired workers fall by 3% and the user cost by 4.5%. This information allows constructing the wage of new hires and the user cost of labor by adjusting average hourly earnings for the respective different comovement with respect to the observed unemployment series.

The impulse responses of the two extensive margin price markups are shown in Figure 13. The left panel shows the response of the price markup when using the wage of new hires as the relevant firm cost measure. After an initial, insignificant drop, the price markup increases significantly after about one year. The right panel displays the price markup based on the user cost of labor. It also increases in a hump-shaped manner, but already becomes significant after about 6 months and exhibits a larger peak. Thus, these tentative measures of extensive margin price markups provide the strongest evidence yet for the presence of a markup channel. The results suggest that recent modeling efforts combining search-and-matching models with uncertainty shocks (Leduc and Liu (2016), den Haan, Freund, and Rendahl (2020)) may be a particularly promising avenue for obtaining data-consistent model responses to uncertainty shocks.

However, these findings come with two important caveats. First, while BKM were only interested in the unconditional cyclicality of price markups, their mechanical unemployment-based adjustment of average hourly earnings is problematic in our context of a conditional analysis. It carries the risk of introducing a spurious effect of uncertainty shocks. Empirically, uncertainty shocks tend to exhibit a significant effect on unemployment, which—by construction—will affect the measurement of new hire wages

[40]We verified that our baseline intensive margin results are unaltered if we restrict our analysis to this shorter sample period. For details on the construction of extensive margin price markups, we refer interested readers to the original paper.

[41]Kudlyak (2014) defined the user cost as the expected difference between the present value of wages paid to a worker hired in period t and that hired in $t+1$. If the labor market were a spot market, this difference would simply be the wage.

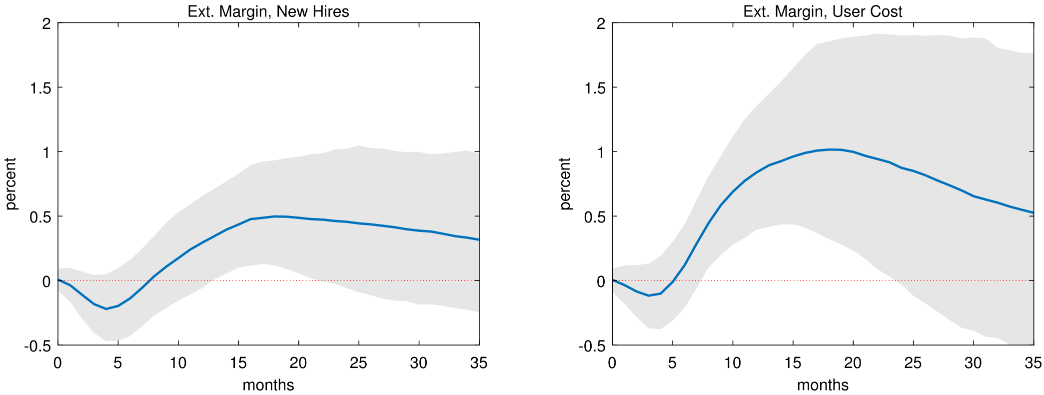


Figure 13. IRFs to JLN-based two-standard deviation uncertainty shocks in the mixed-frequency 11+1-VAR using the BKM extensive margin price markups based on the wage of new hires (left panel) and the user cost of labor (right panel). Sample range: 1987M1:2012M12.

and the user cost of labor. For this reason, we consider the evidence presented above to be tentative and pointing toward the need for further investigation.

Second, and perhaps even more importantly, it needs to be pointed out that—in contrast to the other markup measures considered in the present paper—constructing price markups in a search-and-matching framework requires dynamic equilibrium conditions. Therefore, results will strongly depend on the model assumptions and the employed empirical models to infer expectations about future variables from the data. We leave an investigation of these issues for future research.

5. Industry-level evidence

In the previous section, we have documented that there is only mixed empirical evidence for price markup increases after uncertainty shocks at the aggregate level. In this section, we dig deeper, turning to disaggregated industry-level evidence to investigate whether the model-predicted price markup response may simply be hidden by (i) heterogeneity in price stickiness at the industry level or (ii) measuring price markups along the labor margin instead of the potentially more flexible intermediate input margin. The results in this section need to be interpreted with caution. First, the markup channel provides clear-cut predictions for aggregate markups based on aggregate equilibrium conditions (what BKM have called the representative-agent labor wedge). Strictly speaking it is silent on what happens at a more disaggregated level. Aggregation from the average markup of firms or industries to the markup of the average firm is not trivial (see, e.g., De Loecker, Eeckhout, and Unger (2020)). However, we expect this issue to be less problematic if aggregation is at the industry rather than the firm level.[42] Second, input-output-relationships between sectors can lead to non-trivial interactions with nominal rigidities (see, e.g., Pasten, Schoenle, and Weber (2018)). We abstract from this issue as

[42] The different level of aggregation is also the reason why BKM's industry-level analysis does not reveal a trend in the average markup, while De Loecker, Eeckhout, and Unger (2020)'s firm-level analysis does.

it is beyond the scope of the present paper, but think it deserves more future attention. Despite these limitations, we still consider the industry-level analysis to be an additional useful piece of evidence.

5.1 *Constructing industry-specific markups*

Based on the NBER CES Manufacturing Industry Database (Becker, Gray, and Marvakov (2016), Bartelsman and Gray (1996)) we construct price markups and output measures at the four digit SIC-industry level (see Appendix C.5 for details). As we have argued before, a robust result of representative agent models with convex adjustment costs is that negative output effects of uncertainty are directly related to nominal stickiness. As a first pass at the data, we therefore estimate the contemporaneous response of real output for each SIC4 industry and plot it against average price durations for these industries. To compute this response, for each industry we regress the log of real output y_t on the aggregate uncertainty shock, a constant, and a linear time trend:

$$\log(y_t) = \alpha_0 + \alpha_1 t + \alpha_2 \bar{e}_t + \varepsilon_t. \tag{5.1}$$

Again, the aggregate uncertainty shock $\bar{e}_t$ is the annual average of the monthly uncertainty shocks estimated using the VAR (4.2). Implied average price durations are computed for SIC4 industries based on the estimated New Keynesian Phillips Curves in Petrella and Santoro (2012).[43] Figure 14 plots the resulting estimates $\hat{\alpha}_2$ against average

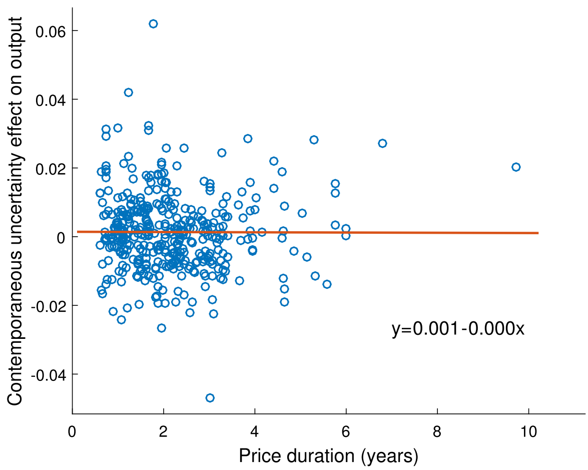


FIGURE 14. Implied average price duration at the SIC4 industry-level vs. output effects of aggregate uncertainty shock. *Notes:* Implied average price durations are based on Petrella and Santoro (2012); output effect estimates based on regression (5.1) using mean annual JLN shocks from VAR-11.

[43]For that purpose, we translate their estimated slope of the New Keynesian Phillips Curve into a Calvo price duration parameter, using $\beta = 0.99$.

price durations. There does not seem to be a linear relationship between price stickiness and the output effects of uncertainty shocks. The regression line is flat and the slope coefficient is insignificant at the 5% level.

5.2 *Regression evidence*

As price stickiness per se does not seem seem to be related to the output effects of uncertainty, we now investigate the markup channel itself. Specifically, we run a panel version of the local projection (4.1)

$$x_{i,t+h} = \alpha_{i,h} + \beta_{i,h} t + \gamma_h \bar{e}_t + \eta_{i,t+h}. \tag{5.2}$$

Again, γ_h denotes the response of a particular variable x_{t+h} at horizon h to an exogenous variation in uncertainty at time t, $\bar{e}_t$, where x_{t+h} is either the industry-specific price markup or industry-specific real output. $\alpha_{i,h}$ and $\beta_{i,h} t$ are industry-specific constant and time trend, respectively. Given the short annual panel, we restrict ourself to $h = 0$ and $h = 1$. The results of the pooled OLS regression are shown in Table 4. Standard errors are robust to serial and cross-sectional correlation based on the approach by Driscoll and Kraay (1998). Qualitatively, the results look quite similar to the aggregate evidence. Industry-level output (first column) declines after a one-standard deviation uncertainty shock. While the price markup based on a CES production function and production-worker compensation shows an initial, marginally significant increase (which disappears after year), markups constructed using all workers (column [2]) and a Cobb–Douglas production function (column [3]) fall (insignificantly) on impact.

In a final robustness check, we use price markups constructed by BKM based on the share of intermediate inputs. Arguably, the markup measured along the intermediate inputs margin is less affected by the type of implicit contracting that may make wages not allocative.[44] These markups, based on the KLEMS database, are available for 60 sec-

Table 4. Short-run response of industry-level price markup to aggregate macroeconomic uncertainty shock.

	Output	Markup			
		[1]	[2]	[3]	[4]
$h = 0$	−1.45	1.61	−0.10	−0.45	−0.44
	(1.73)	(0.94)	(0.36)	(0.41)	(0.37)
$h = 1$	−3.13	0.66	−0.31	−0.24	0.78
	(1.20)	(0.68)	(0.24)	(0.20)	(0.67)
Sectors	459	451	458	458	60
Observations	21,463	21,197	21,416	21,416	1500

Note: Responses, based on local projection (5.2), are in percent. Markup [1]: based on CES production function and production-worker compensation; markup [2]: based on CES production function and all-worker compensation; markup [3]: based on Cobb–Douglas production function and production-worker compensation; markup [4]: markup based on BKM intermediates share. Driscoll–Kray standard errors in parentheses.

[44] Following the evidence in BKM that their measured markup does not contain a trend, we do not include a trend in the regression.

tors, 42 of those outside of manufacturing, on an annual basis from 1987 to 2012. The results are shown in the last column of Table 4 and corroborate our earlier findings of no consistent evidence for a price markup increase after uncertainty shocks.

6. Conclusion

The question of the markup channel as an empirically plausible transmission mechanism of uncertainty shocks into the macroeconomy is highly relevant for the policy debate given that the supposedly negative influence of policy uncertainty has become a recurring theme in the political discourse. With much of the model-based evidence featuring this supposed transmission mechanism, it is of paramount importance to subject it to a rigorous empirical assessment.

We construct a DSGE model to measure markups and to generate theoretical markup responses following uncertainty shocks. We then provide econometric evidence on the response of markups to identified uncertainty shocks. The model-implied effects of uncertainty shocks are generally much smaller than their empirical counterparts. This is due to (i) employing a microestimate-based, conservative model parameterization and (ii) our estimated driving processes not featuring large and persistent increases in uncertainty.

Contrary to the model's prediction, *price* markups do not consistently increase after identified uncertainty shocks. The only tentative evidence for an increase in price markups we can find is for price markups measured along the extensive margin. However, *wage* markups increase after uncertainty shocks, suggesting that sticky wages play a more important role in the transmission of aggregate uncertainty shocks to economic variables than sticky prices.[45]

Of course, it is important to understand why model-consistently measured price markups do not increase as predicted by the model. We can think of at least three potential reasons. First, the model assumes that any demand always has to be satisfied. In reality, firms might avoid having to satisfy demand at disadvantageous prices by "being out of stock." This potential violation of a crucial model assumption may be one reason why we find less evidence of a precautionary pricing for firms. Second, instead of hiking their prices, firms may care about protecting their customer base and invest into market shares.[46] However, while the evidence in Gilchrist, Schoenle, Sim, and Zakrajšek (2017) is consistent with the relevance of customer markets, it suggests that, together with empirically realistic financial frictions, customer markets actually strengthen the countercyclical model behavior of markups.

Finally, average wages may not be allocative. When we tentatively analyze price markups measured along the extensive margin, we find that they increase. The intensive margin-only labor market structure in the spirit of Erceg, Henderson, and Levin (2000) embedded in most medium-scale NK models may therefore require to be augmented by

[45] See also Barattieri, Basu, and Gottschalk (2014) and Daly and Hobijn (2014) on the importance of sticky wages.

[46] We thank an anonymous referee for suggesting this possibility.

an extensive margin. A crucial open question in that regard is how to resolve the fundamental indeterminacy of wages within the bargaining set. The exact type of wage setting mechanism employed is important for understanding the effects of uncertainty shocks (see den Haan, Freund, and Rendahl (2020)) and the behavior of model-consistent wage and price markups. A rigorous analysis of this nexus must be left for future research.

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Co-editor Kjetil Storesletten handled this manuscript.

Manuscript received 22 February, 2019; final version accepted 8 September, 2020; available online 19 October, 2020.