Uncertainty Shocks in Networks

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May 28, 2022

Abstract

Existing studies on uncertainty shocks focus on economy-wide shocks that affect all sectors symmetrically and simultaneously. However, as the recent COVID-19 pandemic underscores, a rise in uncertainty often appears to be concentrated in several specific sectors. In this paper, I study how these sector-specific uncertainty shocks propagate and affect aggregate outcomes. First, using sector-level data, I estimate sectoral TFP and demand processes allowing for stochastic volatility. I show that sectoral TFP and demand display nontrivial fluctuations in volatility even after controlling for economy-wide variations. I estimate local projections and find that an increase in sector-specific TFP or demand volatility reduces output in that sector. Second, I use the estimated sectoral TFP and demand processes to simulate the impact of sector-specific volatility shocks in a calibrated multi-sector New Keynesian model that features input-output networks. I find that sectoral volatility shocks generate contractions in aggregate output, hours, consumption, and investment. The key mechanism is the precautionary pricing motive that multiplies and propagates to other sectors.

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1 Introduction

Business analysts and policymakers have emphasized fluctuations in uncertainty as a significant contributor to aggregate fluctuations. A number of studies, including Bloom (2009), Fernández-Villaverde et al. (2015), and Basu and Bundick (2017), have confirmed this view. In most studies, fluctuations in uncertainty are economy-wide shocks; they are changes in aggregate risk, firm-level volatility, or policy uncertainty, but they affect all sectors symmetrically and simultaneously. In reality, however, a rise in uncertainty often appears to be concentrated in several specific sectors. For example, an oil crisis would disproportionately raise the volatility of energy-intensive sectors. The recent trade tension between China presumably has increased uncertainty in tradable-goods sectors. It is likely that the COVID-19 pandemic in 2020 has significantly raised risks surrounding the tourism and restaurant industries. In this paper, I study the aggregate implications of these sector-specific uncertainty shocks using sector-level data and a multi-sector business cycle model.

I begin by estimating sectoral TFP and demand processes featuring time-varying volatility in their innovations using U.S. quarterly sector-level data. I interpret an unexpected rise in volatility in these TFP innovations as a TFP uncertainty shock that represents an increase in risk. Similarly, an unexpected increase in volatility to demand is interpreted as a demand uncertainty shock. Fluctuations in TFP and demand volatility are allowed to be sector-specific, meaning that a change in uncertainty in one sector could be distinct from changes in uncertainty in other sectors or at the economy-wide level. I find that sector-specific TFP, which controls for economy-wide TFP variations, exhibits fluctuations in volatility that are as sizable as the economy-wide TFP. Similarly, sector-specific demand volatility also shows substantial time-variation. To examine the economic impact of these sector-specific volatility shocks, I estimate local projection (Jordá 2005) that includes sector-specific TFP level and volatility shocks for a panel of sectors. I show that an increase in sectoral TFP level raises that sector's gross output, while an increase in sectoral TFP volatility reduces the sector's own gross output. Similarly, an increase in sectoral demand level raises that sector's gross output, while an increase in sectoral demand volatility reduces the sector's own gross output. This finding indicates that sector-specific uncertainty shocks reduce their own sectors' economic activity. However, to study the macroeconomic effects, it is necessary to go beyond the local projection estimation. First, the local projections do not show how those shocks propagate to other sectors. Second, they are only informative about the average effect; in reality, the impact of sectoral uncertainty shocks could be quite heterogeneous depending on which sector the shock originated in.

Thus, I consider a multi-sector New Keynesian model similar to Bouakez et al. (2009) and others. The main innovation here compared to other multi-sector models is that sector-specific TFP and demand are subject to volatility shocks. Both nominal rigidities and input-output networks are critical ingredients. With nominal rigidities, uncertainty shocks could have sizable impact due to countercyclical markups (Fernández-Villaverde et al. 2015 and Basu and Bundick 2017). Input-output networks matter because they propagate the effects of sectoral uncertainty shocks across sectors through linkages.

To solve the model, I use the risk-adjusted log-linearization method as in Jermann (1998), Uhlig (2010), Dew-Becker (2012), Malkhozov (2014), and others. The advantage of this method is that it captures the effects of sectoral uncertainty shocks through the risk-adjustment terms while preserving tractability. As in Bianchi et al. (2019), the method also allows me to explicitly decompose the propagation mechanism of uncertainty shocks. In my model, there are four transmission channels. The first is the precautionary saving channel in the consumption Euler equation. The second is the capital return risk channel in the capital Euler equation that captures the fact that the future return on capital is uncertain. The third channel is the investment adjustment cost channel, which is connected to the fact that the impact of current investment on a future adjustment cost is uncertain. Finally, there is a nominal pricing bias channel, which captures the idea that when firms choose their current prices, their effects on future profits are uncertain because the future demand condition is uncertain.

To quantitatively evaluate the impact of sectoral uncertainty shocks, I consider a 66-sectors version of the model and calibrate it to U.S. sectoral and macro facts. I find that sectoral uncertainty shocks reduce aggregate output but the magnitude of the impact depends critically on the identity of the sector in which the shocks originate. In particular, sizable aggregate output impacts are concentrated on a few sectors such as "Oil and gas extraction", "Transportation equipment", "Chemical products", "Rental and leasing services", and to a lesser extent, "Textile mills and textile production mills", "Air transportation", and "Miscellaneous professional services". This suggests that the macroeconomic impact of an increase in uncertainty depends crucially on the the identity of the sectors in which that increase takes place. In the model, sectoral uncertainty shocks reduce not only aggregate output but also hours, investment, and consumption. Nominal variables such as inflation and the nominal interest rate rise. To understand the mechanism, consider a sectoral TFP uncertainty shock to a specific sector (say, the air transportation sector). In response to the increase of TFP volatility in the air transportation sector, firms raise their prices due to the nominal pricing bias. Intuitively, an increase in TFP volatility raises dispersion of future marginal costs and hence the range of optimal prices. Since firms' profit function is asymmetric (it is more costly to sell goods at too low a price than the other way around), firms self-insure against the risk of being stuck at low prices by raising their prices when uncertainty rises. The price increase raises markups and hence gross output of the air transportation sector drops. The volatility shock in the air transportation sector propagates to downstream sectors in two ways. First, the increase in air transportation price raises the level of marginal costs in downstream sectors (level effect). Second, the *volatility* of air transportation price rises, and hence uncertainty about the marginal costs in downstream sectors rises as well (volatility effect). The level and volatility effects both act to raise downstream sectors' prices, which in turn raise their markups and reduce output in downstream sectors. I show that the nominal pricing bias and sectoral linkages are quantitatively critical. Without them, the macroeconomic impact of sectoral uncertainty shocks is negligible.

This paper is related to two strands of the literature. First, the paper belongs to the expansive literature on uncertainty shocks, such as Bloom (2009), Fernández-Villaverde et al. (2011), Christiano et al. (2014), and Basu and Bundick (2017). I consider a network economy, which allows me to study sector-specific uncertainty shocks and their propagations instead of the economy-wide uncertainty shocks as in the previous literature. Second, this paper contributes to the research agenda that studies how microeconomic shocks drive aggregate fluctuations, such as Gabaix (2011) and Acemoglu et al. (2012). In particular, it is closely related to Baqaee and Farhi (2019), who explore the aggregate implications of sectoral productivity shocks in a non-linear environment and how they depend on micro-level details such as network linkages. I focus on a particular form of non-linearity, namely, sectoral volatility shocks, and study how they shape macro outcomes.

The rest of the paper is organized as follows. In Section 2, using sectoral data, I estimate sectoral TFP and demand processes featuring stochastic volatility. Section 2 presents the model. In Section 3, I describe the solution procedure and show that sectoral uncertainty shocks transmit through four distinct risk-adjustment channels. In Section 4, I calibrate the model to U.S. sectoral and macro facts and present results.

2 Sectoral TFP and Demand Process with Stochastic Volatility

In this section, I estimate sectoral TFP and demand processes with stochastic volatility using sectoral data.

Sectoral TFP Data.

To measure sectoral TFP, I consider the following production function:

$$y_{i,t} = z_{i,t}(k_{i,t-1})^{\alpha_i^k}(h_{i,t})^{\alpha_i^h}\prod_{j=1}^{n}(m_{ij,t})^{a_{ij}}, \tag{1}$$

where $y_{i,t}$ is the gross output of sector i at period t, $z_{i,t}$ is the TFP level, $k_{i,t-1}$ is the capital stock, $h_{i,t}$ is hours worked, and $m_{ij,t}$ is sector j goods used as intermediate inputs. The production function exhibits constant returns to scale:

$$\alpha_i^k + \alpha_i^h + \sum_{j=1}^{n} a_{ij} = 1, \tag{2}$$

where $\alpha_i^k > 0$, $\alpha_i^h > 0$, and $a_{ij} \geq 0$ for all j. TFP is then measured using the standard accounting method:

$$z_{i,t} = \ln y_{i,t} - \alpha_i^k \ln k_{i,t-1} - \alpha_i^h \ln h_{i,t} - \sum_{j=1}^{n} a_{ij} \ln m_{ij,t}.$$

To measure $y_{i,t}$, I use the quarterly sectoral real gross output series by the BEA. The series starts from 2005:Q1 until 2019:Q3. The number of sectors in the dataset is 71. I exclude 5 government sectors so the total number of sectors I consider is $n = 66$. Since capital stock data is not available at quarterly frequencies, I simply assume sectoral capital stock is constant: $k_{i,t} = k_i$. This assumption can be partially justified by the fact that capital stock is a slow-moving variable. I measure sectoral hours worked, $h_{i,t}$, using the sectoral quarterly hours worked index of production and nonsupervisory employees by the BLS.

I estimate the values of factor shares $\{\alpha_i^k\}_{i=1}^n$, $\{\alpha_i^h\}_{i=1}^n$, and the input-output matrix $\{a_{ij}\}_{i,j=1}^n$ from the "use tables" of the input-output accounts constructed by the BEA. The use table shows the uses of commodities by sectors as intermediate inputs and their final uses. It also shows the sector's value added components, which is the labor income (compensation to employees) and capital income (gross operating surplus). The sum of the value of intermediate inputs and value added, given by a column sum of the table, is the industry's gross output. Thus, to compute the intermediate shares a_{ij}, I compute the value of payments from sector i to sector j divided by sector i's gross output. To obtain α_i^k and α_i^h, I compute the ratios of capital and labor income to gross output, respectively. Finally, I take the averages of these objects ($\{\alpha_i^k\}_{i=1}^n$, $\{\alpha_i^h\}_{i=1}^n$, and $\{a_{ij}\}_{i,j=1}^n$) calculated year by year from the use table from 2005 to 2018.

Finally, I explain how I measure sectoral intermediate inputs, $m_{ij,t}$. BEA provides data for quarterly nominal expenditures on total intermediate inputs for each sector, $\sum_{j=1}^n P_{j,t} m_{ij,t}$, where $P_{j,t}$ is the nominal price for goods j. I first convert them into real terms by dividing them by the GDP deflator P_t so now I have real expenditures on inputs, $\sum_{j=1}^n p_{j,t} m_{ij,t}$, where $p_{j,t} \equiv P_{j,t}/P_t$ is the real price for goods j. Next, the optimality conditions for firms' cost minimization problem given the production function (1) imply that the expenditure on each intermediate input must be proportional to its share:

$$\frac{p_{j,t} m_{ij,t}}{p_{j',t} m_{ij',t}} = \frac{a_{ij}}{a_{ij'}},$$

which in turn implies that

$$p_{j,t} m_{ij,t} = \frac{a_{ij}}{\sum_{j=1}^n a_{ij}} \sum_{j=1}^n p_{j,t} m_{ij,t}.$$

Taking logs and re-arranging,

$$\ln m_{ij,t} = const. + \ln\left(\sum_{j=1}^n p_{j,t} m_{ij,t}\right) - \ln p_{j,t},$$

and hence we have

$$\sum_{j=1}^n a_{ij} \ln m_{ij,t} = const. + \sum_{j=1}^n a_{ij} \ln\left(\sum_{j=1}^n p_{j,t} m_{ij,t}\right) - \sum_{j=1}^n a_{ij} \ln p_{j,t}.$$

Sectoral Demand Data.

To measure household demand shocks to individual sectoral goods, I assume that households aggregate sectoral goods using the following Cobb-Douglas function:

$$C_t = \Pi_{i=1}^{n} c_{i,t}^{\omega_i}, \tag{3}$$

where $c_{i,t}$ is consumption of sector i goods and C_t is the composite consumption goods. $\omega_i \in (0,1)$ is a preference weight attached to the consumption of good i with the normalization $\sum_{i=1}^{n} \omega_i = 1$. I assume that there is a time-varying wedge $d_{i,t}$ that is specific to each sector in the demand function derived from the equation (3):

$$\ln p_{i,t} + \ln c_{i,t} = \ln \omega_i + \ln C_t + \ln d_{i,t}. \tag{4}$$

Thus the demand shock can be computed by

$$\ln d_{i,t} = const. + \ln p_{i,t} + \ln c_{i,t} - \ln C_t,$$

where I normalize the mean of $d_{i,t}$ to unity. To measure sectoral nominal consumption, I first measure sectoral quarterly consumption from National Income and Product Accounts (NIPA). To match these sectoral consumption from NIPA classification to the IO account classification, I use the PCE Bridge Table provided by the BEA. The aggregate consumption is simply the sum of these sectoral consumption.

Stochastic Volatility Process.

I assume that sectoral TFP can be decomposed into a common component and a sector-specific component:

$$\ln z_{i,t} = \ln \bar{z}_t + \ln u_{z_i,t}, \tag{5}$$

where the common component $\bar{z}_t$ is the cross-sectional average of sectoral productivity, $\bar{z}_t \equiv n^{-1} \sum_{i=1}^{n} z_{i,t}$.[1] $\bar{z}_t$ and sector-specific TFP shocks $u_{z_i,t}$ follow independent AR(1) processes with stochastic volatility:

$$\ln \bar{z}_t = \rho_{\bar{z}} \ln \bar{z}_{t-1} + \epsilon_{\bar{z},t}, \quad \epsilon_{\bar{z},t} \sim N(0, \sigma_{\bar{z},t}^2), \tag{6}$$

$$\ln u_{z_i,t} = \rho_{z_i} \ln u_{z_i,t-1} + \epsilon_{z_i,t}, \quad \epsilon_{z_i,t} \sim N(0, \sigma_{z_i,t}^2), \quad i = 1, \ldots, n, \tag{7}$$

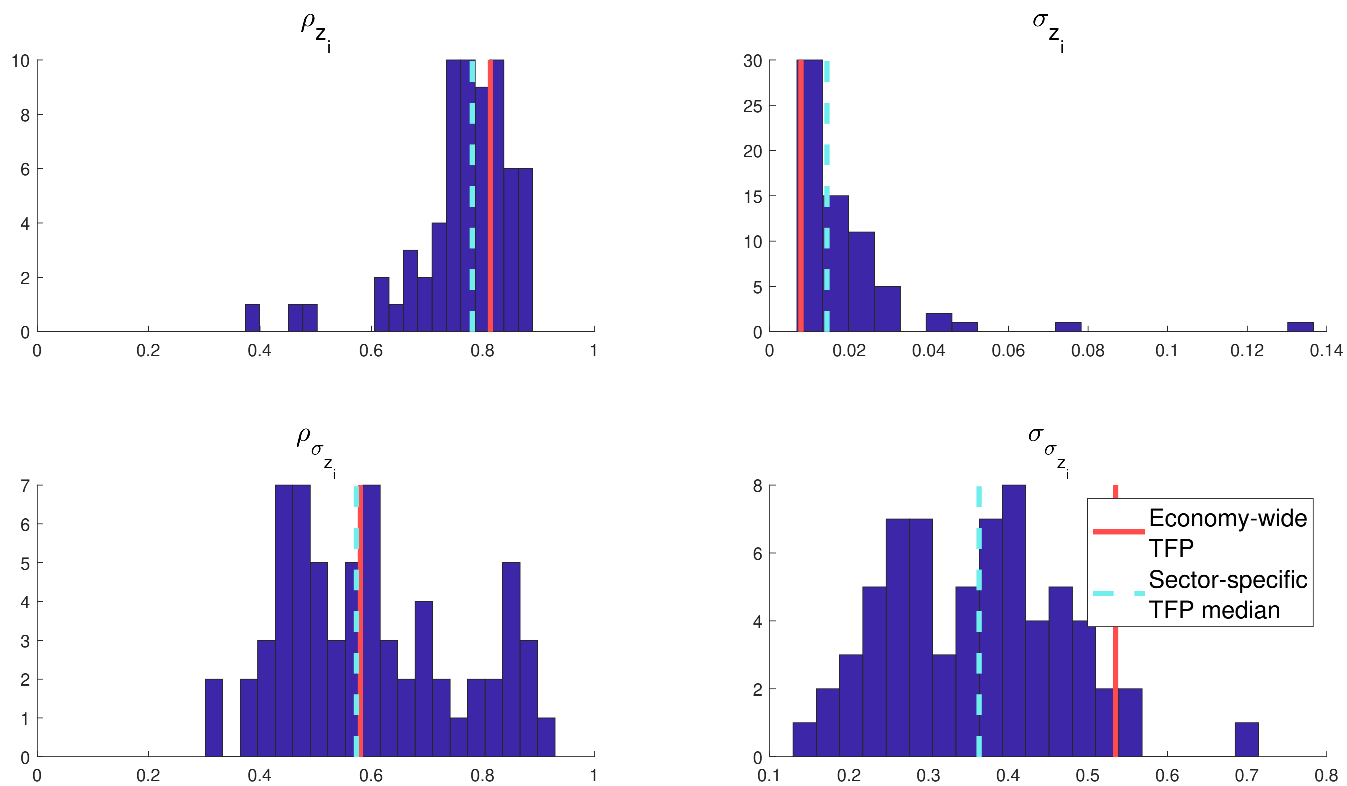
with

$$\ln \sigma_{\bar{z},t} = (1 - \rho_{\sigma_{\bar{z}}}) \ln \sigma_{\bar{z}} + \rho_{\sigma_{\bar{z}}} \ln \sigma_{\bar{z},t-1} + \epsilon_{\sigma_{\bar{z}},t}, \quad \epsilon_{\sigma_{\bar{z}},t} \sim N(0, \sigma_{\sigma_{\bar{z}}}^2), \tag{8}$$

$$\ln \sigma_{z_i,t} = (1 - \rho_{\sigma_{z_i}}) \ln \sigma_{z_i} + \rho_{\sigma_{z_i}} \ln \sigma_{z_i,t-1} + \epsilon_{\sigma_{z_i},t}, \quad \epsilon_{\sigma_{z_i},t} \sim N(0, \sigma_{\sigma_{z_i}}^2), \quad i = 1, \ldots, n. \tag{9}$$

[1] I de-trend $\bar{z}_t$ and $u_{z_i,t}$ by applying HP-filter with $\lambda = 1600$.

Figure 1: Estimated TFP level and volatility processes



Notes: The figure shows the cross-sectional distribution of posterior mean estimates of sector-specific TFP process parameters. To facilitate comparison, I also show the posterior mean estimates for the economy-wide TFP process (red solid lines) and median estimates of sector-specific TFP processes (light blue dashed lines).

The sectoral demand shocks follow independent AR(1) processes with stochastic volatility:

$$\ln d_{i,t} = \rho_{d_i} \ln d_{i,t-1} + \epsilon_{d_i,t}, \quad \epsilon_{d_i,t} \sim N(0, \sigma^2_{d_i,t}), \quad i = 1, \dots, n, \tag{10}$$

with

$$\ln \sigma_{d_i,t} = (1 - \rho_{\sigma_{d_i}}) \ln \sigma_{d_i} + \rho_{\sigma_{d_i}} \ln \sigma_{d_i,t-1} + \epsilon_{\sigma_{d_i},t}, \quad \epsilon_{\sigma_{d_i},t} \sim N(0, \sigma^2_{\sigma_{d_i}}), \quad i = 1, \dots, n. \tag{11}$$

I estimate the macro TFP level and volatility processes ((6) and (8)), sector-specific TFP level and volatility processes ((7) and (9)), and sector-specific demand level and volatility processes ((10) and (11)) separately for each sector using a Bayesian Markov-Chain-Monte-Carlo approach with flat prior. Because of the nonlinearity induced by stochastic volatility, the likelihood of each posterior draw is evaluated using the particle filter as in Fernández-Villaverde et al. (2011), Born and Pfeifer (2014), and Fernández-Villaverde et al. (2015).

Figure 1 displays the cross-sectional distributions of posterior mean estimates of sector-specific TFP level and volatility process parameters.[2] To facilitate comparison, I also show the posterior mean estimates for the economy-wide TFP process (red solid lines) and median estimates of sector-specific TFP processes (light blue dashed lines). First, the economy-wide TFP process parameters are broadly comparable to the median parameter estimates for sector-specific TFP process. Second, there is a substantial degree of cross-sectional heterogeneity in terms of estimates, especially for the volatility process. For the persistence parameter $\rho_{\sigma_{z_i}}$, the estimates range from 0.3 ('Forestry, fishing, and related activities') to 0.93 ('Rental and leasing services and lessors of intangible assets'). For the standard deviation $\sigma_{\sigma_{z_i}}$, the estimates range from 0.13 ('Pipeline transportation') to 0.71 ('Waste management and remediation services'). The demand process parameters (not shown) show similar properties. For example, the cross-sectional median estimates are $\rho_{d_i} = 0.77$, $\sigma_{d_i} = 0.009$, $\rho_{\sigma_{d_i}} = 0.49$, and $\sigma_{\sigma_{d_i}} = 0.26$ for sector-specific demand and $\rho_{z_i} = 0.78$, $\sigma_{z_i} = 0.014$, $\rho_{\sigma_{z_i}} = 0.57$, and $\sigma_{\sigma_{z_i}} = 0.36$ for sector-specific TFP. In the Appendix, I provide time series of smoothed economy-wide and sector-specific TFP volatility as well as smoothed demand volatility series.

To study the economic impact of sector-specific TFP and demand volatility shocks, I estimate the following fixed effect version of local projection by Jordá (2005):

$$x_{i,t+h} = \alpha_i + \gamma_t + \sum_{j=1}^{J} \beta_j^{(h)} e_{i,t-j} + \varepsilon_{i,t+h}, \quad h = 0, \ldots, H$$

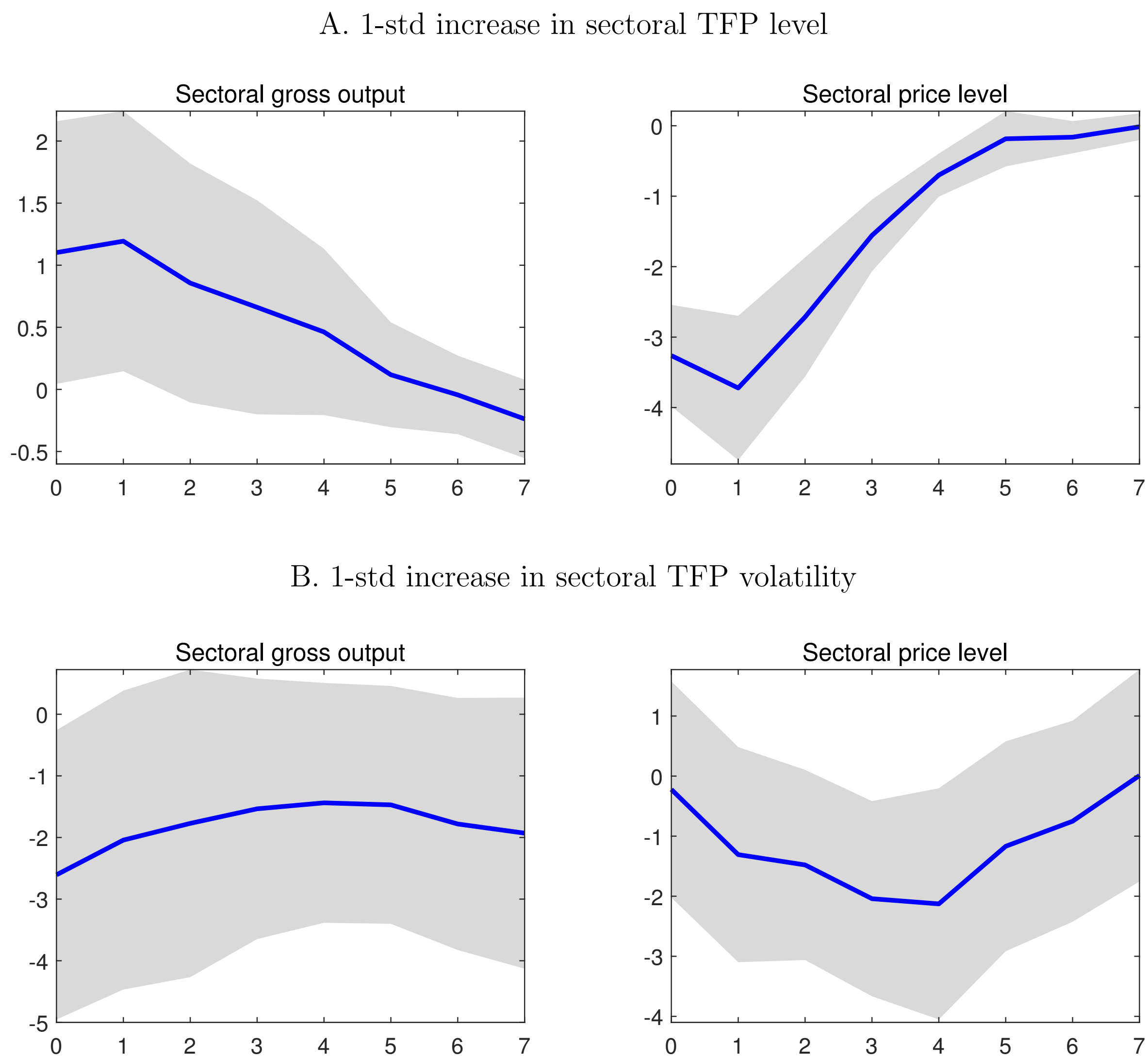
where $x_{i,t}$ is the variable of interest, $e_{i,t}$ is the sectoral shock, α_i is the individual fixed effect for sector i, and γ_t is the time fixed effect. I set $J = 10$ to control for the lagged shocks. $\{\beta_0^{(h)}\}_{h=0}^{H}$ is the coefficient of interest. I compute the impulse responses for $H = 7$ quarter horizons and estimate the responses of sectoral gross output and sectoral nominal price level. I consider four shocks ($e_{i,t}$): sectoral TFP level ($u_{z_{i,t}}$), sectoral TFP volatility ($\sigma_{z_{i,t}}$), sectoral demand level ($u_{d_{i,t}}$), and sectoral demand volatility ($\sigma_{d_{i,t}}$).[3]

Figure 2 reports the estimated responses to sectoral TFP level and volatility shocks. Panel A shows that, at the point estimate, a one-standard-deviation increase in sectoral TFP level causes a 1 percent increase in their own sectoral gross output and reduces their own price level by 3 percent on impact. Panel B shows that an increase in sectoral TFP volatility reduces their own sectoral gross output although the magnitude is imprecisely estimated. In addition, the response of the price level is not significant. Figure 3 reports the estimated responses to sectoral demand shocks. Panel A shows that, at the point estimate, a 1 standard deviation increase in sectoral demand level causes a 0.6 percent increase in their own sectoral gross output and raises their own price level by 2 percent on impact. Panel B shows that an increase in sectoral demand volatility reduces their own sectoral gross output. However, as in the TFP volatility shock, the magnitude is imprecisely estimated and

[2] I present posterior mean estimates for each sector in Tables 3-5 and Tables 6-8 in the Appendix.

[3] To be precise, I estimate 8×4×2 regressions; 8 (lags)×4 (shocks) with log real sectoral gross output level as a dependent variable and 8×4 with log sectoral price level as a dependent variable.

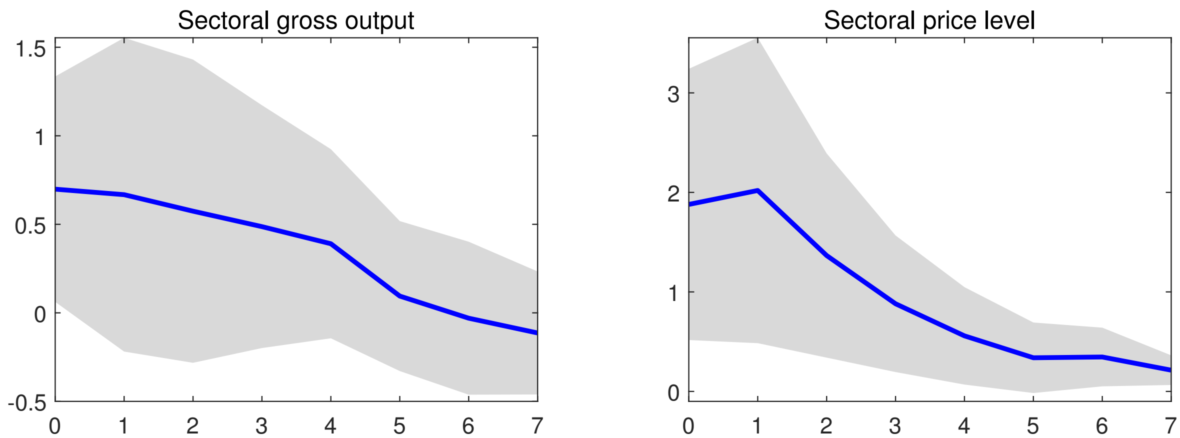
Figure 2: Local projection impulse responses: sectoral TFP level and volatility



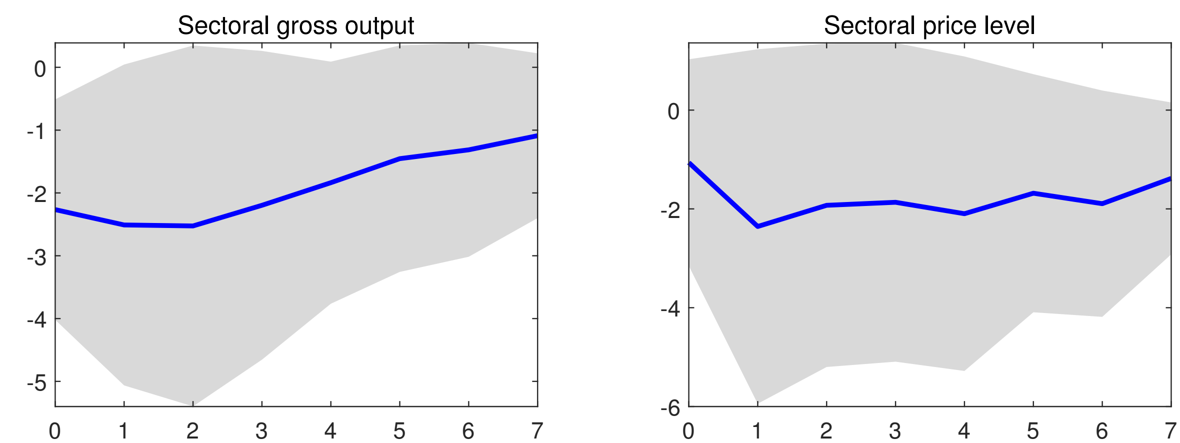
Notes: Panel A shows the responses of sectoral variables to a 1 standard deviation increase in their own TFP level. Panel B shows the responses of sectoral variables to a 1 standard deviation increase in their own TFP volatility. The unit is in percents. The shaded areas are the 90% confidence intervals. The standard errors are clustered by sectors.

Figure 3: Local projection impulse responses: sectoral demand level and volatility

A. 1-std increase in sectoral demand level



B. 1-std increase in sectoral demand volatility



Notes: Panel A shows the responses of sectoral variables to a 1 standard deviation increase in their own demand level. Panel B shows the responses of sectoral variables to a 1 standard deviation increase in their own demand volatility. The unit is in percents. The shaded areas are the 90% confidence intervals. The standard errors are clustered by sectors.

the response of the price level is not significant.

To study the macroeconomic effects of sector-specific volatility shocks, it is necessary to go beyond the local projection estimation. First, the above regressions only uncover sectoral impact of volatility shocks and do not show how those shocks propagate to other sectors. Second, they are only informative about the average effect; in reality, the impact of sectoral uncertainty shocks could be quite heterogeneous depending on which sector the shock originated in. Thus, in the next section I construct a DSGE model to examine the aggregate implications of sector-specific volatility shocks.

3 Model

I consider a multi-sector New Keynesian model similar to Bouakez et al. (2009) but extended to allow for stochastic volatilities in both economy-wide and sector-specific shocks.

3.1 Household

A representative household maximizes utility

$$\max E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\sigma}}{1-\sigma} - \frac{H_t^{1+\eta}}{1+\eta} \right],$$

where C_t and H_t are aggregate consumption and hours respectively, β is the discount factor, σ is the coefficient of relative risk aversion, and η is the inverse Frisch elasticity. Their budget constraint is

$$P_t C_t + \sum_{i=1}^{n} P_{i,t} x_{i,t} + B_t = \sum_{i=1}^{n} W_{i,t} h_{i,t} + \sum_{i=1}^{n} R_{i,t}^k k_{i,t-1} + R_{t-1} B_{t-1} + \Pi_t + T_t,$$

where P_t is the nominal price of aggregate consumption unit, $P_{i,t}$ is the nominal price of goods i, $x_{i,t}$ is the investment in sector i capital, and B_t is the nominal bond holding. $W_{i,t}$ is the nominal wage rate in sector i, $h_{i,t}$ is hours worked at sector i, $R_{i,t}^k$ is the nominal capital rental rate in sector i, $k_{i,t}$ is the capital stock in sector i, R_t is the nominal interest rate, Π_t is the nominal profits from all intermediate firms, and T_t is lump-sum transfer/taxes.

Household aggregates consumption from each sector according to (3). Accordingly, the price level is given by

$$P_t = \Pi_{i=1}^{n} P_{i,t}^{\omega_i}.$$

The equation (3) leads to the demand function for each good i (4). The sector-specific demand level and volatility follow AR(1) processes described in equations (10) and (11).

To capture the notion of imperfect labor mobility across sectors in a parsimonious manner, as in Bouakez et al. (2009), total hours worked are aggregated according to a CES function of hours worked at each sector:

$$H_t = \left[\sum_{i=1}^{n} h_{i,t}^{\frac{1+\nu}{\nu}} \right]^{\frac{\nu}{1+\nu}},$$

where ν is the elasticity of substitution of labor across sectors.

Capital accumulation in each sector i is subject to an investment adjustment cost:

$$k_{i,t} = (1-\delta)k_{i,t-1} + \left\{ 1 - \frac{\kappa}{2} \left(\frac{x_{i,t}}{x_{i,t-1}} - 1 \right)^2 \right\} x_{i,t},$$

where δ is the depreciation rate and κ is a parameter that controls the investment adjustment cost. Using input $q_{ij,t}$ from sector j, investment in sector i is produced using a constant returns to scale technology

$$x_{i,t} = \prod_{j=1}^{n} q_{ij,t}^{b_{ij}}, \qquad \sum_{j=1}^{n} b_{ij} = 1.$$

A capital use matrix $\mathbf{B}$ describes the contribution of each sector's output to other sectors' capital goods production:

$$\mathbf{B} = \begin{pmatrix} b_{11} & b_{12} & \dots & b_{1n} \\ b_{21} & & & \\ & & \ddots & \\ b_{n1} & & & b_{nn} \end{pmatrix}.$$

3.2 Production

In each sector i, final goods $y_{i,t}$ are produced by a perfectly competitive representative firm that combines a continuum of intermediate goods, indexed by $l \in [0,1]$, with technology

$$y_{i,t} = \left[\int_0^1 (y_{i,t}(l))^{\frac{\theta-1}{\theta}} dl \right]^{\frac{\theta}{\theta-1}}.$$

$y_{i,t}(l)$ denotes the time t input of intermediate good l and θ controls the price elasticity of demand for each intermediate good. The demand function for good l is then

$$y_{i,t}(l) = \left(\frac{P_{i,t}(l)}{P_{i,t}} \right)^{-\theta} y_{i,t}, \tag{12}$$

$P_{i,t}$ is related to $P_{i,t}(l)$ via the relationship

$$P_{i,t} = \left[\int_0^1 P_{i,t}(l)^{1-\theta} dl \right]^{\frac{1}{1-\theta}}.$$

Intermediate goods for each sector i are produced by monopolistically competitive firms, indexed by l and s, who produce according to

$$y_{i,t}(l) = z_{i,t}(k_{i,t}(l))^{\alpha_i^k}(h_{i,t}(l))^{\alpha_i^h}\prod_{j=1}^{n}(m_{ij,t}(l))^{a_{ij}},$$

where $m_{ij,t}$ is the amount of materials produced by sector j used as inputs by sector i. The production function exhibits constant returns to scale as in (2). An input-output matrix $\mathbf{A}$ summarizes the network structure of the economy:

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & & & \\ & & \ddots & \\ a_{n1} & & & a_{nn} \end{pmatrix}.$$

The sectoral TFP consists of an economy-wide component and a sector-specific component as in (5). In turn, economy-wide and sector-specific TFP follow AR(1) processes with stochastic volatility described in equations (6)–(9).

The optimality conditions for input choice are given by

$$\begin{aligned} r_{i,t}^k &= mc_{i,t}\alpha_i^k \frac{y_{i,t}(l)}{k_{i,t}(l)} \\ w_{i,t} &= mc_{i,t}\alpha_i^h \frac{y_{i,t}(l)}{h_{i,t}(l)} \\ p_{j,t} &= mc_{i,t}a_{ij}\frac{y_{i,t}(l)}{m_{ij,t}(l)} \end{aligned}$$

where $w_{i,t} \equiv W_{i,t}/P_t$, $r_{i,t}^k \equiv R_{i,t}^k/P_t$, $p_{j,t} \equiv P_{j,t}/P_t$, and $mc_{i,t}$ is the real marginal cost for sector i, given by

$$mc_{i,t} = \frac{1}{z_{i,t}}\left(\frac{1}{\alpha_i^k}\right)^{\alpha_i^k}\left(\frac{1}{\alpha_i^h}\right)^{\alpha_i^h}\prod_{j=1}^{n}\left(\frac{1}{a_{ij}}\right)^{a_{ij}}(r_{i,t}^k)^{\alpha_i^k}(w_{i,t})^{\alpha_i^h}\prod_{j=1}^{n}(p_{j,t})^{a_{ij}}.$$

Intermediate firms face a Calvo pricing friction: in each period, $1-\xi_i$ fraction of firms adjust their prices while the remaining simply index their prices to the steady-state inflation rate π. Firms that are able to adjust choose a price so as to maximize a sum of present discounted values of real profits:

$$\max_{P_{i,t}(l)} E_t\sum_{s=0}^{\infty}(\beta\xi_i)^s\left\{\frac{\lambda_{t+s}}{\lambda_t}\left[\frac{\pi^s P_{i,t}(l)}{P_{t+s}} - mc_{i,t+s}\right]y_{i,t+s}(l)\right\},$$

subject to the demand (12). The first-order condition for the optimal price $P_{i,t}(l) = P_{i,t}^*$ is given by

$$E_t\sum_{s=0}^{\infty}(\beta\xi_i)^s\left\{\frac{\lambda_{t+s}}{\lambda_t}\left[(1-\theta)\left(\frac{\pi^s P_{i,t}^*}{P_{i,t+s}}\right)\left(\frac{P_{i,t+s}}{P_{t+s}}\right) + \theta mc_{i,t+s}\right]\left(\frac{1}{P_{i,t}^*}\right)\left(\frac{\pi^s P_{i,t}^*}{P_{i,t+s}}\right)^{-\theta} y_{i,t+s}\right\} = 0.$$

Taking into account the demand for inputs from other industries, the market-clearing condition for sector i is given by

$$y_{i,t} = c_{i,t} + \sum_{j=1}^{n} m_{ji,t} + \sum_{j=1}^{n} q_{ji,t}.$$

The value-added of sector i, $\tilde{y}^v_{i,t}$, is given by

$$y^v_{i,t} = p_{i,t} y_{i,t} - \sum_{j=1}^{n} p_{j,t} m_{ij,t}, \tag{13}$$

where $p_{i,t}$ is the real price of goods i: $p_{i,t} \equiv \frac{P_{i,t}}{P_t}$.

3.3 Aggregation

To derive the relationship between sectoral inputs and sectoral output, I define

$$\widetilde{y}_{i,t} \equiv \int_0^1 y_{i,t}(l) dl,$$

where $\widetilde{y}_{i,t}$ is related to $y_{i,t}$ via the relationship

$$\widetilde{y}_{i,t} = \Delta_{i,t} y_{i,t}$$

where $\Delta_{i,t} \equiv \int_0^1 \left(\frac{p_{i,t}(l)}{p_{i,t}}\right)^{-\theta} dl$ is a measure of price dispersion that follows the law of motion

$$\Delta_{i,t} = (1 - \xi_i) \left(\frac{p^*_{i,t}}{p_{i,t}}\right)^{-\theta} + \xi_i \left(\frac{\pi}{\pi_{i,t}}\right)^{-\theta}.$$

The aggregate output of this economy is

$$Y_t = C_t + X_t,$$

where $X_t \equiv \sum_{i=1}^{n} \sum_{j=1}^{n} p_{j,t} q_{ij,t}$. The central bank follows a Taylor-type rule given by

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_R} \left\{ \left(\frac{\pi_t}{\pi}\right)^{\phi_\pi} \left(\frac{Y_t}{Y}\right)^{\phi_Y} \right\}^{1-\rho_R},$$

where ρ_R is the smoothing parameter and ϕ_π and ϕ_Y are the response coefficients to inflation and output, respectively.

4 Solution

This is a large model; in the quantitative analysis below I calibrate the model to 66 sectors and hence it is important to use the solution method that allows me to capture the effect of uncertainty shocks while preserving computational tractability. Thus, to solve the model, I use the risk-adjusted log-linearization method as in Jermann (1998), Uhlig (2010), Dew-Becker (2012), Malkhozov (2014), and others. The risk-adjustment method utilizes the fact that log-linearized variables follow a normal distribution. In turn, this implies that variables follow a log-normal distribution. Thus, the method risk-adjusts all the expectational variables as these variables are log-normal. In this respect, my paper is closely related to Bianchi et al. (2019), who study the effects of macro uncertainty shocks in a single-sector New Keynesian model using the risk-adjustment technique. The main difference is that I study a multi-sector New Keynesian model, which allows me to consider the impact of sector-specific uncertainty shocks, propagated through input-output linkages.

Below I list the expectational equations in the model and their risk-adjusted log-linear equations. This is useful, because as in Bianchi et al. (2019), I can decompose the effects of uncertainty shocks into expectational wedges. First, consider the consumption Euler equation by the representative household:

$$\lambda_t = \beta E_t \left[\lambda_{t+1} \frac{R_t}{\Pi_{t+1}} \right].$$

In the risk-adjusted log-linearization form,

$$\hat{\lambda}_t = \hat{R}_t + E_t\hat{\lambda}_{t+1} - E_t\hat{\Pi}_{t+1} + \underbrace{\frac{1}{2}Var_t(\hat{\lambda}_{t+1}) + \frac{1}{2}Var_t(\hat{\Pi}_{t+1}) - Cov_t(\hat{\lambda}_{t+1}, \hat{\Pi}_{t+1})}_{\text{Precautionary savings}},$$

where the risk-adjustment term captures the precautionary savings channel as in Basu and Bundick (2017). First, note that the risk-adjustment terms are functions of endogenous variables and thus are policy variant. This highlights that the impact of volatility shocks could be affected for example by monetary policy. Second, not only the variances of marginal utility and inflation, but also their co-variance enter into the risk-adjustment term.

Next, consider the capital Euler equation for each sector i:

$$\mu_{i,t} = \beta E_t \left[\lambda_{t+1} mc_{i,t+1} \alpha_i^k \frac{y_{i,t+1}}{k_{i,t}} + \mu_{i,t+1}(1-\delta) \right],$$

where $\mu_{i,t}$ is the Lagrangian multiplier for the sector i capita; accumulation equation. In the risk-adjusted log-linearized form, the equations are given by

$$\begin{aligned}\hat{\mu}_{i,t} = {} & \{1-\beta(1-\delta)\}(E_t\hat{\lambda}_{t+1} + E_t\hat{mc}_{i,t+1} + E_t\hat{y}_{i,t+1} - \hat{k}_{i,t}) + \beta(1-\delta)E_t\mu_{i,t+1} \\ & + \underbrace{\{1-\beta(1-\delta)\}\left[\frac{1}{2}Var_t(\hat{\lambda}_{t+1} + \hat{mc}_{i,t+1}) + \frac{1}{2}Var_t(\hat{y}_{i,t+1}) + Cov_t(\hat{\lambda}_{t+1} + \hat{mc}_{i,t+1}, \hat{y}_{i,t+1})\right] + \frac{1}{2}\beta(1-\delta)Var_t(\hat{\mu}_{i,t+1})}_{\text{Capital return risk}},\end{aligned}$$

where the risk-adjustment term captures the fact that the future return on capital is uncertain.

Consider also the optimality condition for investment in each sector i:

$$\lambda_t p_{j,t} = \mu_{i,t} \left\{ 1 - \frac{\kappa}{2} \left(\frac{x_{i,t}}{x_{i,t-1}} - 1 \right)^2 - \kappa \left(\frac{x_{i,t}}{x_{i,t-1}} - 1 \right) \frac{x_{i,t}}{x_{i,t-1}} \right\} b_{ij} \frac{x_{i,t}}{q_{ij,t}}$$
$$+ \beta\kappa E_t \left\{ \mu_{i,t+1} \left(\frac{x_{i,t+1}}{x_{i,t}} - 1 \right) \left(\frac{x_{i,t+1}}{x_{i,t}} \right)^2 \right\} b_{ij} \frac{x_{i,t}}{q_{ij,t}},$$

which can be log-linearized as

$$\hat{q}_{ij,t} = \hat{\mu}_{i,t} + \hat{x}_{i,t} - \hat{\lambda}_t - \hat{p}_{j,t} - \kappa \Delta \hat{x}_{i,t} + \beta\kappa E_t \Delta \hat{x}_{i,t+1} + \underbrace{\beta\kappa \left\{ \frac{5}{2} Var_t(\Delta \hat{x}_{i,t+1}) + Cov_t(\hat{\mu}_{i,t+1}, \Delta \hat{x}_{i,t+1}) \right\}}_{\text{Investment adjustment cost}},$$

where the risk-adjustment term captures the fact that the impact of current investment on a future adjustment cost is uncertain.

Finally, consider sticky prices. The optimal reset price $p^*_{i,t}$ for retailers in sector i is given by

$$p^*_{i,t} = \left(\frac{\theta}{\theta - 1} \right) \frac{P^n_{i,t}}{P^d_{i,t}},$$

where we define

$$P^n_{i,t} \equiv \lambda_t mc_{i,t} y_{i,t} + \xi_i \beta E_t \left(\frac{\pi_{i,t+1}}{\Pi} \right)^{\theta} P^n_{i,t+1},$$
$$P^d_{i,t} \equiv \lambda_t y_{i,t} + \xi_i \beta E_t \left(\frac{\pi_{i,t+1}}{\Pi} \right)^{\theta - 1} \left(\frac{\pi_{i,t+1}}{\Pi_{t+1}} \right) P^d_{i,t+1}.$$

$P^n_{i,t}$ and $P^d_{i,t}$ can be risk-adjusted as

$$\hat{P}^n_{i,t} = (1 - \xi_i \beta)(\hat{\lambda}_t + \hat{mc}_{i,t} + \hat{y}_{i,t})$$
$$+ \xi_i \beta E_t \Bigg\{ \theta E_t \hat{\pi}_{i,t+1} + E_t \hat{P}^n_{i,t+1} + \underbrace{\frac{\theta^2}{2} Var_t(\hat{\pi}_{i,t+1}) + \frac{1}{2} Var_t(\hat{P}^n_{i,t+1}) + \theta Cov_t(\hat{\pi}_{i,t+1}, \hat{P}^n_{i,t+1})}_{\text{Nominal pricing bias}} \Bigg\},$$

and

$$\hat{P}^d_{i,t} = (1 - \xi_i \beta)(\hat{\lambda}_t + \hat{y}_{i,t})$$
$$+ \xi_i \beta E_t \Bigg\{ (\theta - 1) E_t \hat{\pi}_{i,t+1} + E_t \hat{P}^d_{i,t+1} + \underbrace{\frac{\theta^2}{2} Var_t(\hat{\pi}_{i,t+1}) + \frac{1}{2} Var_t(\hat{P}^d_{i,t+1} - \hat{\Pi}_{t+1}) + \theta Cov_t(\hat{\pi}_{i,t+1}, \hat{P}^d_{i,t+1} - \hat{\Pi}_{t+1})}_{\text{Nominal pricing bias}} \Bigg\}$$

The risk-adjustment term, or the nominal pricing bias, is related to the precautionary price setting motive in Fernández-Villaverde et al. (2015). It captures the fact that when firms choose their current prices, their effects on future profits is uncertain because the future demand condition is uncertain.

The rest of the equations in the equilibrium conditions do not involve expectations, and hence there is no risk-adjustment term for those equations. It is now clear that volatility shocks to productivity affect endogenous variables by affecting second moments in the risk-adjustment terms.

5 Quantitative Analysis

I now calibrate the model to the U.S. economy to simulate the impact of sectoral uncertainty shocks and their contribution to aggregate fluctuations.

5.1 Parameterization

First, I explain the calibration. I set the discount factor β to 0.99, depreciation rate δ to 0.025, risk-aversion parameter σ to 1, and inverse Frisch elasticity to $\eta = 0.5$. Following Horvath (2000), I choose $\nu = 1$ for the elasticity of substitution of labor across sector. The investment adjustment cost is set to $\kappa = 0.5$. Following Fernández-Villaverde et al. (2015), I choose $\theta = 21$, which gives a steady-state markup of 5%. To calibrate sectoral price stickiness ξ_i, I use the values considered in Bouakez et al. (2018). In turn, they set the sectoral price rigidity parameters based on the micro evidence in Nakamura and Steinsson (2008) and DSGE estimates in Bouakez et al. (2014). For the Taylor rule I set $\rho_R = 0.8$, $\phi_\pi = 1.5$, and $\phi_Y = 0.2$.

As explained in Section 2, I estimate the values of factor shares $\{\alpha_i^k\}_{i=1}^n$, $\{\alpha_i^h\}_{i=1}^n$, the input-output matrix $\mathbf{A}$ and the preference weights $\mathbf{\Omega}$ from the "use tables" of the input-output accounts constructed by the BEA. I use the 1997 capital flows table provided by the BEA to estimate the parameters (b_{ij}'s) for the capital goods production. The capital flow table describes the distribution of new structures, equipment and softwares produced by individual sectors to using industries. Hence, to obtain the investment ratio b_{ij}, I use the table to calculate the share of the value of commodities purchased by sector i from sector j in total investment made by sector i. For the TFP and demand level and volatility processes, I use the estimates from the particle filter in Section 2.

5.2 Results

First, to quantify the contributions of sectoral uncertainty shocks, Table 1 reports the standard deviations of macro variables both in the data and in the model. The model explains a substantial fraction of macro fluctuations (labeled "All shocks"). For example, in the model the output standard deviation is 1.02 while in the data it is 1.03. Thus, the model explains almost all output variations in data. The model also matches the volatility of hours, consumption, and the nominal interest rate, although it understates the volatility of investment and overstates the volatility of inflation. When I shut down economy-wide shocks (labeled "Sectoral level and volatility shocks"), the model accounts for (0.62/1.03=) 60% of output volatility. For other real variables, sectoral shocks explain

Table 1: Standard deviations of macro variables

	Output	Hours	Investment	Consumption	Inflation	Nominal rate
Data	1.03	1.68	4.46	0.73	0.18	0.25
All shocks	1.02	2.24	1.49	0.94	0.77	0.29
Sectoral level and volatility shocks	0.62	0.91	0.91	0.63	0.51	0.17
Sectoral TFP volatility shocks only	0.07	0.10	0.18	0.05	0.04	0.02
Sectoral demand volatility shocks only	0.001	0.002	0.003	0.001	0.001	0.000

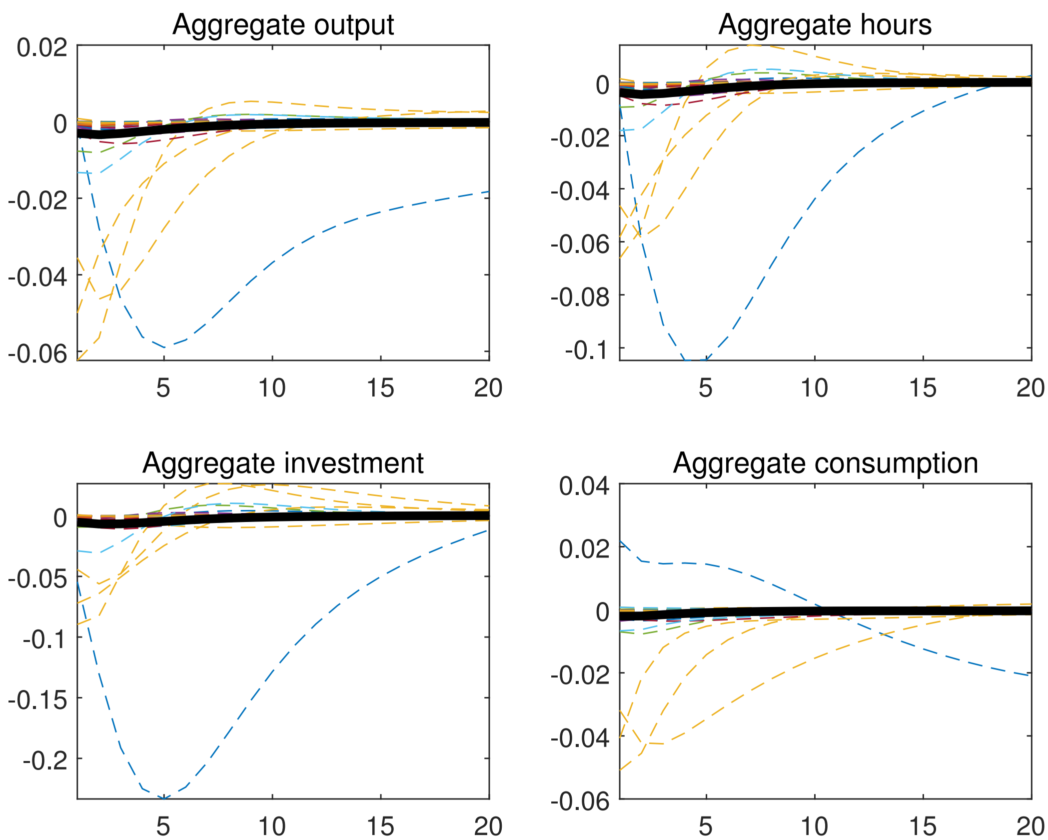
Notes: The sample period is 1985Q1–2019Q4. Moments are logged, HP-filtered ($\lambda = 1600$), and are multiplied by 100 to express them in percentage terms.

54, 20, and 86% of hours, investment, and consumption fluctuations, respectively. To isolate the contribution of sectoral TFP volatility shocks, in the third row (labeled "Sectoral volatility shocks only"), I report the standard deviations when there is only sector-specific volatility shocks. In this version, the model-implied standard deviation of output is 0.07. Thus, while sector-specific TFP volatility shocks are non-trivial, but not dominant, source of aggregate fluctuations. Finally, the fourth row isolates the impact of sectoral demand volatility shocks. Interestingly, in contrast to the TFP volatility shock, the contribution of demand volatility shocks is negligible. The main reason sectoral demand volatility shocks have smaller effect than TFP volatility shocks is because sectoral demand level shocks have smaller effect in the first place. Indeed, when I simulate the model with sectoral demand level shocks only, the output standard deviation is 0.08. In contrast, when I simulate the model with sectoral TFP level shocks only, the output standard deviation is 0.61. Thus, in the analysis below I focus on sectoral TFP volatility shocks.

Figure 4 shows the impulse responses of aggregate variables in response to two-standard-deviation sectoral TFP uncertainty shocks. Each dashed line represents a sectoral uncertainty shock originating in each of the 66 sectors. The thick black line is the mean response across all sectoral uncertainty shocks. First, a sectoral increase in volatility initially generates a reduction in aggregate output, hours, and investment. Second, the magnitude of the effect on aggregate variables varies widely depending on which sector the uncertainty shock originates from. To further visualize how the aggregate output response depends on the identity of the sector in which the uncertainty shock takes place, Figure 5 reports the maximum aggregate output increases to a two-standard-deviation reduction in sector-specific TFP volatility for each sector.[4] Importantly, sizable aggregate output impacts are concentrated on a few sectors: "Oil and gas extraction", "Transportation equipment", "Chemical products", "Rental and leasing services", and to a lesser extent, "Textile mills and textile production mills", "Air transportation", and "Miscellaneous professional services". This suggests that aggregate impact of a change in uncertainty depends crucially on the the identity of the sectors in which that change takes place.

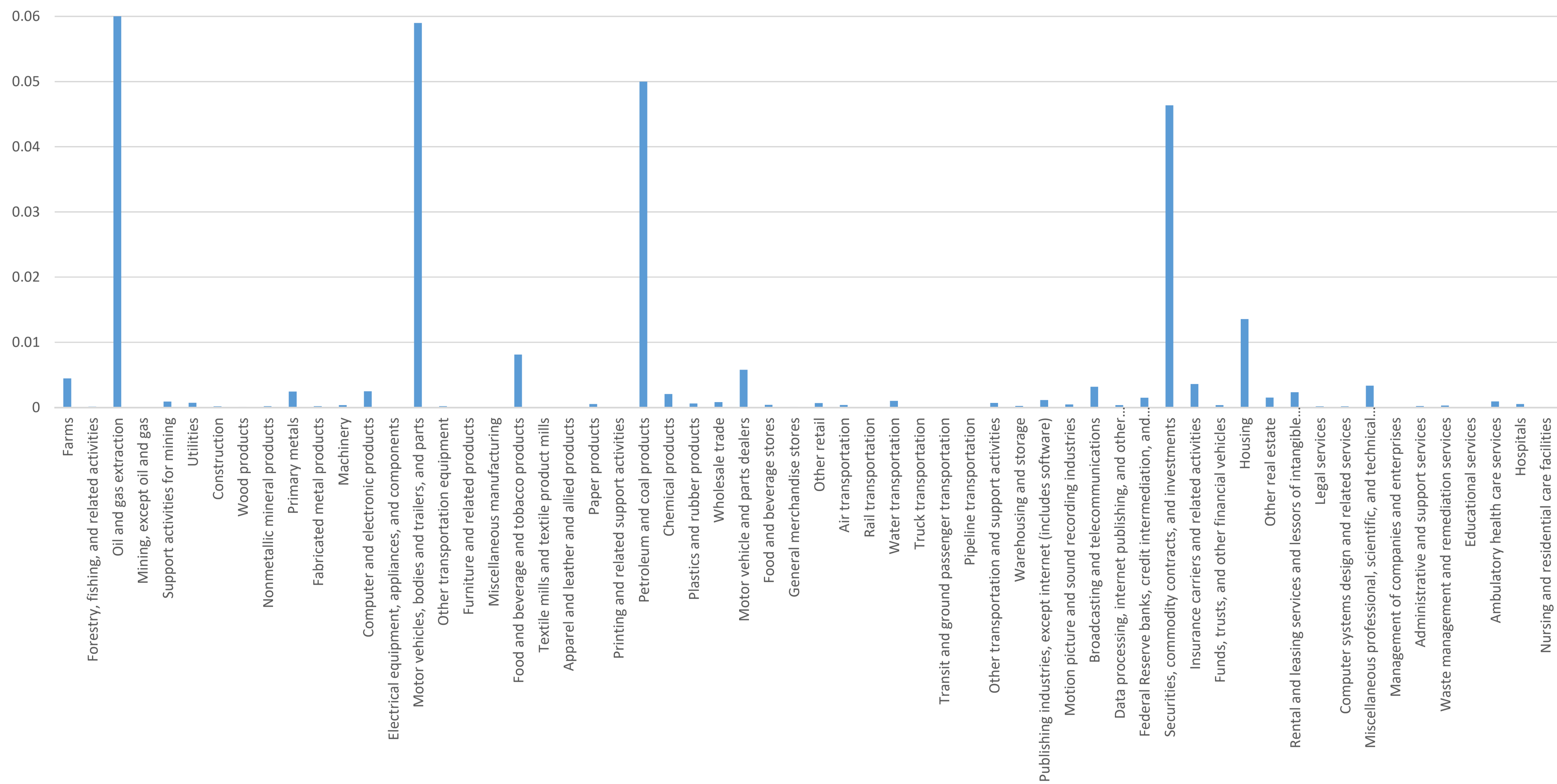
[4]Since in my solution method the increase and the decrease in volatility generate symmetric responses, Figure 5 essentially shows mirror-image information displayed in Figure 4 for aggregate output.

Figure 4: Responses of aggregate variables to sectoral uncertainty shocks



Notes: The figure reports the impulse responses to two-standard-deviation positive shock to σ_{z_i} (sector-specific TFP volatility). The units are in percents. The thick black line is the mean response across all sectoral uncertainty shocks.

Figure 5: Response of aggregate output to sector-specific uncertainty shocks



Notes: The chart reports the maximum aggregate output increases to a two-standard-deviation negative shock to σ_{z_i} (sector-specific TFP volatility) for each sector. The units are in percents.

Table 2: Determinants of aggregate output impact of sector-specific TFP uncertainty shocks

Calvo price rigidities	Value added share	Value-added-based labor share	Centrality	ρ_{z_i}	σ_{z_i}	$\rho_{\sigma_{z_i}}$	$\sigma_{\sigma_{z_i}}$	R^2	N
0.001	0.14*	0.005	-0.017	0.017	0.52***	0.015*	0.016	0.56	66
(0.005)	(0.08)	(0.007)	(0.490)	(0.013)	(0.077)	(0.008)	(0.011)		

Notes: I report results for regressions of aggregate output impact of sector-specific TFP uncertainty shocks on various sectoral characteristics. Standard errors are reported in parentheses. $***$ and $*$ indicate significance at 1% and 10% levels, respectively.

To understand what drives the heterogeneity in the aggregate output impact, I regress the maximum aggregate output increases to different sector-specific TFP uncertainty shocks on several sectoral characteristics.[5] They are: Calvo probability of adjusting prices, ξ_i; the value-added-based sectoral share in steady-state value added (i.e., total GDP), y_i^v/Y; the sectoral labor share, $\alpha_i^h/(\alpha_i^k + \alpha_i^h)$; Katz-Bonacich eigenvector centrality measure;[6] parameters of the TFP processes $(\rho_{z_i}, \sigma_{z_i}, \rho_{\sigma_{z_i}}, \sigma_{\sigma_{z_i}})$. Table 2 reports the results of this regression. First, the Table indicates that the aggregate output impact of a TFP uncertainty shock is larger when it originates in sectors with high value added share. Intuitively, a change in the sectoral value added due to a sector-specific uncertainty shocks translate into a larger change in aggregate value added when that sector's share in aggregate value added is high. Second, the aggregate output impact is large when the steady-state standard deviation of sectoral TFP, σ_{z_i}, is high. Sectoral TFP uncertainty shock has a larger effect when steady-state TFP uncertainty is high to begin with. Third, the aggregate effect is large when the persistence of a TFP uncertainty shock, $\rho_{\sigma_{z_i}}$, is high.

To further investigate the propagation of sectoral uncertainty shocks, in Figure 6 I show the average aggregate variables responses to an increase in TFP volatility; I take the cross-sectoral mean of aggregate variables responses to each sector-specific TFP volatility shock. Thus, the impulse response in Figure 6 can interpreted as a "representative" impulse response to sector-specific TFP volatility shocks. I decompose the aggregate impact of the shock into the sector's response to its own uncertainty shock (blue dashed lines) and the total effect, which takes into account the propagation of sectoral uncertainty shock to other sectors (black lines). Focusing on the total response (black lines), the uncertainty shock reduces not only aggregate output but also hours, investment, and consumption. Nominal variables such as inflation and the nominal interest rate rise. The mechanism

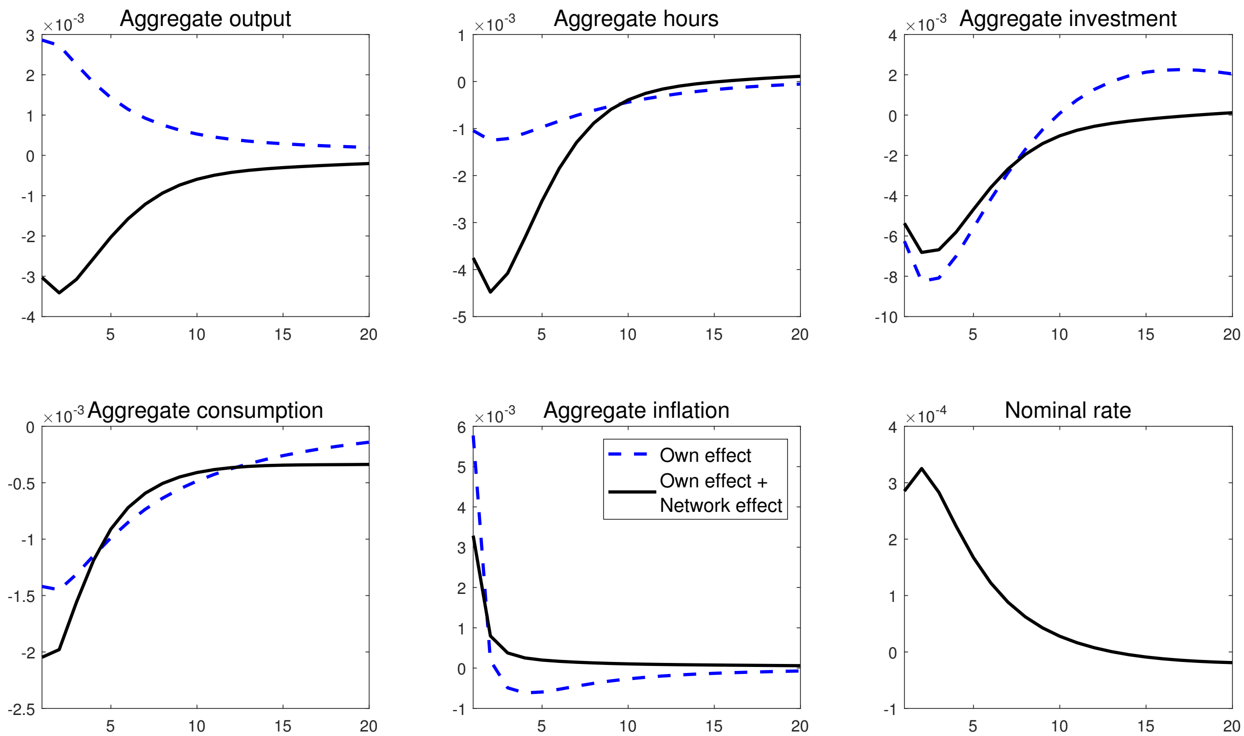
[5]Bouakez et al. (2018) undertake a similar exercise in the context of examining factors that drive sectoral heterogeneity in aggregate output multiplier for sector-specific government spending.

[6]The centrality measure has been used, for example, in Carvalho (2014) to assess the position of each sector in the production network. Intuitively, high values of centrality mean the sectors are upstream in the network and low values mean downstream. Following Bouakez et al. (2018), the vector of centralities $\mathbf{c}$ is calculated as:

$$\mathbf{c} = \frac{1 - \bar{\alpha}^k - \bar{\alpha}^h}{n}\left(I - (\bar{\alpha}^k + \bar{\alpha}^h)A'\right)^{-1}\mathbf{1},$$

where $\bar{\alpha}^k = \frac{1}{n}\sum_{i=1}^n \alpha_i^k$ and $\bar{\alpha}^h = \frac{1}{n}\sum_{i=1}^n \alpha_i^h$.

Figure 6: Mean responses of aggregate variables to a sector-specific TFP uncertainty shock



Notes: The figure reports the mean impulse responses to a two-standard-deviation increase in $\sigma_{\sigma_{z_i}}$. The units are in percents. The black solid lines are the full responses while the blue dashed lines are the contributions of the impacted sector's own response.

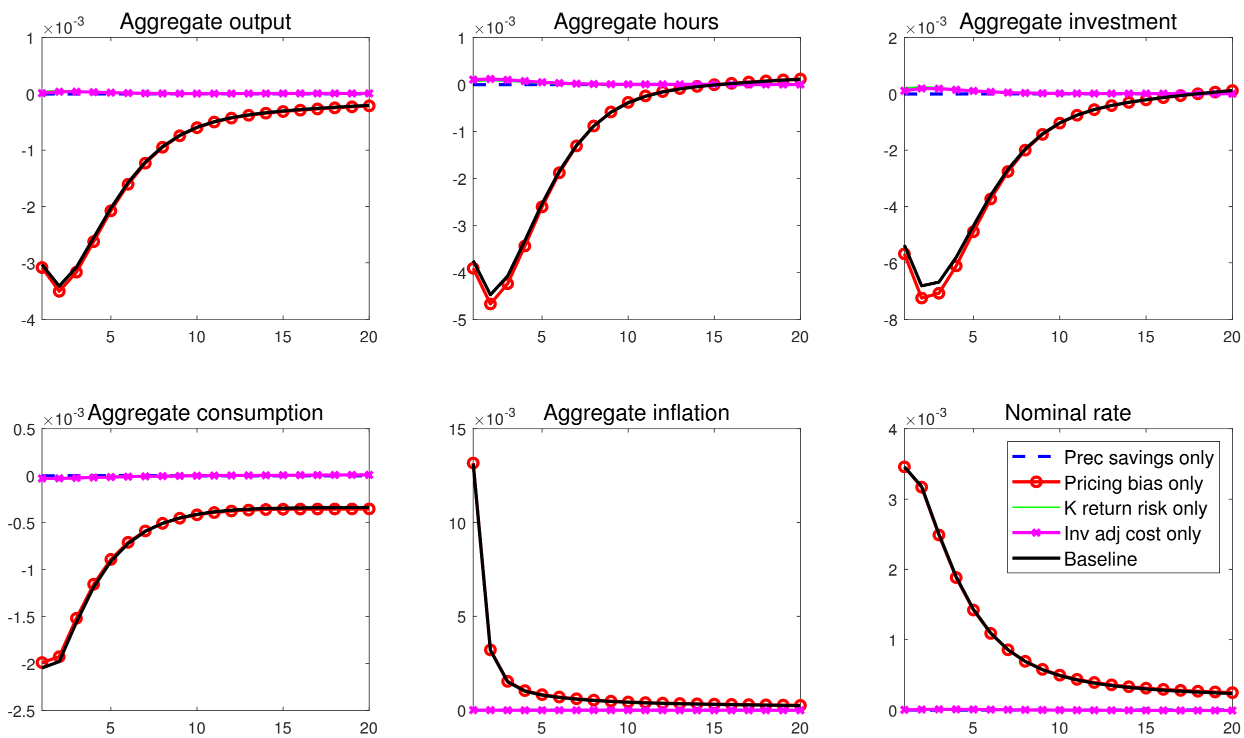
is as follows. In response to an increase of TFP volatility, firms in the impacted sector raise their prices due to the nominal pricing bias. Intuitively, an increase in TFP volatility raises dispersion of future marginal costs and hence the range of optimal prices. Since firms' profit function is asymmetric (it is more costly to sell goods at too low a price than the other way around), firms self-insure against the risk of being stuck at low prices by raising their prices when uncertainty rises.[7] The price increase raises markups and hence gross output of the impacted sector drops.[8] The sectoral volatility shock propagates to downstream sectors in two ways. First, the increase in sectoral price raises marginal costs in downstream sectors (level effect). Second, the *volatility* of sectoral price rises, and hence uncertainty about the marginal costs in downstream sectors rises as well (volatility effect). The level and volatility effects both act to raise downstream sectors' prices, which in turn raise their markups and reduce output in downstream sectors.

The propagation through input-output network is important. Indeed, for variables such as aggre-

[7] See Fernández-Villaverde et al. (2015) for further details.

[8] Value added of the impacted sector increases because the effect of the increase in the relative price dominates the effect of the output drop. See equation (13).

Figure 7: Mean responses of aggregate variables to a sector-specific TFP uncertainty shock: the role of risk propagation channels



Notes: The figure reports the mean impulse responses to a two-standard-deviation increase in $\sigma_{\sigma_{z_i}}$. The units are in percents. The black solid lines are the baseline responses. The blue dashed lines are the responses where only the precautionary savings channel is turned on, red lines with circles are the responses where only the pricing bias channel is turned on, green lines are the responses where only the capital return risk channel is turned on, and purple lines with stars are where only the investment adjustment cost channel is turned on.

gate hours, a substantial fraction of the response is due to the network effect. For output, the own effect is an increase, rather than a decrease in value added. Finally, the nominal pricing bias channel is crucial for the transmission of sectoral uncertainty shocks. In Figure 7, as in Figure 6 I show the average aggregate variables responses to an increase in sectoral TFP volatility. However, in addition to the baseline impulse response, I also report the counterfactual impulse responses where only one of the four risk propagation channels described in Section 4 is turned on. When nominal pricing bias channel is present, the counterfactual impulse response is very similar to the baseline impulse response. In contrast, risk propagation channels other than the nominal pricing bias channel have negligible impact.

6 Conclusion

In this paper, I have studied how sector-specific uncertainty shocks propagate and affect aggregate outcomes. First, using sector-level data, I estimated sectoral TFP and demand processes allowing for time-varying volatility. I showed that sectoral TFP and demand displays nontrivial fluctuations in volatility even after controlling for economy-wide variations. I estimated local projections and found that an increase in sector-specific TFP or demand volatility reduces output in that sector. Second, I used the estimated sectoral TFP and demand processes to simulate the impact of sector-specific volatility shocks in a calibrated multi-sector New Keynesian model that features input-output networks. I found that sectoral volatility shocks generate contractions in aggregate output, hours, consumption, and investment. The key mechanism is the precautionary pricing motive that multiplies and propagates to other sectors.

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Appendices

A Additional Tables and Figures

Table 3: Posterior mean estimates of TFP level and volatility processes

	ρ_{z_i}	σ_{z_i}	$\rho_{\sigma_{z_i}}$	$\sigma_{\sigma_{z_i}}$
Economy-wide TFP	0.81	0.008	0.58	0.53
	[0.69,0.93]	[0.005,0.012]	[0.14,0.93]	[0.25,0.92]
Sector-specific TFP				
Farms	0.83	0.025	0.75	0.25
	[0.68,0.97]	[0.014,0.04]	[0.11,0.99]	[0.05,0.51]
Forestry, fishing, and related activities	0.61	0.029	0.3	0.54
	[0.45,0.76]	[0.019,0.04]	[0.01,0.84]	[0.15,0.96]
Oil and gas extraction	0.71	0.072	0.7	0.46
	[0.55,0.88]	[0.04,0.154]	[0.17,0.98]	[0.22,0.81]
Mining, except oil and gas	0.74	0.015	0.47	0.4
	[0.55,0.91]	[0.01,0.021]	[0.02,0.97]	[0.05,0.84]
Support activities for mining	0.88	0.63	0.03	0.38
	[0.77,0.98]	[0.019,0.054]	[0.08,0.98]	[0.07,0.76]
Utilities	0.69	0.03	0.44	0.36
	[0.53,0.86]	[0.021,0.045]	[0.03,0.94]	[0.03,0.75]
Construction	0.46	0.008	0.52	0.35
	[0.21,0.71]	[0.005,0.013]	[0.03,0.98]	[0.1,0.66]
Wood products	0.72	0.016	0.45	0.19
	[0.52,0.92]	[0.013,0.021]	[0.03,0.92]	[0.01,0.5]
Nonmetallic mineral products	0.75	0.009	0.61	0.56
	[0.61,0.88]	[0.005,0.019]	[0.12,0.98]	[0.21,0.95]
Primary metals	0.76	0.04	0.78	0.25
	[0.59,0.93]	[0.025,0.068]	[0.21,0.99]	[0.08,0.5]
Fabricated metal products	0.76	0.011	0.82	0.24
	[0.57,0.94]	[0.006,0.023]	[0.27,1]	[0.07,0.49]
Machinery	0.89	0.009	0.43	0.3
	[0.78,0.99]	[0.007,0.012]	[0.02,0.9]	[0.04,0.59]
Computer and electronic products	0.74	0.014	0.72	0.24
	[0.55,0.92]	[0.009,0.022]	[0.13,0.99]	[0.06,0.5]
Electrical equipment, appliances, and components	0.82	0.013	0.43	0.18
	[0.67,0.96]	[0.01,0.016]	[0.02,0.94]	[0.01,0.5]
Motor vehicles, bodies and trailers, and parts	0.89	0.021	0.87	0.41
	[0.74,0.99]	[0.009,0.05]	[0.55,1]	[0.21,0.67]
Other transportation equipment	0.78	0.012	0.57	0.39
	[0.61,0.94]	[0.007,0.024]	[0.04,0.98]	[0.11,0.78]
Furniture and related products	0.78	0.009	0.46	0.48
	[0.65,0.93]	[0.006,0.019]	[0.03,0.98]	[0.17,0.84]
Miscellaneous manufacturing	0.86	0.009	0.44	0.24
	[0.72,0.98]	[0.007,0.012]	[0.03,0.93]	[0.01,0.59]
Food and beverage and tobacco products	0.83	0.022	0.6	0.29
	[0.7,0.96]	[0.015,0.039]	[0.04,1]	[0.05,0.65]
Textile mills and textile product mills	0.81	0.01	0.67	0.34
	[0.65,0.96]	[0.006,0.015]	[0.12,0.99]	[0.12,0.64]
Apparel and leather and allied products	0.75	0.013	0.46	0.41
	[0.6,0.9]	[0.009,0.017]	[0.03,0.9]	[0.17,0.7]
Paper products	0.65	0.016	0.83	0.38
	[0.47,0.85]	[0.008,0.04]	[0.44,0.99]	[0.16,0.75]
Printing and related support activities	0.82	0.007	0.49	0.39
	[0.65,0.96]	[0.005,0.01]	[0.03,0.94]	[0.15,0.71]

Notes: I report posterior means and, in brackets, 95 percent intervals.

Table 4: Posterior mean estimates of TFP level and volatility processes (continued)

Sector	ρ_{z_i}	σ_{z_i}	$\rho_{\sigma_{z_i}}$	$\sigma_{\sigma_{z_i}}$
Petroleum and coal products	0.79	0.137	0.66	0.38
	[0.63,0.95]	[0.088,0.245]	[0.16,0.97]	[0.17,0.66]
Chemical products	0.86	0.019	0.37	0.41
	[0.71,0.98]	[0.014,0.025]	[0.01,0.88]	[0.16,0.7]
Plastics and rubber products	0.8	0.014	0.79	0.26
	[0.63,0.96]	[0.008,0.027]	[0.19,1]	[0.07,0.57]
Wholesale trade	0.72	0.01	0.74	0.3
	[0.53,0.9]	[0.006,0.016]	[0.26,0.98]	[0.13,0.55]
Motor vehicle and parts dealers	0.79	0.024	0.85	0.52
	[0.62,0.94]	[0.009,0.07]	[0.6,0.99]	[0.28,0.85]
Food and beverage stores	0.74	0.012	0.64	0.39
	[0.59,0.91]	[0.006,0.018]	[0.07,0.97]	[0.12,0.84]
General merchandise stores	0.49	0.021	0.47	0.16
	[0.26,0.72]	[0.017,0.027]	[0.03,0.94]	[0.01,0.5]
Other retail	0.77	0.011	0.44	0.37
	[0.62,0.9]	[0.008,0.016]	[0.02,0.94]	[0.03,0.79]
Air transportation	0.87	0.026	0.62	0.24
	[0.72,0.99]	[0.018,0.036]	[0.07,0.97]	[0.04,0.52]
Rail transportation	0.76	0.011	0.5	0.2
	[0.59,0.92]	[0.009,0.016]	[0.03,0.98]	[0.01,0.52]
Water transportation	0.73	0.025	0.87	0.25
	[0.55,0.9]	[0.014,0.048]	[0.54,1]	[0.11,0.47]
Truck transportation	0.84	0.009	0.38	0.43
	[0.69,0.97]	[0.007,0.013]	[0.02,0.87]	[0.15,0.76]
Transit and ground passenger transportation	0.37	0.021	0.56	0.28
	[0.06,0.72]	[0.014,0.03]	[0.03,0.97]	[0.05,0.57]
Pipeline transportation	0.62	0.045	0.43	0.13
	[0.42,0.84]	[0.036,0.056]	[0.02,0.95]	[0,0.39]
Other transportation and support activities	0.7	0.021	0.88	0.32
	[0.52,0.86]	[0.007,0.059]	[0.29,1]	[0.12,0.73]
Warehousing and storage	0.82	0.017	0.62	0.3
	[0.66,0.96]	[0.011,0.04]	[0.06,1]	[0.04,0.64]
Publishing industries, except internet (includes software)	0.81	0.017	0.57	0.44
	[0.66,0.95]	[0.01,0.025]	[0.04,0.97]	[0.13,0.83]
Motion picture and sound recording industries	0.68	0.02	0.59	0.36
	[0.48,0.86]	[0.012,0.045]	[0.04,0.98]	[0.08,0.73]
Broadcasting and telecommunications	0.68	0.017	0.84	0.32
	[0.45,0.91]	[0.009,0.039]	[0.44,0.99]	[0.13,0.64]
Data processing, internet publishing, and other information services	0.77	0.032	0.85	0.28
	[0.62,0.93]	[0.016,0.073]	[0.3,1]	[0.1,0.63]
Federal Reserve banks, credit intermediation, and related activities	0.73	0.021	0.43	0.2
	[0.53,0.94]	[0.016,0.026]	[0.02,0.95]	[0.01,0.51]
Securities, commodity contracts, and investments	0.76	0.046	0.87	0.35
	[0.59,0.93]	[0.023,0.096]	[0.63,0.99]	[0.19,0.59]
Insurance carriers and related activities	0.75	0.017	0.47	0.26
	[0.58,0.92]	[0.013,0.024]	[0.03,0.95]	[0.02,0.57]

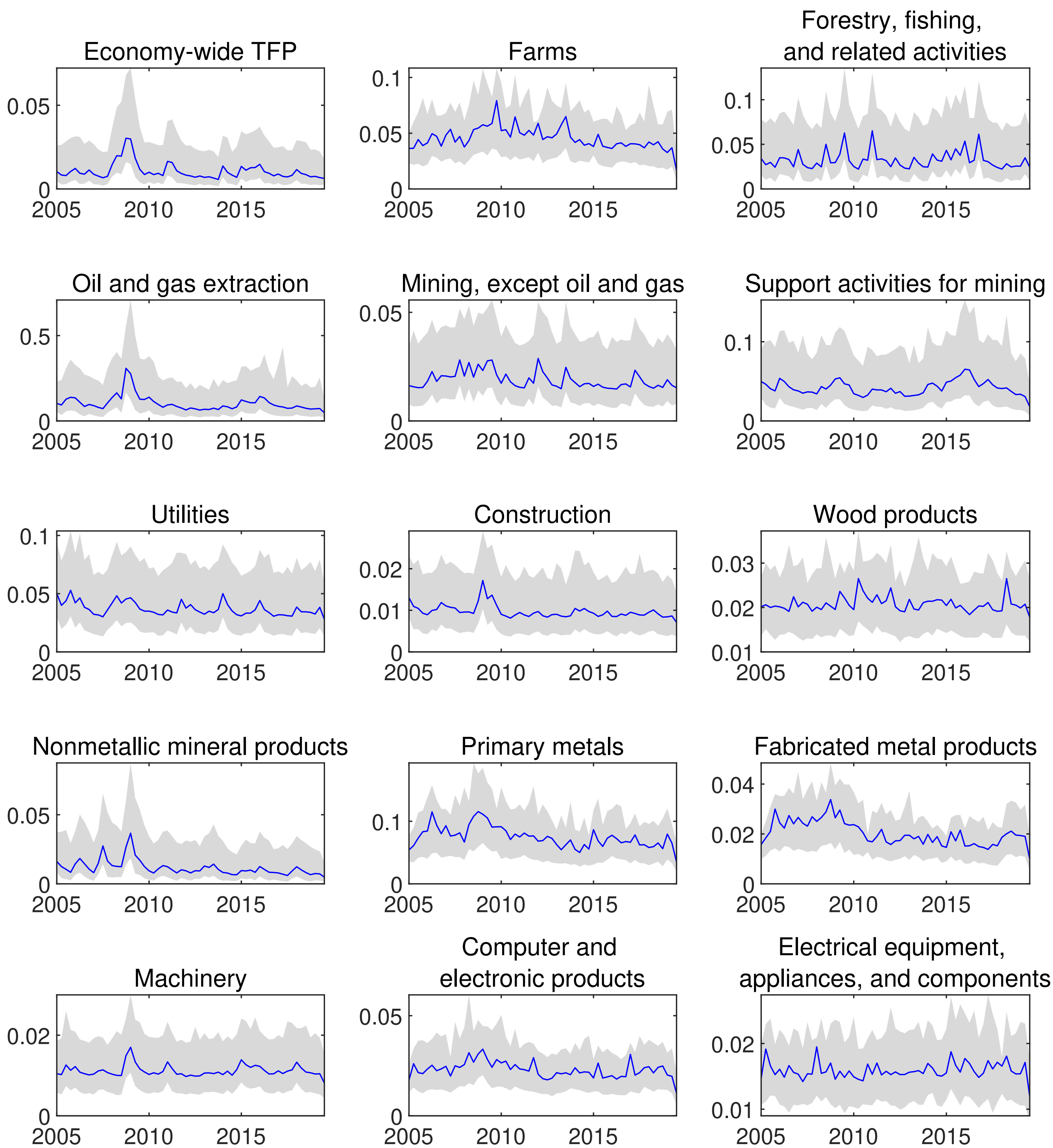
Notes: See notes from Table 3.

Table 5: Posterior mean estimates of TFP level and volatility processes (continued)

Sector	ρ_{z_i}	σ_{z_i}	$\rho_{\sigma_{z_i}}$	$\sigma_{\sigma_{z_i}}$
Funds, trusts, and other financial vehicles	0.8	0.015	0.3	0.42
	[0.64,0.94]	[0.01,0.019]	[0.01,0.88]	[0.06,0.81]
Housing	0.75	0.01	0.67	0.56
	[0.62,0.9]	[0.005,0.025]	[0.25,0.96]	[0.26,0.94]
Other real estate	0.86	0.018	0.56	0.26
	[0.75,0.97]	[0.012,0.032]	[0.03,0.99]	[0.03,0.59]
Rental and leasing services and lessors of intangible assets	0.68	0.027	0.93	0.3
	[0.47,0.86]	[0.011,0.065]	[0.63,1]	[0.13,0.58]
Legal services	0.78	0.014	0.85	0.36
	[0.6,0.95]	[0.007,0.027]	[0.47,0.99]	[0.16,0.66]
Computer systems design and related services	0.81	0.013	0.53	0.3
	[0.65,0.96]	[0.009,0.017]	[0.06,0.94]	[0.04,0.65]
Miscellaneous professional, scientific, and technical services	0.86	0.01	0.7	0.42
	[0.73,0.97]	[0.006,0.02]	[0.22,0.98]	[0.17,0.75]
Management of companies and enterprises	0.77	0.013	0.49	0.48
	[0.62,0.92]	[0.009,0.02]	[0.05,0.91]	[0.22,0.79]
Administrative and support services	0.84	0.01	0.6	0.39
	[0.71,0.97]	[0.006,0.015]	[0.11,0.95]	[0.17,0.68]
Waste management and remediation services	0.86	0.012	0.54	0.71
	[0.72,0.99]	[0.007,0.025]	[0.04,0.96]	[0.36,1.12]
Educational services	0.8	0.009	0.49	0.29
	[0.63,0.96]	[0.006,0.015]	[0.04,0.96]	[0.05,0.58]
Ambulatory health care services	0.83	0.009	0.56	0.5
	[0.68,0.98]	[0.005,0.013]	[0.08,0.95]	[0.18,0.96]
Hospitals	0.82	0.007	0.55	0.48
	[0.67,0.96]	[0.005,0.011]	[0.08,0.95]	[0.17,0.86]
Nursing and residential care facilities	0.79	0.007	0.49	0.5
	[0.66,0.92]	[0.005,0.01]	[0.06,0.88]	[0.22,0.85]
Social assistance	0.84	0.009	0.49	0.46
	[0.69,0.97]	[0.006,0.013]	[0.05,0.92]	[0.16,0.83]
Performing arts, spectator sports, museums, and related activities	0.8	0.017	0.41	0.23
	[0.64,0.95]	[0.013,0.021]	[0.02,0.92]	[0.01,0.56]
Amusements, gambling, and recreation industries	0.84	0.009	0.62	0.47
	[0.69,0.97]	[0.005,0.013]	[0.11,0.97]	[0.15,0.84]
Accommodation	0.84	0.011	0.67	0.45
	[0.72,0.96]	[0.006,0.022]	[0.2,0.97]	[0.21,0.76]
Food services and drinking places	0.79	0.008	0.59	0.41
	[0.64,0.94]	[0.006,0.013]	[0.12,0.95]	[0.17,0.69]
Other services, except government	0.85	0.008	0.51	0.5
	[0.74,0.96]	[0.005,0.012]	[0.07,0.89]	[0.18,0.87]

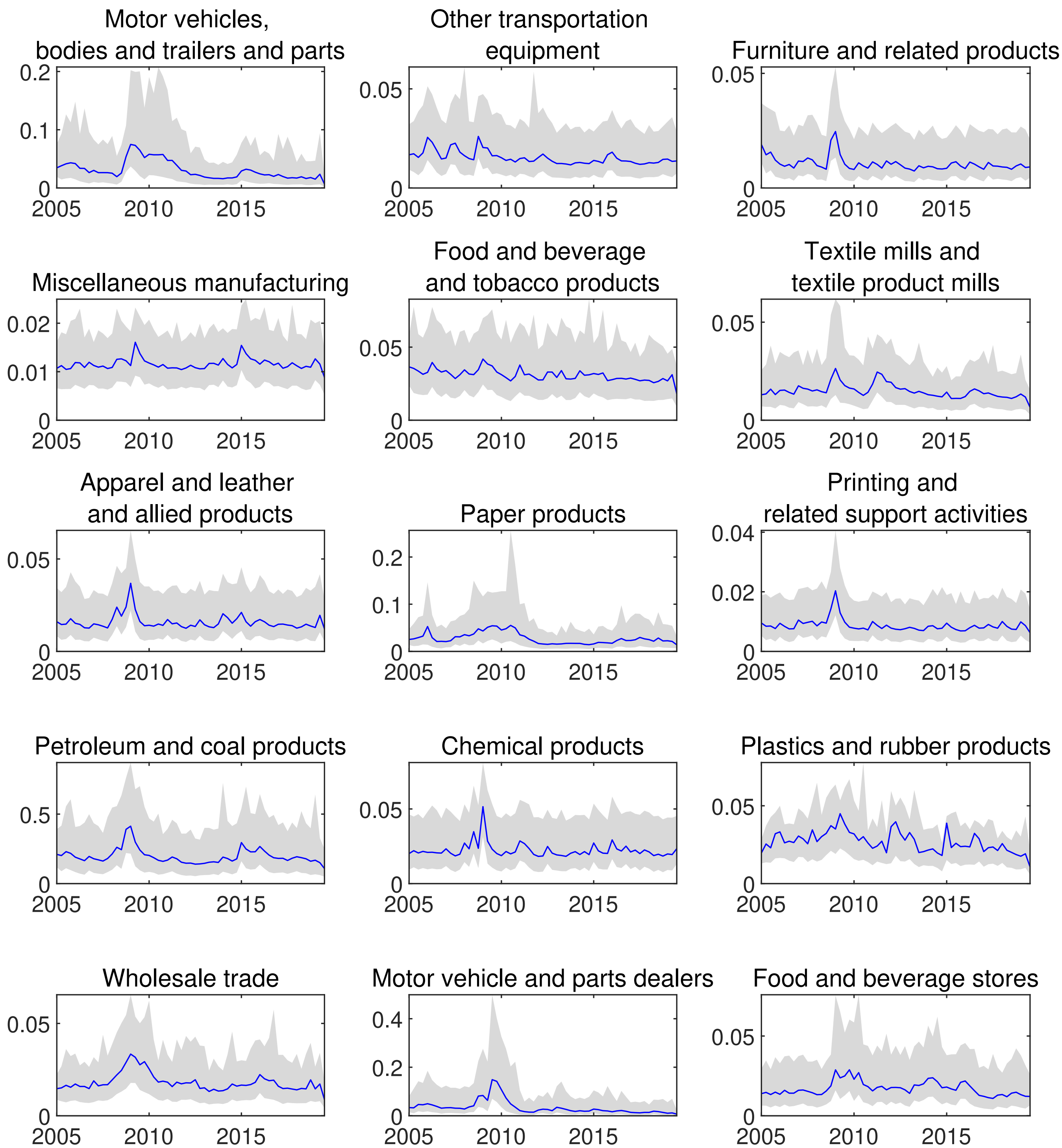
Notes: See notes from Table 3.

Figure 8: Smoothed economy-wide and sector-specific TFP volatility



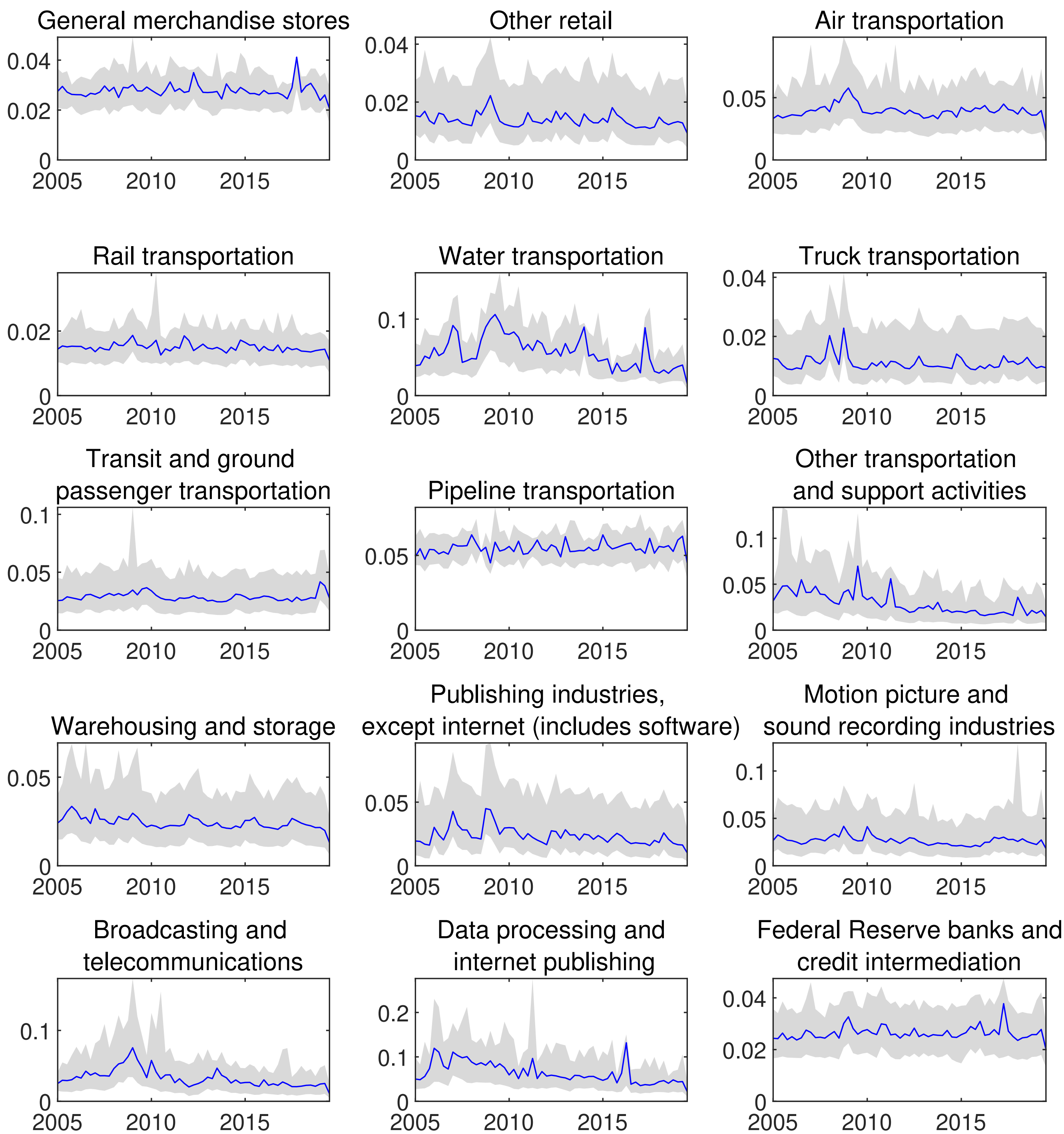
Notes: I report the smoothed economy-wide TFP volatility ($\sigma_{\bar{z},t}$) and sector-specific TFP volatility ($\sigma_{z_i,t}$). The shaded areas are the 95 percent confidence bands.

Figure 9: Smoothed economy-wide and sector-specific TFP volatility (continued)



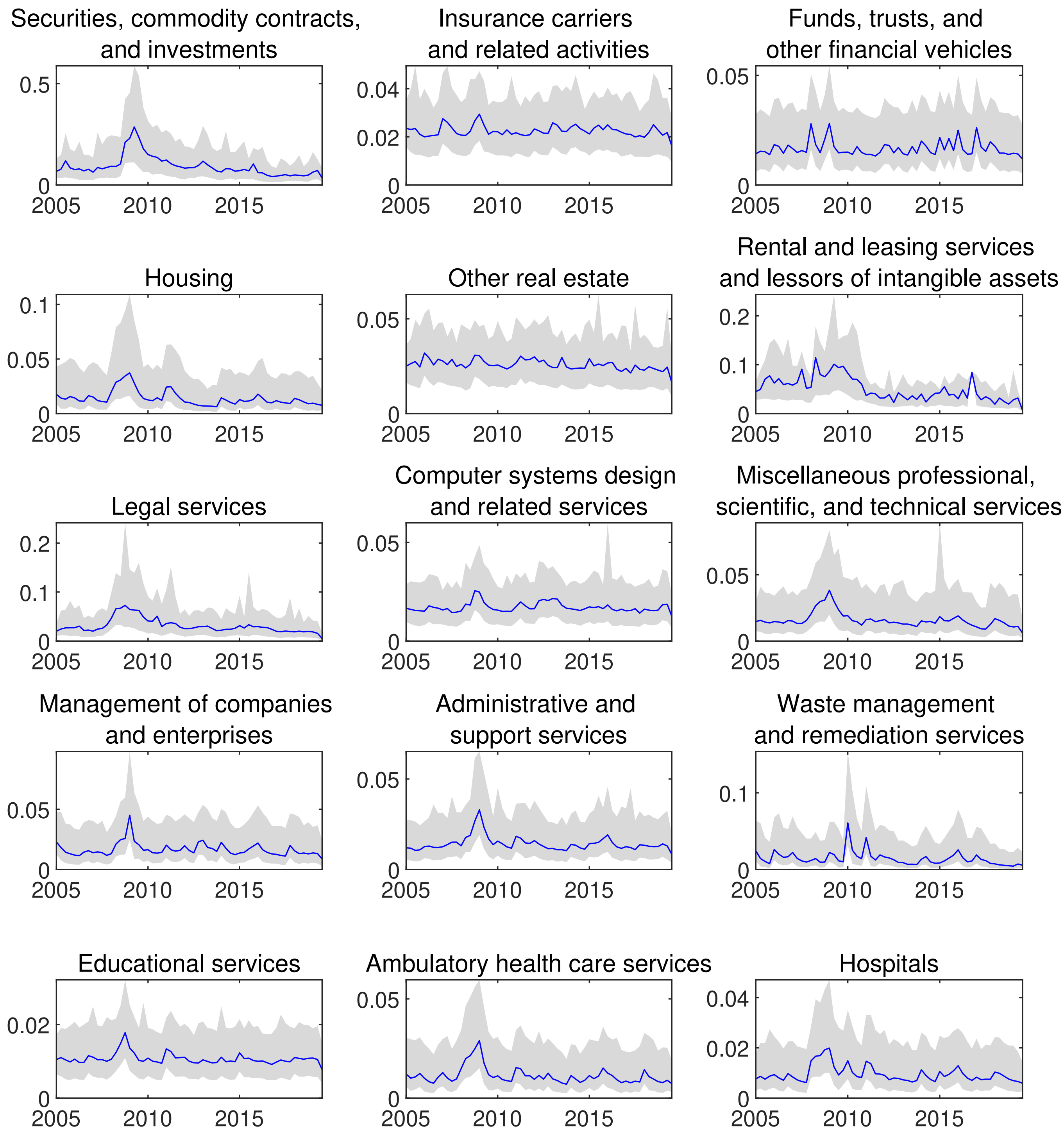
Notes: See notes from Figure 8.

Figure 10: Smoothed economy-wide and sector-specific TFP volatility (continued)



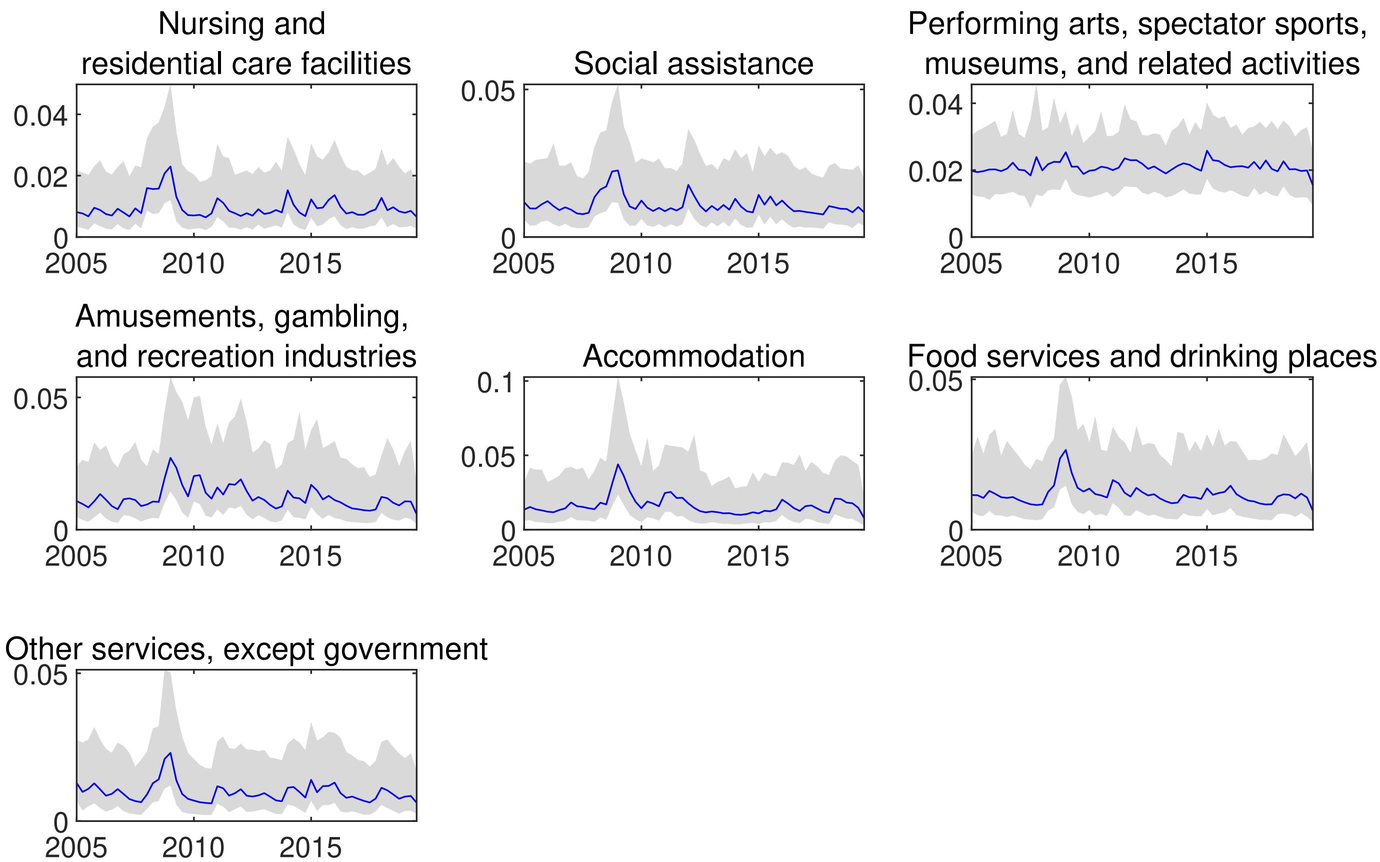
Notes: See notes from Figure 8.

Figure 11: Smoothed economy-wide and sector-specific TFP volatility (continued)



Notes: See notes from Figure 8.

Figure 12: Smoothed economy-wide and sector-specific TFP volatility (continued)



Notes: See notes from Figure 8.

Table 6: Posterior mean estimates of demand level and volatility processes

	ρ_{d_i}	σ_{d_i}	$\rho_{\sigma_{d_i}}$	$\sigma_{\sigma_{d_i}}$
Farms	0.74	0.005	0.76	0.35
	[0.55,0.92]	[0.003,0.011]	[0.23,0.99]	[0.13,0.69]
Forestry, fishing, and related activities	0.49	0.007	0.45	0.29
	[0.23,0.72]	[0.005,0.009]	[0.03,0.93]	[0.03,0.61]
Oil and gas extraction	0.76	0.014	0.54	0.29
	[0.58,0.93]	[0.008,0.019]	[0.04,0.98]	[0.03,0.61]
Mining, except oil and gas	0.74	0.015	0.47	0.4
	[0.55,0.91]	[0.01,0.021]	[0.02,0.97]	[0.05,0.84]
Support activities for mining	0.88	0.63	0.03	0.38
	[0.77,0.98]	[0.019,0.054]	[0.08,0.98]	[0.07,0.76]
Utilities	0.33	0.028	0.36	0.24
	[0.1,0.57]	[0.022,0.037]	[0.02,0.91]	[0.01,0.57]
Wood products	0.84	0.02	0.96	0.27
	[0.69,0.97]	[0.007,0.045]	[0.83,1]	[0.12,0.49]
Nonmetallic mineral products	0.76	0.009	0.48	0.13
	[0.59,0.93]	[0.007,0.011]	[0.02,0.97]	[0.01,0.37]
Primary metals	0.84	0.013	0.74	0.23
	[0.67,0.98]	[0.007,0.032]	[0.06,1]	[0.06,0.54]
Fabricated metal products	0.73	0.009	0.6	0.39
	[0.55,0.9]	[0.006,0.019]	[0.07,0.98]	[0.11,0.74]
Machinery	0.72	0.011	0.56	0.25
	[0.52,0.91]	[0.008,0.017]	[0.04,0.99]	[0.02,0.58]
Computer and electronic products	0.73	0.013	0.65	0.27
	[0.55,0.91]	[0.008,0.026]	[0.06,0.99]	[0.03,0.63]
Electrical equipment, appliances, and components	0.67	0.008	0.62	0.25
	[0.46,0.88]	[0.006,0.013]	[0.07,0.99]	[0.03,0.52]
Motor vehicles, bodies and trailers, and parts	0.75	0.055	0.87	0.33
	[0.55,0.92]	[0.022,0.134]	[0.36,1]	[0.13,0.76]
Other transportation equipment	0.82	0.029	0.64	0.27
	[0.67,0.96]	[0.018,0.056]	[0.04,1]	[0.06,0.63]
Furniture and related products	0.88	0.028	0.86	0.37
	[0.74,0.99]	[0.007,0.091]	[0.27,1]	[0.12,0.79]
Miscellaneous manufacturing	0.72	0.009	0.66	0.19
	[0.52,0.9]	[0.006,0.019]	[0.05,1]	[0.02,0.43]
Food and beverage and tobacco products	0.64	0.007	0.87	0.33
	[0.43,0.85]	[0.003,0.018]	[0.36,1]	[0.13,0.7]
Textile mills and textile product mills	0.84	0.011	0.69	0.36
	[0.7,0.97]	[0.005,0.027]	[0.06,1]	[0.08,0.82]
Apparel and leather and allied products	0.79	0.008	0.52	0.26
	[0.63,0.95]	[0.006,0.012]	[0.03,0.99]	[0.02,0.63]
Paper products	0.5	0.005	0.62	0.2
	[0.25,0.73]	[0.004,0.008]	[0.04,0.99]	[0.02,0.47]
Printing and related support activities	0.63	0.007	0.53	0.22
	[0.42,0.85]	[0.005,0.01]	[0.04,0.97]	[0.01,0.55]
Petroleum and coal products	0.81	0.07	0.62	0.4
	[0.65,0.97]	[0.044,0.132]	[0.08,0.98]	[0.16,0.7]

Notes: See notes from Table 3.

Table 7: Posterior mean estimates of demand level and volatility processes (continued)

	ρ_{d_i}	σ_{d_i}	$\rho_{\sigma_{d_i}}$	$\sigma_{\sigma_{d_i}}$
Chemical products	0.82	0.007	0.46	0.25
	[0.69,0.96]	[0.005,0.009]	[0.03,0.96]	[0.02,0.57]
Plastics and rubber products	0.79	0.008	0.74	0.2
	[0.62,0.96]	[0.005,0.017]	[0.08,1]	[0.03,0.46]
Wholesale trade	0.81	0.008	0.5	0.42
	[0.66,0.96]	[0.005,0.015]	[0.03,0.96]	[0.18,0.75]
Motor vehicle and parts dealers	0.85	0.004	0.42	0.4
	[0.71,0.97]	[0.003,0.007]	[0.02,0.95]	[0.16,0.68]
Food and beverage stores	0.84	0.004	0.42	0.4
	[0.72,0.96]	[0.003,0.007]	[0.02,0.95]	[0.17,0.68]
General merchandise stores	0.84	0.004	0.42	0.4
	[0.71,0.96]	[0.003,0.006]	[0.02,0.92]	[0.18,0.66]
Other retail	0.84	0.004	0.43	0.39
	[0.69,0.96]	[0.003,0.006]	[0.02,0.93]	[0.17,0.65]
Air transportation	0.77	0.009	0.49	0.62
	[0.59,0.92]	[0.006,0.014]	[0.06,0.91]	[0.26,1.02]
Rail transportation	0.8	0.006	0.66	0.32
	[0.65,0.94]	[0.004,0.013]	[0.06,0.99]	[0.11,0.61]
Water transportation	0.67	0.015	0.57	0.56
	[0.39,0.88]	[0.009,0.026]	[0.09,0.97]	[0.19,1.15]
Truck transportation	0.92	0.005	0.42	0.39
	[0.81,0.99]	[0.004,0.008]	[0.02,0.92]	[0.14,0.68]
Transit and ground passenger transportation	0.73	0.012	0.41	0.11
	[0.54,0.92]	[0.01,0.015]	[0.02,0.93]	[0,0.34]
Warehousing and storage	0.92	0.01	0.45	0.17
	[0.83,0.99]	[0.008,0.013]	[0.02,0.95]	[0.01,0.48]
Publishing industries, except internet (includes software)	0.69	0.009	0.47	0.21
	[0.48,0.89]	[0.007,0.012]	[0.02,0.96]	[0.01,0.62]
Motion picture and sound recording industries	0.68	0.009	0.42	0.11
	[0.49,0.88]	[0.007,0.011]	[0.02,0.94]	[0,0.36]
Broadcasting and telecommunications	0.73	0.009	0.46	0.26
	[0.56,0.9]	[0.007,0.014]	[0.02,0.96]	[0.02,0.59]
Data processing, internet publishing, and other information services	0.66	0.007	0.45	0.09
	[0.45,0.89]	[0.006,0.008]	[0.02,0.95]	[0,0.27]
Federal Reserve banks, credit intermediation, and related activities	0.63	0.011	0.47	0.19
	[0.41,0.85]	[0.007,0.014]	[0.03,0.97]	[0.01,0.53]
Securities, commodity contracts, and investments	0.78	0.014	0.41	0.32
	[0.61,0.95]	[0.01,0.018]	[0.02,0.93]	[0.07,0.62]
Insurance carriers and related activities	0.85	0.01	0.6	0.18
	[0.7,0.97]	[0.007,0.014]	[0.04,0.98]	[0.01,0.41]
Funds, trusts, and other financial vehicles	0.68	0.013	0.53	0.37
	[0.48,0.87]	[0.008,0.017]	[0.04,0.95]	[0.09,0.73]
Housing	0.86	0.005	0.6	0.41
	[0.74,0.98]	[0.003,0.007]	[0.09,0.95]	[0.18,0.7]
Other real estate	0.92	0.01	0.47	0.16
	[0.82,0.99]	[0.008,0.013]	[0.03,0.94]	[0.01,0.48]

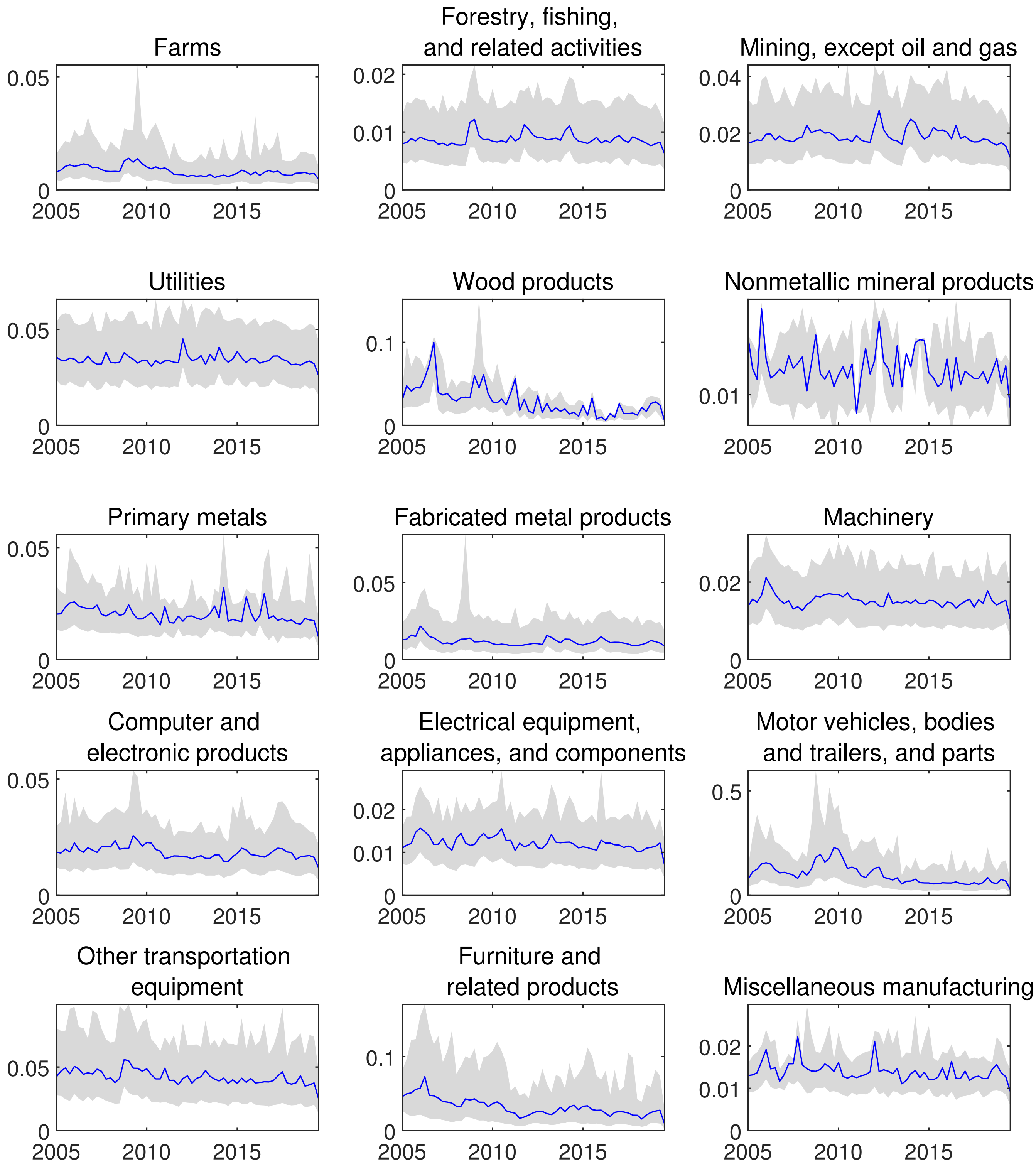
Notes: See notes from Table 3.

Table 8: Posterior mean estimates of demand level and volatility processes (continued)

	ρ_{d_i}	σ_{d_i}	$\rho_{\sigma_{d_i}}$	$\sigma_{\sigma_{d_i}}$
Rental and leasing services and lessors of intangible assets	0.93	0.009	0.56	0.16
	[0.84,0.99]	[0.007,0.016]	[0.03,0.99]	[0.01,0.46]
Legal services	0.37	0.015	0.46	0.14
	[0.11,0.62]	[0.012,0.02]	[0.02,0.96]	[0.01,0.39]
Miscellaneous professional, scientific, and technical services	0.77	0.009	0.44	0.12
	[0.59,0.94]	[0.007,0.011]	[0.02,0.96]	[0,0.36]
Administrative and support services	0.92	0.006	0.61	0.29
	[0.81,1]	[0.004,0.01]	[0.07,0.99]	[0.04,0.64]
Waste management and remediation services	0.82	0.007	0.43	0.41
	[0.67,0.96]	[0.005,0.012]	[0.02,0.96]	[0.14,0.74]
Educational services	0.87	0.006	0.5	0.28
	[0.75,0.98]	[0.005,0.01]	[0.03,0.98]	[0.05,0.6]
Ambulatory health care services	0.82	0.008	0.39	0.4
	[0.67,0.96]	[0.005,0.011]	[0.02,0.9]	[0.1,0.7]
Hospitals	0.77	0.01	0.48	0.23
	[0.59,0.93]	[0.007,0.013]	[0.03,0.94]	[0.02,0.52]
Nursing and residential care facilities	0.81	0.01	0.45	0.19
	[0.64,0.96]	[0.007,0.012]	[0.02,0.95]	[0.01,0.5]
Social assistance	0.59	0.01	0.55	0.18
	[0.36,0.81]	[0.008,0.013]	[0.03,0.97]	[0.01,0.46]
Performing arts, spectator sports, museums, and related activities	0.45	0.013	0.52	0.22
	[0.21,0.7]	[0.009,0.016]	[0.03,0.97]	[0.02,0.52]
Amusements, gambling, and recreation industries	0.5	0.01	0.4	0.13
	[0.27,0.73]	[0.008,0.012]	[0.02,0.94]	[0,0.45]
Accommodation	0.85	0.008	0.28	0.43
	[0.68,0.97]	[0.005,0.01]	[0.01,0.87]	[0.02,0.86]
Food services and drinking places	0.5	0.007	0.42	0.23
	[0.25,0.74]	[0.005,0.009]	[0.02,0.94]	[0.01,0.58]
Other services, except government	0.27	0.007	0.43	0.13
	[0.04,0.53]	[0.006,0.009]	[0.02,0.95]	[0.01,0.37]

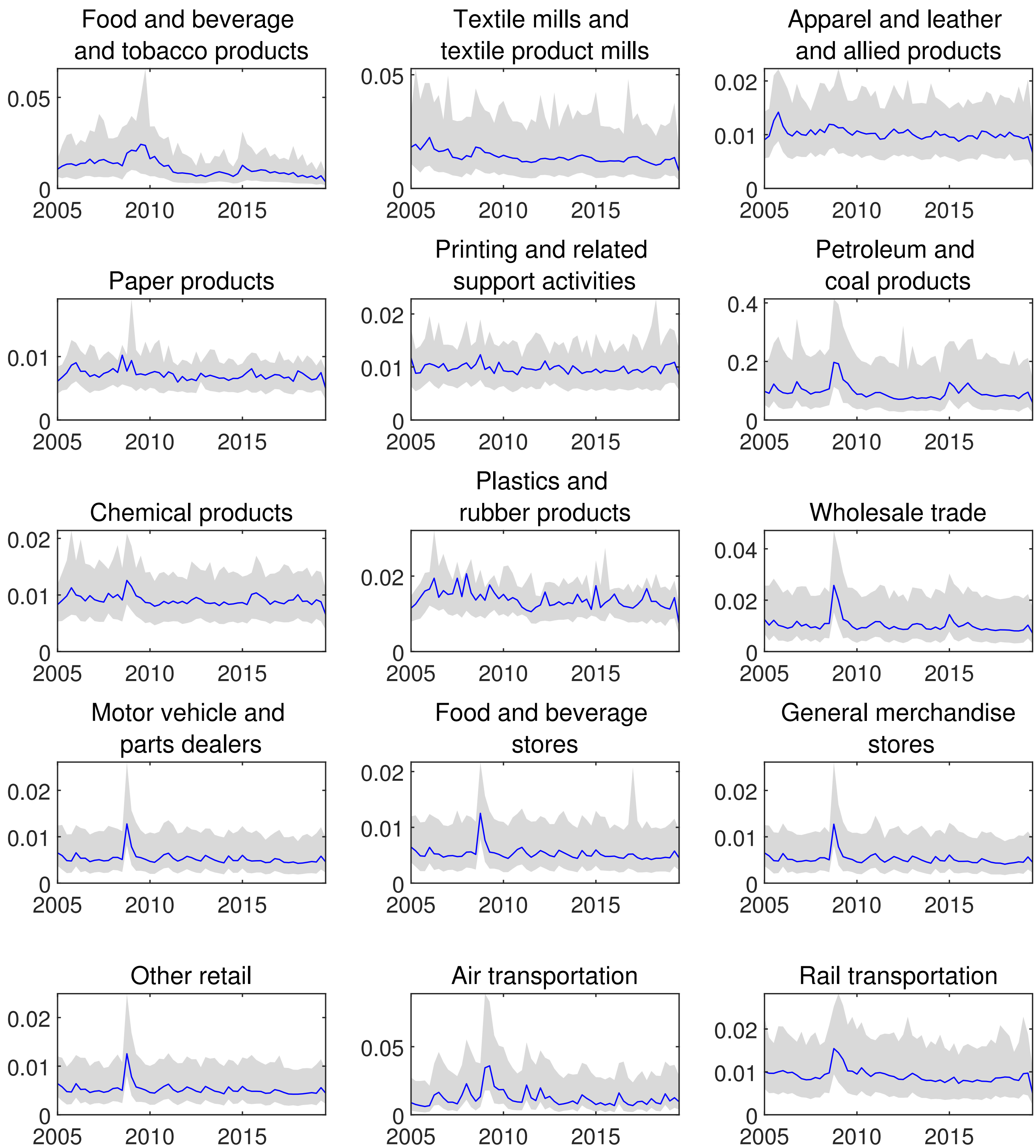
Notes: See notes from Table 3.

Figure 13: Smoothed sector-specific demand volatility (continued)



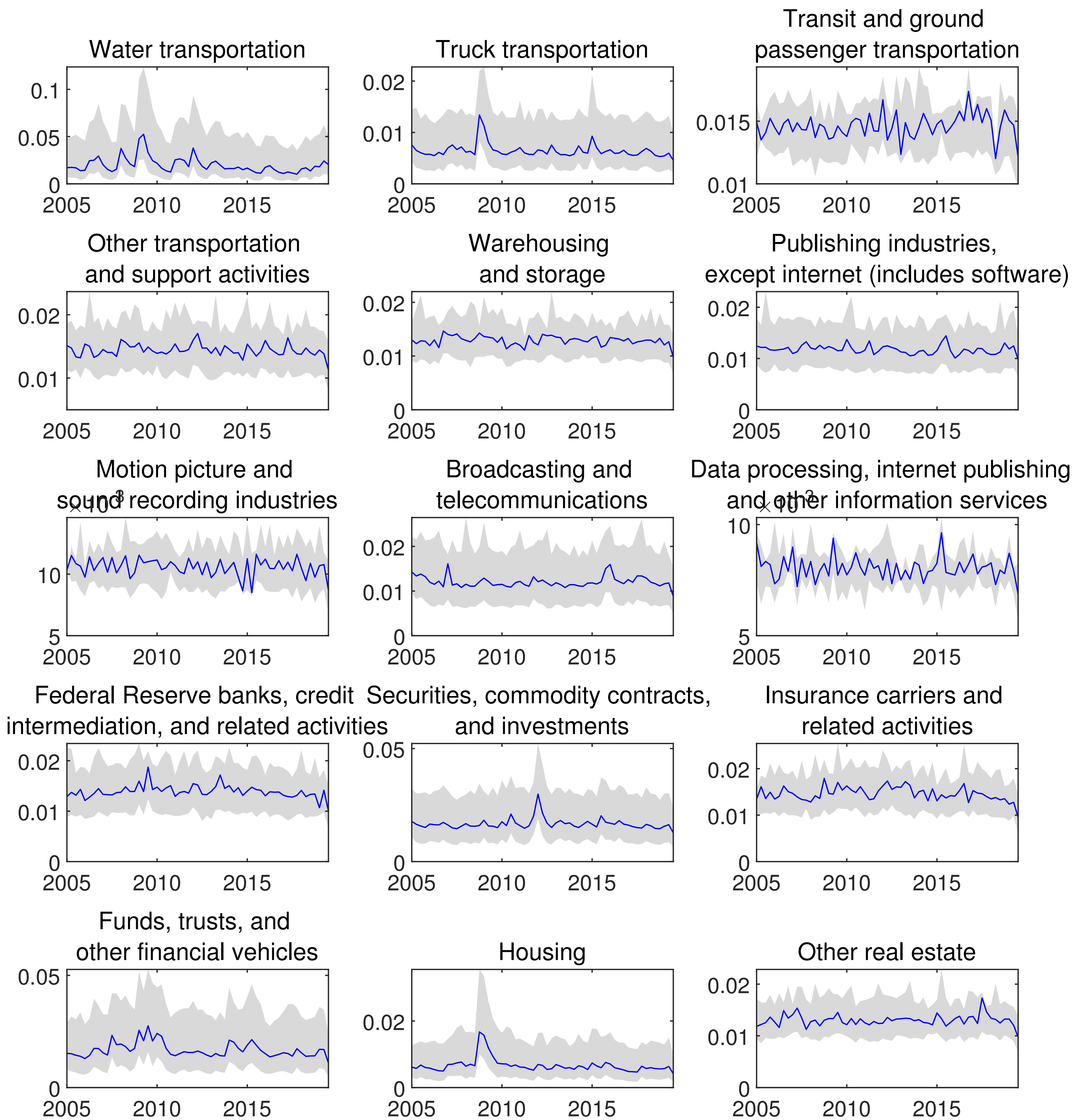
Notes: I report the smoothed sector-specific demand volatility ($\sigma_{d_i,t}$). The shaded areas are the 95 percent confidence bands.

Figure 14: Smoothed sector-specific demand volatility (continued)



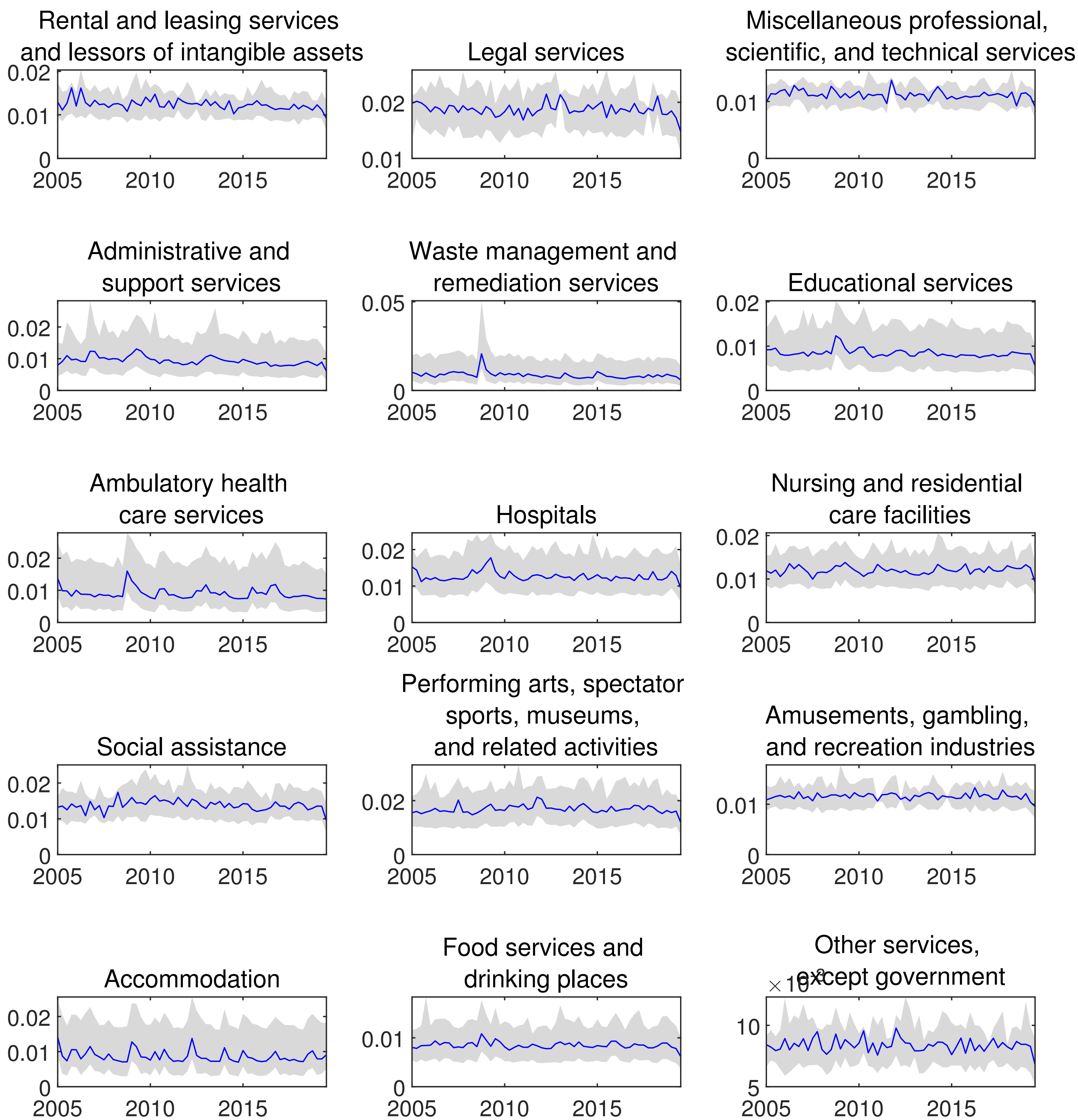
Notes: See notes from Figure 13.

Figure 15: Smoothed sector-specific demand volatility (continued)



Notes: See notes from Figure 13.

Figure 16: Smoothed sector-specific demand volatility (continued)



Notes: See notes from Figure 13.