Uncertainty through the Production Network: Sectoral Origins and Macroeconomic Implications*

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Abstract

We study how uncertainty propagates through production networks. Using option-implied volatility data for U.S. firms, we construct a granular, forward-looking measure of industry-level uncertainty. We then estimate its effects within industries, across supply chains, and at the aggregate level. Uncertainty in upstream sectors (e.g., chemicals, steel) acts like a supply shock, raising prices and reducing employment across the network. In contrast, uncertainty in downstream sectors (e.g., automotive, insurance) resembles a demand shock, lowering prices and employment. Aggregate inflation dynamics depend on the origin of uncertainty. A multi-sector model with time-varying sectoral uncertainty shows that network propagation explains these results.

Keywords: uncertainty; production networks; shocks propagation; implied volatility.
JEL Classification: E23, E31, E32.

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1 Introduction

A vast body of literature examines how sector-specific shocks propagate through production networks, generating aggregate economic fluctuations (e.g., Acemoglu et al., 2012; Baqaee and Farhi, 2019b; Carvalho et al., 2020). A striking example of this phenomenon emerged in 2023 when supply shortages and rising relative prices in key upstream industries (e.g., semiconductor manufacturing and energy production) became primary drivers of the global inflation surge (e.g., Bernanke and Blanchard, 2024).

While substantial progress has been made in tracing the real-side transmission of first-moment shocks, considerably less is known about how increased uncertainty–a second-moment shock–propagates through the production network. Discussions in policy and financial circles often highlight the potential supply chain implications of heightened volatility in commodity markets, trade tensions, and sector-specific financial instability or regulatory changes, to name a few. Yet key questions remain unanswered: How does uncertainty arising in a particular industry affect uncertainty, production, and prices in upstream suppliers and downstream customers? Do the aggregate effects of uncertainty depend on where in the production network it originates? This paper provides the first empirical and theoretical framework to study the dynamics of uncertainty shocks across industries.

Our results break new ground on two fronts. First, using a novel measure of industry-level uncertainty based on option-implied volatility, we show that heightened uncertainty in one industry propagates through the production network, increasing uncertainty and reducing employment across linked sectors. Second, we find that the network propagation of uncertainty depends on its origin: upstream uncertainty (from industries supplying intermediate inputs) behaves like a negative supply shock, reducing employment while raising prices throughout the supply chain, whereas downstream uncertainty behaves like a negative demand shock, lowering both employment and prices. At the aggregate level, the inflation response depends on where uncertainty originates, with upstream uncertainty resulting in persistently higher prices.

In the first part of the paper, we tackle the challenge of estimating how heightened uncertainty propagates through the production network. Identifying network effects requires uncertainty variation that is uncorrelated with first-moment shocks and not common across interconnected sectors (e.g., economy-wide uncertainty). However, disaggregated, industry-level measures of uncertainty are not readily available.

Our first contribution is to construct sectoral uncertainty measures using high-frequency, option-implied volatility data from publicly traded U.S. firms. We focus on NAICS 4-digit industry-level measures, as this is the finest level of aggregation at which comprehensive data on employment, prices, and input-output relationships are consistently available. The use of implied volatility data offers several advantages. As it is derived from market prices, it captures forward-looking uncertainty and is available at high frequency. Option data also provides extensive sectoral coverage, unlike more aggregated measures that lack the necessary granularity to measure cross-industry spillovers.[1] Variation in implied volatility stems from uncertainty about future economic activity (e.g., expected cash flows) or from financial uncertainty (e.g., external financing conditions, financial restructuring, or changes in ownership).[2] Our sample spans over one hundred industries, including upstream and downstream sectors (as defined in Antràs and Chor, 2013), with the underlying option-issuing firms accounting for a significant share of sectoral output and employment on average.

We document that our measure of sectoral uncertainty, $\sigma_{i,t}$, is both higher on average and more volatile in absolute terms than aggregate uncertainty, yet it exhibits similar persistence. The average bilateral correlation of $\sigma_{i,t}$ across industries is positive but well below one, indicating the presence of significant industry-specific variation. Sectoral uncertainty correlates positively with aggregate uncertainty and negatively with industrial production for most, though not all, industries, displaying substantial cross-sectional heterogeneity. Thus, $\sigma_{i,t}$ largely mimics the well-established countercyclicality of aggregate uncertainty (e.g., Jurado et al., 2015). Importantly, sectoral uncertainty does not exhibit a clear-cut correlation pattern with aggregate inflation: the comovement is positive for approximately two-thirds of the industries, while it is negative for the remaining sectors.

Our second contribution is to identify variations in sectoral uncertainty suitable for estimating network effects. Such variation must be uncorrelated with first-moment shocks and with uncertainty originating in other industries. Building on Berger et al. (2019), we require that uncertainty shocks be orthogonal to realized volatility, which

[1]The use of option data has become a consolidated approach in macroeconomics to measure aggregate uncertainty since Bloom (2009). Other measures of uncertainty not based on financial data include survey-based measures of uncertainty (e.g., Bachmann et al., 2013; Bloom et al., 2018) and various macroeconomic and financial uncertainty indices (e.g. Jurado et al., 2015). For a comprehensive review, see Cascaldi-Garcia et al. (2023).

[2]Influential studies show that implied volatility increases in response to uncertainty about expected cash flows, firm fundamentals, and external financing constraints (e.g., Merton, 1974; Pan and Poteshman, 2006; Cremers and Weinbaum, 2010).

captures actual stock return volatility driven by first-moment shocks. In addition, we leverage the high-frequency nature of options data to construct within-month controls for contemporaneous changes in implied volatility originating from upstream suppliers and downstream customers. Thus, our approach conservatively exploits variation in industry-level implied volatility not explained by past or current realized volatility or uncertainty from supplier and customer industries. The identified shocks capture both unexpected changes in uncertainty affecting multiple firms within an industry and uncertainty impacting large firms in the sector. The largest shocks are associated with notable events that created uncertainty in specific sectors, such as regulatory changes (e.g., insurance), financial restructuring (e.g., automotive), technological transformations (e.g., advertising), and trade tensions (e.g., iron and steel), to name a few.

Our third contribution is to estimate the dynamic response of uncertainty, employment, and prices in affected industries (where uncertainty shocks arise) and along the supply chain (in industries that supply intermediate inputs to or buy output from industries that face heightened uncertainty).[3] We then analyze the macroeconomic implications of uncertainty by aggregating sectoral shocks.

Our empirical findings are as follows. Higher uncertainty leads to a persistent decline in employment and a rise in producer prices within the affected industry. The increase in sectoral producer prices is consistent with precautionary pricing, where firms raise prices today to hedge against the risk of future marginal cost increases—a mechanism featured in benchmark macroeconomic models with time-varying uncertainty (see Fernández-Villaverde et al. (2015) and references therein).[4] The price increase is also consistent with models featuring customer markets and financial frictions, which predict that firms with weaker balance sheets pass on higher financing costs to their customers during periods of heightened uncertainty (e.g., Gilchrist et al., 2017).

Uncertainty shocks propagate through the supply chain. Implied volatility rises in upstream and downstream industries, indicating that uncertainty spreads to customer and supplier sectors. However, network transmission is heterogeneous across industries. On the one hand, employment and producer prices decline in supplier industries, consistent with weaker demand for intermediate inputs from industries facing higher uncertainty. On the other hand, in customer industries, employment falls while

[3]We measure an industry's exposure to upstream (downstream) uncertainty variation using total-requirements input-output tables in the spirit of Acemoglu et al. (2016).

[4]This result is also consistent with Kopytov et al. (2024), who shows in a model of endogenous network formation that higher uncertainty leads firms to purchase from more stable suppliers, even though these suppliers might sell at higher prices.

producer prices rise, akin to a negative supply shock for downstream producers. Consistent with sectoral propagation, we find that uncertainty shocks are contractionary at the aggregate level, while their impact on inflation depends on where uncertainty originates within the network. Specifically, uncertainty is inflationary when it increases in relatively upstream sectors.

What explains the network propagation of uncertainty shocks? Our fourth and final contribution is to show that a New Keynesian multi-sector model with input-output linkages and sector-specific time-varying volatility rationalizes the empirical findings. Input-output linkages are crucial for understanding the response of employment and prices across sectors, both qualitatively and quantitatively. The results hold regardless of whether uncertainty arises from supply- or demand-side factors, such as sectoral productivity fluctuations or demand shocks.

When industry-level uncertainty increases, producers in that industry raise markups out of precaution due to the presence of nominal rigidities. Higher markups lead to higher prices and lower employment in that sector. Without production linkages, sectoral spillovers would solely reflect general equilibrium effects driven by households' precautionary saving, leading to counterfactual sectoral comovement, i.e., lower aggregate demand would imply a fall in prices and employment in upstream and downstream industries. Production linkages instead transmit changes in input demand and costs along the supply chain, altering price dynamics across sectors and amplifying the magnitude of sectoral spillovers. First, consistent with the estimated co-movements, suppliers of industries facing the uncertainty shock experience a decline in demand for their output, leading to lower inflation and employment upstream. Second, the price increase in industries affected by the uncertainty shock raises marginal costs for their customer industries, triggering higher inflation and a reduction in the use of intermediate inputs. For an empirically plausible complementarity between labor and intermediate inputs, employment declines downstream. The model also rationalizes the estimated response of aggregate output and inflation: uncertainty shocks are contractionary and become more inflationary the further upstream they originate. Finally, the model demonstrates that sectoral price dynamics following downstream uncertainty differ from those implied by aggregate uncertainty, which does not produce asymmetric price responses across sectors. This result suggests that price dispersion across industries during uncertain times is more likely driven by sector-specific rather than aggregate uncertainty.

Our analysis shows that the macroeconomic effects of uncertainty are not uniform, but depend on where in the supply chain uncertainty originates. The asymmetric network propagation suggests important implications for the design of macroeconomic policy. First, uncertainty arising upstream poses a greater inflationary risk that is more difficult to offset without triggering additional employment losses, thereby intensifying the inflation-output tradeoff. Second, when uncertainty stems from first-moment shocks, it can amplify or dampen their inflationary impact—for example, when uncertainty rises following upstream supply disruptions or downstream demand shortfalls. Central banks need to address both the scale and source of uncertainty shocks in the supply chain to design effective policies.

Related Literature. Our work contributes to a broad research agenda examining how uncertainty influences economic aggregates. Much of this literature has focused on the business cycle effects of aggregate uncertainty, both empirically (e.g., Bloom, 2009; Berger et al., 2019; Cesa-Bianchi et al., 2020) and theoretically (e.g., Christiano et al., 2014; Basu and Bundick, 2017; Bloom et al., 2018; Basu et al., 2021). Beyond its cyclical effects, uncertainty can also have more persistent consequences, as shown by models developed by Nieuwerburgh and Veldkamp (2006) and Fajgelbaum et al. (2017). We contribute to this literature by estimating how uncertainty shocks propagate along the supply chain and their implications for the behavior of aggregate inflation and output.

A handful of recent papers have begun to examine sectoral or production network dimensions of uncertainty. Castelnuovo et al. (2022) estimate a dynamic factor model on industrial production series to construct uncertainty indexes for durable and non-durable goods. Grigoris and Segal (2021) examine how firm-level investment, hiring, and inventories respond to uncertainty originating from suppliers and customers. Our analysis differs in both scope and methodology. First, our focus on disaggregated industry-level outcomes allows us to study both quantity and price dynamics across the production network. Second, we identify high-frequency sectoral uncertainty shocks that are orthogonal to first-moment shocks and to uncertainty originating in connected industries. Our theoretical model shares features with Saijo (2025), who develops a multi-sector New Keynesian framework with sector-specific volatility shocks to show that input-output linkages can amplify the recessionary effects of precautionary pricing.

Our findings contribute to a broad literature investigating how production networks transmit shocks and policies across firms or sectors. Much research has shown that granular supply and demand shocks affecting large firms or sectors can lead to aggregate economic fluctuations (e.g., Gabaix, 2011; Carvalho and Grassi, 2019). Theoretical models have extensively analyzed how these granular shocks propagate along supply chains through input-output linkages, including work by Acemoglu et al. (2012), Acemoglu et al. (2016), Baqaee and Farhi (2019a), and Baqaee and Farhi (2019b). Herskovic et al. (2020) show that production network effects are also essential to explaining the empirical firm size and firm sales volatility distributions. Existing empirical studies primarily focus on first-moment supply-side shocks, exploiting natural-disaster-driven supply chain disruptions.[5] Barattieri et al. (2023) study the network transmission of sectoral public procurement spending. We contribute to this literature empirically and theoretically by studying the network transmission of second-moment shocks.

Our results show that network propagation has first-order implications for price dynamics during periods of heightened uncertainty. In this respect, our analysis also relates to previous findings about the impact of aggregate uncertainty on inflation. While linear VAR-based estimates typically find that aggregate uncertainty shocks are deflationary (e.g., Leduc and Liu, 2016), recent empirical work documents that uncertainty shocks are inflationary in normal or expansionary periods (e.g., Caggiano et al., 2022; Andreasen et al., 2024).

Finally, our paper relates to the literature that uses option data to measure uncertainty and its macroeconomic implications. Building on Bloom (2009), many studies rely on aggregate measures such as the VIX to capture time-varying uncertainty, typically focusing on its one-month horizon. However, recent work by Krogh and Pellegrino (2025) shows that short- and long-term components of uncertainty–extracted from the VIX term structure–have distinct macroeconomic implications. Dew-Becker and Giglio (2023) construct cross-sectional measures of idiosyncratic uncertainty from firm-level options, while Alfaro et al. (2023) use firm-level implied volatility to study the role of financial frictions in amplifying the impact of uncertainty shocks. We are the first to exploit option-implied volatility to measure industry-level uncertainty and study its propagation across the supply chain.

[5] Barrot and Sauvagnat (2016) identify downstream effects following various disaster events in the U.S., while Boehm et al. (2019) document large output losses in the U.S. subsidiaries of Japanese multinationals after the 2011 earthquake in Japan. Carvalho et al. (2020) also examine this event, utilizing detailed firm-to-firm network data from Japanese companies to highlight downstream and upstream propagation. Barattieri and Cacciatore (2023) study the network propagation of tariffs.

2 Data and Identification of Uncertainty Shocks

The first part of the analysis involves constructing industry-level measures of uncertainty using options data and identifying suitable variation to estimate its production network effects. In this section, we describe the data that we use and our empirical strategy to identify such variation in uncertainty.

2.1 Data

Stock market data. We obtain stock options data from OptionMetrics (OM), a comprehensive database containing millions of historical option prices, underlying security information, and implied volatilities. Implied volatility in OM is calculated using the Black and Scholes (1973) formula. Computing implied volatility only requires observing a single option price instead of multiple puts and calls over a wide range of strike prices (such as the calculation of the VIX requires). It is the only feasible measure of conditional volatility for individual stock options as their trading volume is significantly smaller than the trading volume of options on stock indices. In practice, the implied volatility of the stock market is 99.5% correlated with the VIX.

We extract implied volatilities for all the option-issuing firms listed in the NYSE / AMEX / NASDAQ exchanges. We focus on daily at-the-money implied volatilities for all stock options with a 30-day maturity of firms. 30-day options are the most liquid and share the same time horizon as the VIX.

Focusing on implied volatility offers several advantages for our analysis. First, because it is constructed from market prices, our measure is forward-looking and available at high frequency, which is essential to study the dynamic effect of uncertainty on real outcomes. Second, option data provide extensive granular sectoral coverage, which is necessary to measure cross-industry spillovers accurately. Third, it reflects investors' beliefs about future uncertainty because it is based on actual investment decisions.

We match these option data with Compustat / CRSP to assign firm identity, market capitalization, stock prices, and industry code (NAICS). Whenever the NAICS code assigned by Compustat is missing, we assign a NAICS code by using SIC-NAICS concordance tables. After merging the datasets, we have almost 14 million daily observations for 6,345 firms.

Our analysis focuses on issuers whose options have been traded for at least ten years. To ensure that sectoral uncertainty derived from option data is economically meaningful, we restrict the sample to industries in which the market capitalization of option issuers represents at least 20% of the market capitalization of all publicly listed firms in each NAICS 4-digit industry code. On average, option issuers account for at least 20% total employment in each industry.[6] This approach allows us to construct implied volatility measures for 244 industries.

Additional data. We collect NAICS 4-digit industry-level monthly data on U.S. employment and prices from the Bureau of Labor Statistics (BLS). From the 2007 Use and Make Tables from the BEA, we construct a total requirement input-output table, accounting for direct and indirect sectoral linkages. Finally, we use annual Compustat firm-level sales data and sectoral output data from the BEA to measure the sectoral representativeness of the option issuers underlying our uncertainty measures. Using concordance tables, we convert all BEA industry classifications to the NAICS 4-digit level. We convert NAICS 4-digit industry codes that do not belong to the Census 2007 classification (e.g., 2002, 2012, etc.) to the corresponding 2007 codes.

2.2 Measuring Uncertainty

We first construct a daily measure of sector-level implied volatility. The baseline measure is a weighted average of daily firm-level implied volatility, $IV_{f,i,d}$, for all firms belonging to a specific NAICS 4-digit industry:

$$IV_{i,d} = \left(\sum_{f \in i} s_{f,i,d-1} IV_{f,i,d} \right), \tag{1}$$

where d indicate trading days, f indexes firms, i denotes industries. The weight $s_{f,i,d-1}$ represents the average firm's share of industry market capitalization in the previous month; alternatively, we use the firm's share of industry sales in the previous year.

Regardless of the specific weighting scheme, $IV_{i,d}$ captures the common component of implied volatility across firms on a given day, while also accounting for the disproportionate influence of larger firms within the sector. Importantly, this weighted average does not correspond to the implied volatility of a hypothetical NAICS 4-digit representative portfolio. Constructing such a portfolio would require additional assumptions about cross-firm return correlations, which are not necessary for our purposes: our objective is not to approximate the volatility of a replicable asset, but to construct a

[6]Total employment is computed using data for all firms, not just publicly listed ones.

sector-level measure of implied volatility that reflects investor-perceived risk within a given NAICS 4-digit industry. For robustness, we also consider a measure that isolates only the common component of firm-level implied volatility, as detailed below.

Starting from the daily NAICS 4-digit implied volatility, we construct a monthly measure of sectoral implied volatility, denoted $IV_{i,t}$, by averaging the daily values over the last five trading days of each month. As discussed in the next section, using a short time window allows us to better control for realized volatility—which reflects first-moment shocks—as well as for implied volatility in customer and supplier industries. As a robustness check, we also consider an alternative measure based on the average across all trading days in the month.

While implied volatility measures market expectations of future volatility, we also construct monthly measures of realized volatility (RV), capturing the actual asset price fluctuations from realized shocks:

$$RV_{i,t} = \frac{1}{D} \sum_{d \in t} \left(\sum_{f \in i} s_{f,i,d} r_{f,i,d}^2 \right),$$

where $r_{f,i,d}$ denotes the stock return of firm f. Finally, we construct aggregate monthly measures of realized and implied volatility using the monthly average of daily realized volatility of the $S\&P500$ index and the implied volatility of the same index. We denote these two variables by RV_t and IV_t.

2.3 Uncertainty Measures: Properties

We begin by documenting the time-series properties of our newly constructed measures. We first assess how much of the time variation in firm-level implied volatility can be explained by sector-level implied volatility. Intuitively, if idiosyncratic shocks primarily drive firm-level variation, we would expect the sectoral measure to have little explanatory power on average. Panel A of Table 1 shows this is not the case. The panel reports R^2 from time-series firm-level regressions and indicates that, on average, $IV_{i,t}$ explains between 65% and 75% of the variation in firm-level implied volatility when we do not control for aggregate implied volatility, and up to 30% when we do.[7] These findings suggest that $IV_{i,t}$ accounts for a significant share of firm's implied volatility

[7]The significant explanatory power of aggregate implied volatility in these regressions is consistent with the findings of Herskovic et al. (2016), who document that time variation in firm-level volatilities obeys a strong factor structure and that about 35% of it is explained by a single aggregate factor.

Table 1: Properties of Uncertainty Measures

Panel A: Sectoral Component in Firm Implied Volatility				
	No aggregate IV_t control		Aggregate IV_t control	
	Unweighted	Weighted	Unweighted	Weighted
R^2 (industry average)	0.66	0.75	0.25	0.30
Panel B: Time Series Properties				
	Mean	St.Dev.	Autocorr.	Skewness
Sectoral	0.43	0.15	0.80	1.56
	(0.28, 0.58)	(0.09, 0.23)	(0.68, 0.90)	(0.73, 2.49)
Aggregate	0.18	0.07	0.85	1.79

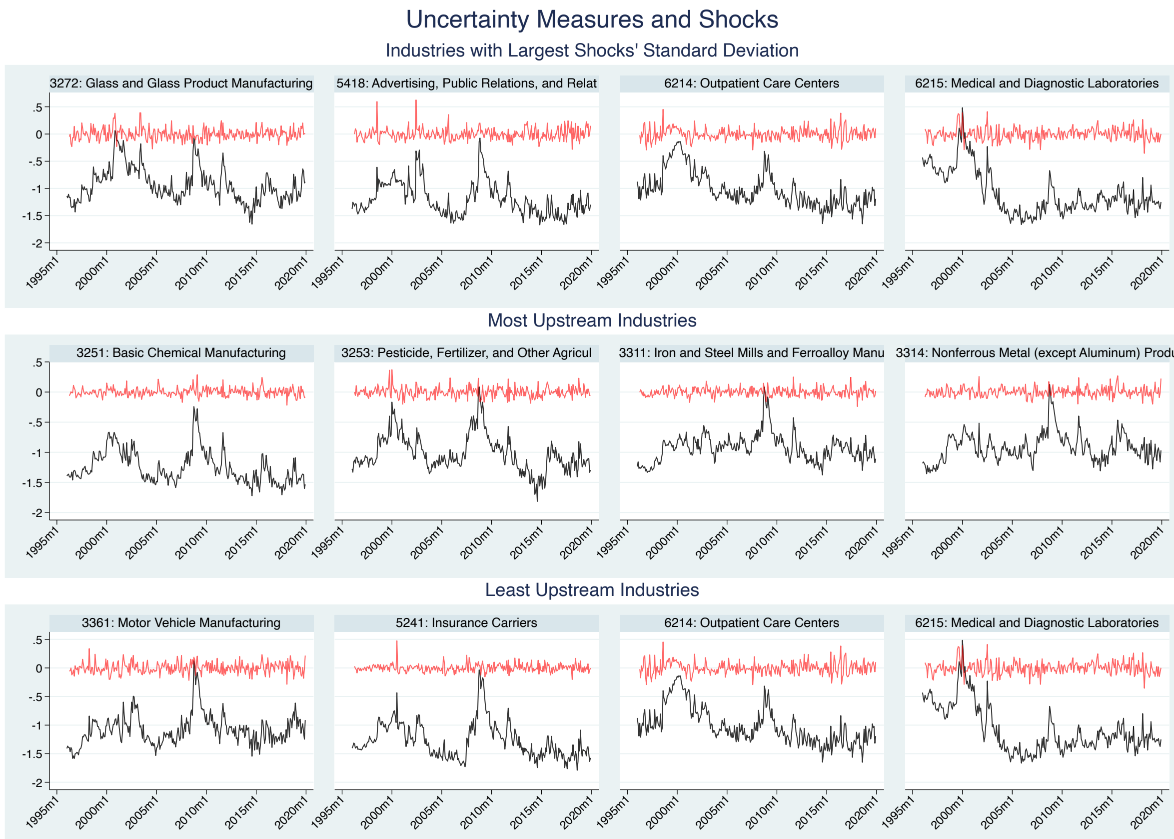
Notes: The first two columns in Panel A present average R^2 coefficients from the monthly firm-level regressions: $IV_{f,i,t} = \alpha_f + \beta_{f,i} IV_{i,t} + \epsilon_{f,i,t}$, where $IV_{f,i,t}$ is the daily firm f's implied volatility averaged over the last 5 trading days of each month, and $IV_{i,t}$ is the corresponding industry-level measure defined in the text. In the first column, for each industry, we compute the unweighted average of the R^2 values across firms and then report the average across industries. In the second column, for each industry, we weigh the R^2 of each firm by the firm's average market capitalization share. The third and fourth columns are constructed analogously but report partial R^2 coefficients attributable to $IV_{i,t}$ from the underlying regressions: $IV_{f,i,t} = \alpha_f + \beta_{f,i} IV_{i,t} + \gamma_{f,i} IV_t + \epsilon_{f,i,t}$. Panel B reports summary statistics for the sectoral ($IV_{i,t}$) and aggregate (IV_t) measures in standard deviation units. 10th and 90th percentiles of the corresponding statistics for $IV_{i,t}$ in parentheses.

within a NAICS4-digit industry.

In Panel B, we examine further time series properties of the measures. Several important features stand out. First, sectoral implied volatility is higher on average than aggregate implied volatility, as measured by the implied volatility of the index of the entire stock market. The mean of $IV_{i,t}$ for the average industry is twice as large as that of IV_t and 1.5 (3.2) times as large when considering the 10th (90th) percentile of the industry distribution. Second, the standard deviation of sectoral implied volatility is approximately twice that of aggregate implied volatility. Third, both aggregate and sectoral implied volatility exhibit similar persistence, with autocorrelation coefficients of 0.85 and 0.80, respectively, for the average industry. Finally, implied volatility at the sectoral and aggregate levels has high positive skewness. Given this high skewness and following common practices in the literature, in the remainder of the article, we focus on the log square root of option-implied and realized volatility ($\sigma_{i,t} = \ln \sqrt{IV_{i,t}}$ and $rv_{i,t} = \ln \sqrt{RV_{i,t}}$). We refer to $\sigma_{i,t}$ as sectoral uncertainty.

Figure 1 shows in black sectoral uncertainty, $\sigma_{i,t}$, for a selection of industries. To conserve space, we focus on NAICS 4-digit industries with the largest share of aggre-

Figure 1: Sectoral Uncertainty and Uncertainty Shocks

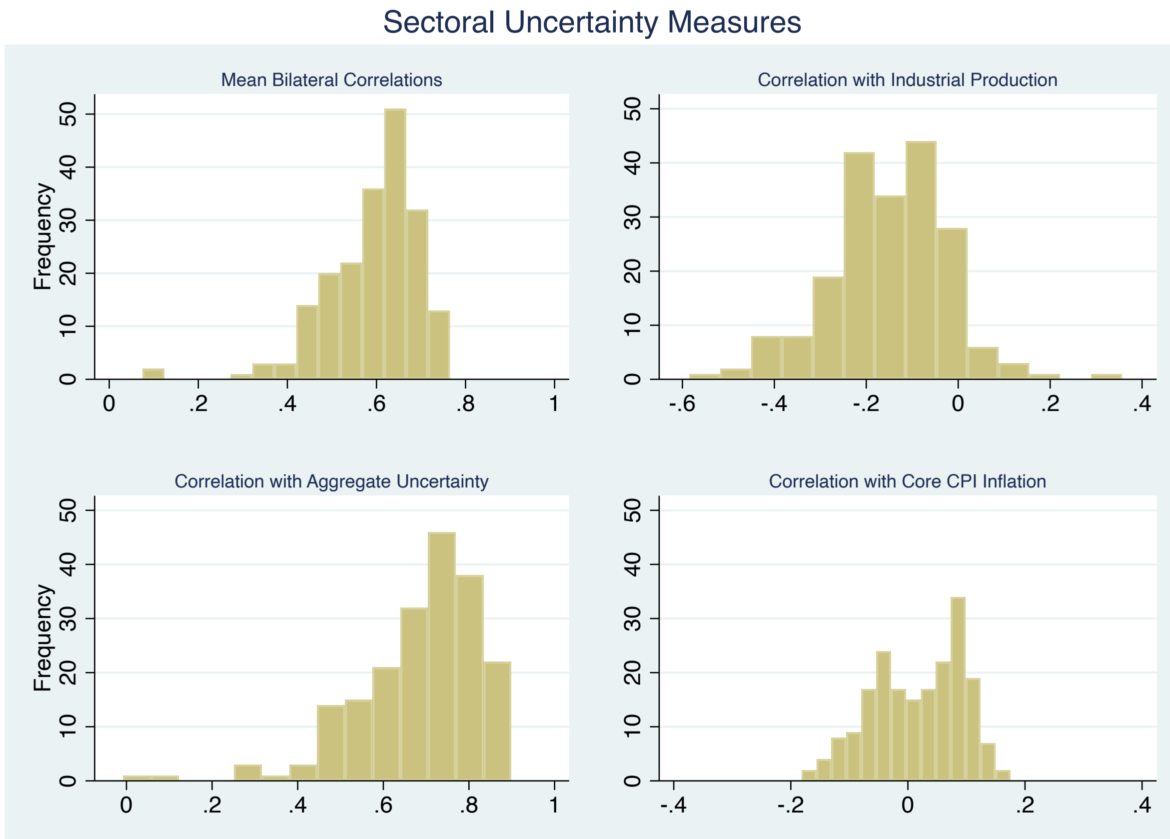


Note: Sectoral uncertainty $\sigma_{i,t}$ (black) and estimated uncertainty shocks $\hat{\nu}_{i,t}$(red).

gate output and where option-issuing firms' sales account for at least 30% of industry output. Among these industries, the continuous black line in the top row of Figure 1 plots uncertainty for the five industries experiencing the largest uncertainty shocks, as measured by their standard deviation. The discussion of uncertainty shock identification is deferred to the next section. The second and third rows show the most and least upstream industries within the same set. We measure upstreamness using the index constructed by Antràs and Chor (2013), which captures the extent to which a sector primarily sells to other industries rather than directly to final consumers.[8] The figure confirms the substantial time variation and persistence in these time series documented above. Some of this variation appears to be common across many series, particularly

[8]An upstream sector is one that sells a small share of its output to final consumers and instead supplies disproportionately to other sectors that themselves engage in limited direct sales to final consumers.

Figure 2: Cyclical Properties of Uncertainty Measures



Note: The first panel shows the distribution of the average correlation between $\sigma_{i,t}$ and $\sigma_{j\neq i,t}$. The second panel plots the distribution of the correlations between $\sigma_{i,t}$ and monthly industrial production HP filtered using a smoothing parameter of 129,600. Analogously, the third and fourth panel depict the distribution of correlations with monthly aggregate uncertainty σ_t and monthly core CPI inflation.

around the Great Recession. However, the series also exhibit numerous idiosyncratic spikes. The first panel of Figure 2, which plots the distribution of the average bilateral correlations of $\sigma_{i,t}$ with $\sigma_{j,t}$ with $j \neq i$, suggests that this pattern holds more generally in our data. Indeed, the average bilateral correlation between uncertainty in a given industry and that in other industries never exceeds 0.8.

The other panels of Figure 2 document additional cyclical properties of sectoral uncertainty. Panels 2 to 4 plot the distribution of correlations between sectoral uncertainty and industrial production (HP-filtered), aggregate uncertainty, and core CPI inflation. The majority of sectoral measures of uncertainty display a negative correlation with the cyclical component of aggregate activity. However, there is substantial heterogeneity in the degree of countercyclicality, as well as some exceptions: uncertainty for a few sectors is mildly procyclical. Moreover, sectoral uncertainty is positively correlated with aggregate uncertainty for all industries, albeit to varying degrees. This is consistent with the well-known fact that aggregate uncertainty is countercyclical (e.g., Jurado et al., 2015): in our sample, the contemporaneous correlation between aggregate uncertainty and industrial production is -0.22. Finally, there is no systematic relationship between sectoral uncertainty and inflation: for 32% of the sectors in our sample, uncertainty comoves negatively with inflation, while for 68% of sectors this comovement is positive. For comparison, the correlation between aggregate uncertainty and inflation is virtually zero (-0.0660 in our sample).

2.4 Identification of Uncertainty Shocks

There are three main challenges to identifying industry-level uncertainty variation suitable for estimating production network transmission. First, implied volatility is endogenous because it can fluctuate in response to first-moment shocks, whether sector-specific or aggregate. For instance, a sharp increase in commodity prices may raise uncertainty in energy-intensive industries. While higher uncertainty affects firms' decisions, the direct impact of rising input costs influences output and employment for a given level of uncertainty. A key econometric challenge lies in disentangling the effects of higher volatility from those of the first-moment shock. Second, sectoral uncertainty may reflect changes in uncertainty originating in supplier and customer industries. Third, industry-level uncertainty may respond to aggregate uncertainty.

We address these issues by purging our uncertainty measures of likely endogenous variation arising from the aforementioned sources. To do this, we estimate the following monthly, industry-level time series regressions using the log square root of sectoral implied volatility, $\sigma_{i,t}$:

$$\sigma_{i,t} = \alpha_i + \sum_{\kappa=1}^{p_\sigma} \varphi_i^\kappa \sigma_{i,t-\kappa} + \sum_{\kappa=0}^{p_\sigma} \psi_{\sigma_i}^\kappa \sigma_{t-\kappa} + \sum_{\kappa=0}^{p_{RV}} \psi_{RV_i}^\kappa rv_{t-\kappa} + \sum_{\kappa=0}^{p} \mathbf{\Psi}_i^\kappa \mathbf{Z}_{i,t-\kappa} + \nu_{i,t}, \tag{2}$$

where $\mathbf{Z}_{i,t-\kappa}$ are additional contemporaneous and lagged sector-specific controls described below, and the left-hand side uncertainty measure is constructed by averaging daily sectoral implied volatility using the last five trading days of the month. The identified shocks correspond to the residuals of these industry-level regressions, $\nu_{i,t}$.

The rationale for the first-stage regression is as follows. First, following the argument in Berger et al. (2019), we assume that first-moment shocks can affect contemporaneously realized volatility while, on average, uncertainty shocks do not immediately cause changes in realized volatility. The reason is that both positive and negative changes in uncertainty result in positive squared returns. Thus, on average, the impact effect of uncertainty shocks on realized volatility is nearly zero. Following this rationale, we control for contemporaneous and lagged realized volatility at the aggregate level ($rv_{t-\kappa}$), industry level ($rv_{i,t-\kappa}$), and in industries that are upstream and downstream relative to industry i ($rv^U_{i,t-\kappa}$ and $rv^D_{i,t-\kappa}$, included in $\mathbf{Z}_{i,t-\kappa}$ and defined just below).[9] These controls purge the effects of current and past first-moment shocks that occur in industry i itself, at the aggregate level, and in its suppliers and customer industries.

Second, the availability of daily data allows us to control for within-month implied volatility originating from upstream suppliers and downstream customers. We construct these measures using the first sixteen trading days of each month to ensure they capture information that does not overlap with the left-hand side variable. Following Acemoglu et al. (2016), supplier uncertainty for industry i is defined by:

$$\sigma^U_{i,t} = \sum_k \omega_{k,i}\sigma_{k,t}, \tag{3}$$

where $\omega_{k,i}$ represents the fraction of i's output sourced from the k-th intermediate in its Leontief Inverse. Customer uncertainty for industry i is defined by:

$$\sigma^D_{i,t} = \sum_k \tilde{\omega}_{i,k}\sigma_{k,t}, \tag{4}$$

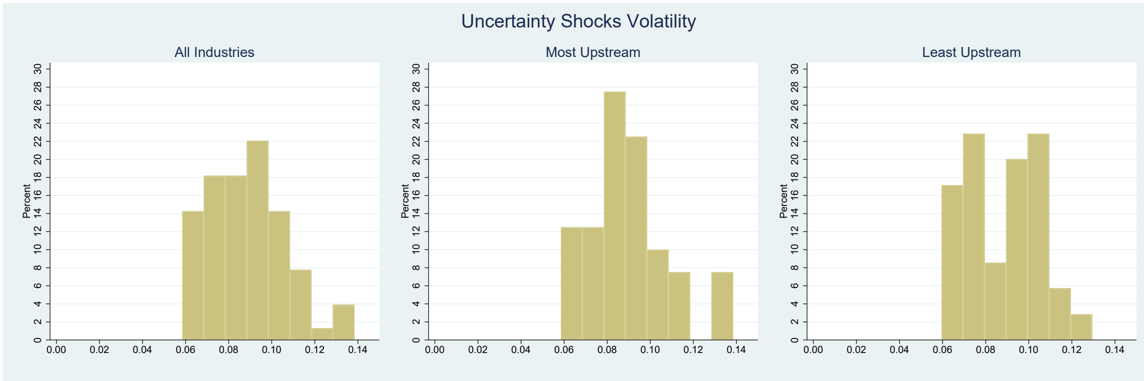
where $\tilde{\omega}_{i,k}$ represents the fraction of i's output demanded by k-th sector in its Leontief Inverse form. The weights $\tilde{\omega}_{i,k}$ and $\omega_{k,i}$ are derived from the 2007 total-requirement input-output table.[10] We include both measures in $\mathbf{Z}_{i,t-\kappa}$. Supplier and customer realized volatility, $rv^U_{i,t}$ and $rv^D_{i,t}$, analogously to equations (3) and (4).

Finally, we assume that uncertainty in a given sector does not affect aggregate uncertainty, while the opposite is not true. This is motivated by the modest size of a

[9] We include three lags of rv_t and $rv_{i,t}$ and one lag of $rv^U_{i,t}$ and $rv^D_{i,t}$.

[10] We combine the make and use tables to construct an industry-by-industry matrix that details how much of an industry's inputs are produced by other industries.

Figure 3: Distribution of standard deviations of shocks



Note: Distribution of standard deviation of estimated shocks. The left panel is the entire distribution, while the middle (right) panel is the distribution in the first (last) quartile of upstreamness.

NAICS 4-digit sector compared to the aggregate economy.[11] Consequently, we control for current and lagged implied volatility both at the aggregate level ($\sigma_{t-\kappa}$) (3 lags) and in upstream and downstream industries (included in $\mathbf{Z}_{i,t-\kappa}$) (1 lag). Finally, we allow for endogenous persistence in our uncertainty measure and control for 3 lags of $\sigma_{i,t-\kappa}$.

As detailed in section 3.2, we consider different alternative specifications of the first-stage regression for robustness. In particular, we construct monthly uncertainty measures using all trading days of the month (rather than the last five days) or using only option issuers that are always in the sample (rather than those that have been in the sample for at least ten years). We also consider a specification with a more parsimonious set of controls (excluding measures of upstream and downstream uncertainty and realized volatility).

Identified uncertainty shocks. The identified shocks have desirable statistical properties: they are not autocorrelated and display a small cross-industry correlation (0.15 on average). Figure 3 shows the distribution of the industry-level standard deviation of the estimated shocks for all industries and for industries in the top and bottom quartiles of the upstreamness distribution. A comparison of the three panels shows that the distribution of shock sizes is relatively similar upstream and downstream.

Figure 1 plots in red the residuals from our first-stage regression for the industries discussed in the previous section. The shock series displays considerably less volatility

[11]If some sectoral shocks have contemporaneous aggregate effects, controlling for aggregate uncertainty would absorb this component of exogenous sectoral uncertainty variation. In this regard, our approach is conservative, as the residuals may capture only a subset of the true sectoral shock.

than the corresponding measures, as the controls absorb most of the variation in the uncertainty series.

The identified shocks capture unexpected increases in uncertainty that affect multiple firms within a sector or disproportionately impact large firms. To isolate shocks suitable for studying propagation through production networks, we conservatively retain only the component of NAICS 4-digit implied volatility not explained by aggregate or network-wide factors. Nonetheless, the largest shocks in Figure 1 correspond to industry-specific events that plausibly generated heightened uncertainty—such as regulatory interventions, financial restructurings, technological transitions, and trade tensions.

For example, the insurance industry (5241) experiences a sharp spike in October 2004 when, in response to a major antifraud investigation, insurance companies halted contingent commission payments, creating uncertainty about the industry's future profitability. In the outpatient care industry (6214), repeated spikes in 2015 align with the rollout of value-based reimbursement reforms by the Centers for Medicare & Medicaid Services, which required major adjustments in service delivery and financial planning. The 1998 Daimler-Benz–Chrysler merger, one of the largest cross-border industrial mergers at the time, generates a pronounced shock in motor vehicle manufacturing (3361), likely reflecting uncertainty about corporate strategy and employment. Upstream sectors such as ferrous and non-ferrous metals (3311, 3314) show rising uncertainty during the late 2010s, consistent with escalating U.S.–China trade tensions. Finally, the advertising industry (5418) exhibits a sequence of large shocks during the early 2000s, corresponding to major technological disruptions—including the launch of Google AdWords (2000) and the emergence of YouTube (2005)—that upended traditional business models in the industry.

3 Uncertainty Propagation Along The Supply Chain

We use panel local projections to estimate the dynamic industry effects of the identified shocks. Our approach enables us to estimate responses to uncertainty shocks that originate within the same industry, as well as to shocks that originate upstream or downstream in the production network. Let $\ln X_{i,t+h} - \ln X_{i,t-1}$ be the cumulative log difference of X_i between time $t-1$ and $t+h$. We estimate the following set of h-steps ahead predictive panel regressions (Jordà, 2005):

$$\ln X_{i,t+h} - \ln X_{i,t-1} = \alpha_{i,h} + \beta_h^O \hat{v}_{i,t} + \beta_h^D \hat{v}_{i,t}^D + \beta_h^U \hat{v}_{i,t}^U + \omega_{t+h} + \sum_{\kappa=1}^{p_x} \Phi_x^\kappa x_{i,t-\kappa} + \epsilon_{i,t+h}. \quad (5)$$

The outcome variables (X) can be uncertainty, employment, or producer prices in a particular industry. We regress the outcome variable on our estimated shocks in that industry $\hat{v}_{i,t}$ as well as on the shocks of industries that are upstream or downstream relative to the industry in question. These shocks $\hat{v}_{i,t}^U$ and $\hat{v}_{i,t}^D$ are weighted averages of shocks in upstream and downstream industries, with weights that come from the 2007 total requirements table, analogously to how we constructed upstream and downstream uncertainty using equations (4) and (3). The assumption is that an increase in uncertainty in industry k is more important for industry i when the input/output share of sector k in i is higher. The local projections also include a horizon-industry fixed effect, a time fixed effect, and twelve lags of ($x_{i,t-\kappa} \equiv \ln X_{i,t-\kappa} - \ln X_{i,t-\kappa-1}$). We compute 90% confidence intervals for each impulse response by clustering at the NAICS 4-digit industry. industry.

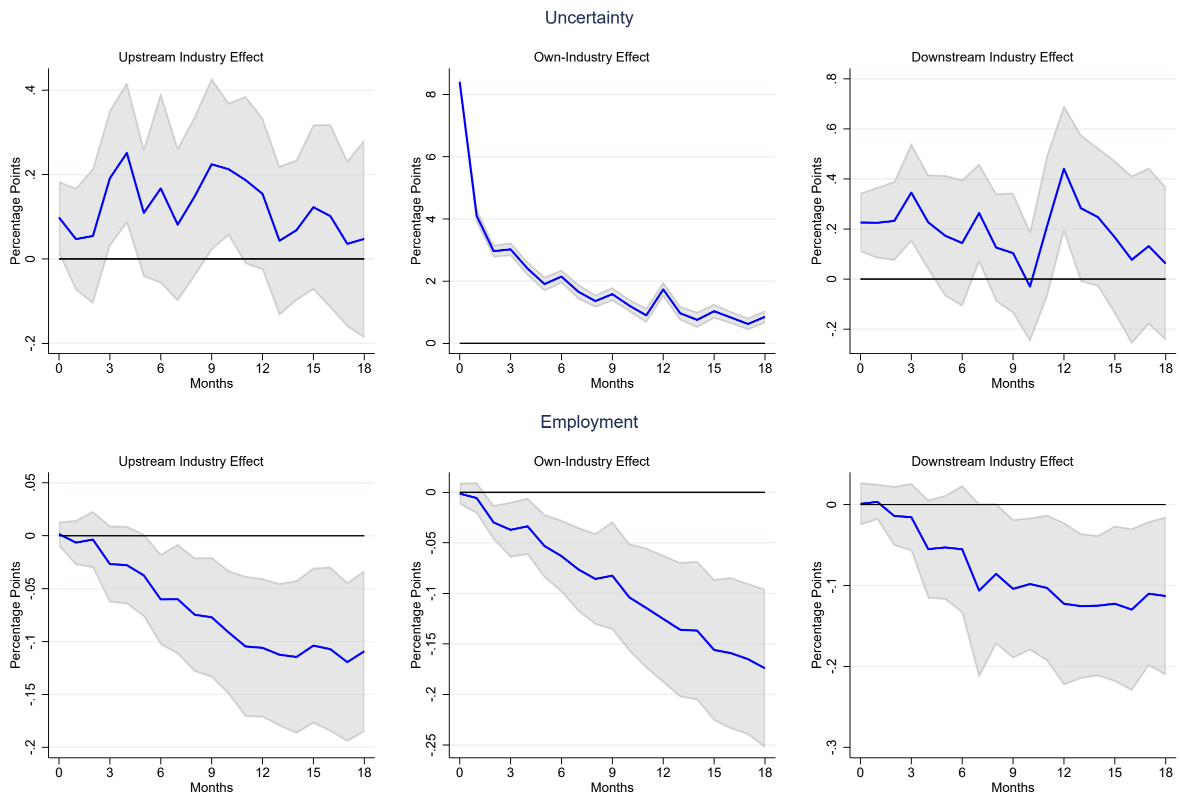
The coefficient β_h^O gives the response of the cumulative log difference of X at time $t+h$ following a shock at time t in that same industry. The network propagation is captured by the coefficients β_h^U and β_h^D, which represent the response of the cumulative log difference of X at time $t+h$ following a shock at time t in upstream or downstream industries, respectively.

3.1 Industry-level Results

We start by analyzing how our measure of uncertainty responds to a positive one-standard-deviation uncertainty shock. The shock corresponds to an 8% increase in industry-level implied volatility. As shown in the first row of Figure 4, an uncertainty shock results in a moderately persistent increase in uncertainty in the industry in which it originates. The uncertainty shock significantly increases uncertainty also in the upstream and downstream sectors, albeit the effect is only significant for a few months.[12] Overall this evidence suggests moderate endogenous transmission of uncertainty across the production network. It follows that the real effects of uncertainty in other industries along the supply chain, if any, are more likely to be driven by first-moment transmission

[12] Note that the magnitude of responses is not directly comparable across the three columns, as each represents the response to a one-standard-deviation innovation in $\hat{v}_{i,t}$, $\hat{v}_{i,t}^D$, and $\hat{v}_{i,t}^U$, respectively, and the standard deviations of these shocks differ.

Figure 4: Responses of Uncertainty and Employment to an Uncertainty Shock



Note: Estimated impulse response functions to one-standard-deviation uncertainty shocks. "Own industry" effect is the effect of a shock originating in that same industry ($\hat{\nu}_{i,t}$). "Upstream effect" refers to the effect of a shock originating in downstream sectors relative to the industry in question ($\hat{\nu}^{D}_{i,t}$). "Downstream effect" refers to the effect of a shock originating in upstream sectors ($\hat{\nu}^{U}_{i,t}$).

(e.g., changes in prices and quantities in the industries facing higher uncertainty).

The second row of Figure 4 plots the employment response to the uncertainty shocks. An uncertainty shock in a given sector triggers a decline in employment in that particular sector, reaching 0.15%. Importantly, the uncertainty shock also reduces employment in upstream and downstream sectors. The decline in upstream employment follows the same timing as in the sector facing higher uncertainty, consistent with the idea that producers simultaneously pause hiring and reduce intermediate input demand. In contrast, the fall in downstream employment occurs with a delay. The delay can, in turn, be rationalized by understanding price dynamics across the network, which we discuss next.

The first row of Figure 5 depicts the response of producer prices to uncertainty

Figure 5: Responses of Prices to an Uncertainty Shock

Note: Estimated impulse response functions to one-standard-deviation uncertainty shocks. "Own industry" effect is the effect of a shock originating in that same industry ($\hat{\nu}_{i,t}$). "Upstream effect" refers to the effect of a shock originating in downstream sectors relative to the industry in question ($\hat{\nu}^{D}_{i,t}$). "Downstream effect" refers to the effect of a shock originating in upstream sectors ($\hat{\nu}^{U}_{i,t}$).

shocks. Starting with the own-industry effect, we note that prices increase significantly and persistently following the increase in uncertainty. We also observe a stronger increase of producer prices in downstream industries and a significant and persistent decline in prices in upstream industries relative to the origin of the uncertainty shock.

Discussion. The impulse responses presented above suggest a significant transmission of uncertainty shocks across the production network. The impact of uncertainty shocks in the industry in which they originate is in line with what the literature has documented for aggregates (e.g. Bloom, 2009). In particular, sectoral uncertainty shocks are contractionary in their own industry, as they reduce employment. At the same time, uncertainty increases producer prices in affected industries. The producer price increase is consistent with precautionary pricing. Intuitively, when firms face nominal price rigidities, an increase in uncertainty means greater incentives to increase prices today to hedge against the risk of future marginal cost increases. This mechanism is a key source of uncertainty propagation in benchmark macroeconomic models with time-varying volatility (see Fernández-Villaverde et al., 2015). The price increase is also consistent with models featuring customer markets and financial frictions, which predict that firms with weaker balance sheets pass on higher financing costs to their customers during periods of heightened uncertainty (e.g., Gilchrist et al., 2017).

Figures 4 and 5 show that uncertainty shocks propagate through the supply chain.

In particular, uncertainty propagates upstream like a negative demand shock, reducing employment and prices in supplier industries. In contrast, uncertainty acts like a negative supply shock for downstream producers, decreasing employment and increasing prices in customer industries. Thus, the implications for price dynamics are asymmetric and depend on the sectoral origins of uncertainty.

Our theoretical contribution in the next section is to show that a New Keynesian production network model can rationalize these empirical findings and explain the upstream and downstream propagation of uncertainty shocks. Central to network transmission is the fact that uncertainty raises prices in the affected industries. As higher prices depress sectoral demand, the industry facing increased uncertainty reduces its demand for intermediate inputs, which in turn lowers employment and prices in supplier industries. Moreover, higher prices in affected industries increase intermediate input and final producer prices in customer industries. Provided that intermediate inputs and employment are complements in production downstream, employment in customer industries also declines.

Before turning to our theoretical analysis, we assess the robustness of these results to various checks and empirically address how the heterogeneous transmission of uncertainty through the production network affects aggregate dynamics.

3.2 Robustness

We assess the robustness of the previous results to alternative methods of constructing NAICS 4-digit implied volatility and to alternative specifications of the first-stage regressions. Concerning the measurement of implied volatility, we first consider using previous-year firm sales relative to industry sales as weights $s_{f,i,d-1}$ to construct daily industry volatility (see equation (1)). Second, we compute NAICS 4-digit implied volatility, $\sigma_{i,t}$, using only the common component of firm-level volatility within a month, $\beta_{i,t}$, estimated from the following fixed-effects regression: $\ln(\sqrt{IV_{f,i,t}}) = \alpha_f + \beta_{i,t} + \varepsilon_{f,i,t}$. Third, we present results using options traded for at least 5 years (instead of 10 years). Finally, we consider a simpler first-stage regression that excludes controls for upstream and downstream implied volatility. In this case, we use all trading days within a month to measure NAICS 4-digit implied volatility, $IV_{i,t}$. Appendix A shows that the results are robust to these alternative specifications.

3.3 Aggregate Implications

The upstream and downstream propagation documented in Section 3.1 raises the question of whether and how network propagation affects aggregate employment and inflation. To address this question, we proceed as follows. First, we construct a time series of aggregate shocks by taking an average of sectoral shocks weighted by the average market capitalization share of each sector:

$$\hat{v}_t^A = \sum_{i=1}^{I} s_{i,t}\hat{v}_{i,t}, \tag{6}$$

where $s_{i,t}$ is industry i market capitalization share at time t. We then estimate aggregate local projections for $h = 1, .., H$:

$$\ln X_{t+h} - \ln X_{t-1} = \gamma_h^A \hat{v}_t^A + \sum_{\kappa=1}^{p} \mathbf{\Phi}_\kappa \mathbf{x}_{t-\kappa} + \epsilon_{t+h}, \tag{7}$$

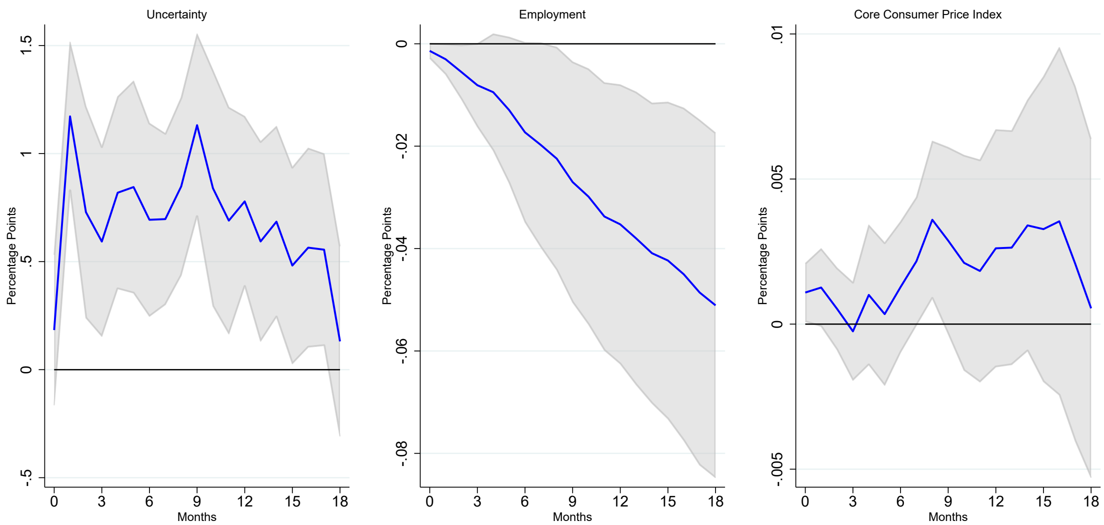
where X is the outcome variable of interest and $\mathbf{x}_{t-\kappa}$ is a vector of aggregate controls that include lags of X, aggregate implied volatility, realized volatility, and the shadow Federal Funds rate of Wu and Xia (2016).[13]

Figure 6 shows the estimated impulse responses for aggregate implied volatility, employment, and core CPI. Aggregate implied volatility exhibits a persistent increase following the shock. In turn, aggregate employment declines persistently. This is consistent with the sectoral results discussed earlier, which show that employment declines not only in the sector where the shock originates but also in upstream and downstream industries.

Figure 6 also shows that the core CPI does not respond significantly, although the point estimates are consistently positive over the considered horizon. To interpret this result, recall that sectoral uncertainty shocks tend to have inflationary effects in the originating and downstream sectors, while exerting deflationary pressure on upstream suppliers. Importantly, the aggregate response does not simply reflect the sum of industry–level effects. General equilibrium forces—such as the response of aggregate demand–also play a role in determining aggregate inflation, as further illustrated by the general equilibrium model presented in the next section.

[13]We include twelve lags of the control variables, except for the shadow rate, for which we include six lags.

Figure 6: Impulse Responses of Aggregate Variables



Note: Estimated impulse response functions of aggregate variables to a one-standard-deviation uncertainty shock $\hat{\nu}_t^A$.

Given the heterogenous sectoral response of producer price inflation previously documented, it is natural to ask whether shocks originating more upstream have different implications for aggregate inflation than those originating downstream. To answer this question, we re-estimate the local projections in equation (7) but consider only shocks from the top or bottom decile of the upstreamness distribution. In other words, in these regressions, we replaced the shock series $\hat{\nu}_t^A$ with:

$$\hat{\nu}_t^{A,top} = \sum_{i=1}^{I} s_{i,t} \hat{\nu}_{i,t} \mathbb{1}[i \in \text{top upstream decile}], \tag{8}$$

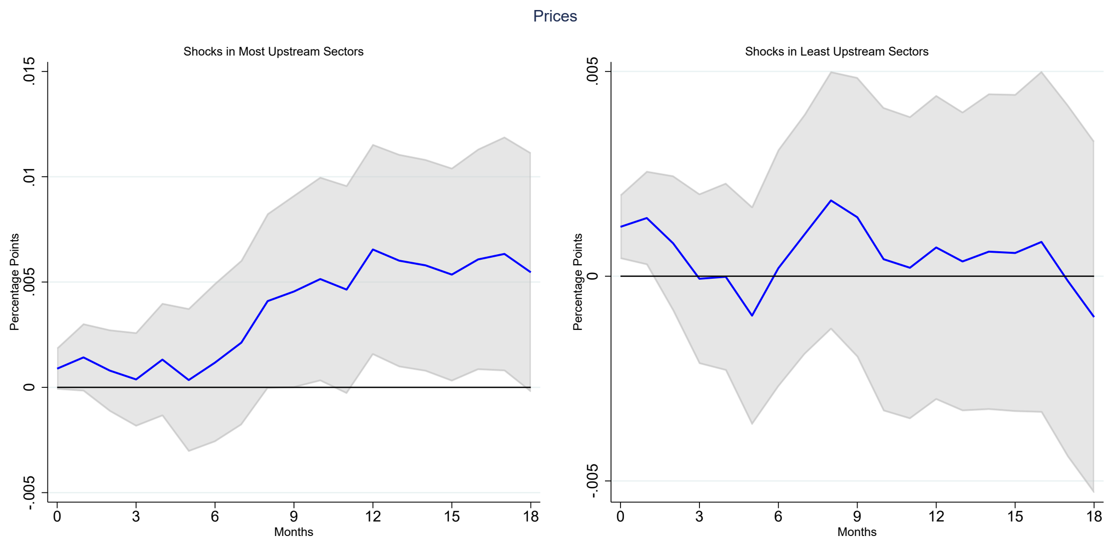
or

$$\hat{\nu}_t^{A,bottom} = \sum_{i=1}^{I} s_{i,t} \hat{\nu}_{i,t} \mathbb{1}[i \in \text{bottom upstream decile}], \tag{9}$$

respectively.

Figure 7 plots the estimated impulse responses from these additional regressions. The first main result is that when shocks originate in the top decile of the upstreamness distribution, core CPI rises significantly for several months starting from a year after the shock. The point estimate of this response is also larger than in the corresponding response in Figure 6, where we were not conditioning on the sectoral origin of the

Figure 7: Response of core CPI - Shocks in Top (left) or Bottom (right) Upstreamness



Note: Estimated impulse response functions of core CPI to a one-standard-deviation uncertainty shock $\hat{v}_t^{A,top}$ (left) and $\hat{v}_t^{A,bottom}$ (right).

shock. This result is consistent with the notion that when shocks originate upstream, aggregate CPI reflects primarely the inflationary effect of the uncertainty shock on the industry of origin and downstream sectors. The second main result is that when shocks originate in the bottom decile of the upstreamness distribution, core CPI does not respond significantly and follows a pattern more similar to the inflation pattern observed when we do not condition on the origin of the shock. This behavior may partly reflect the offsetting effects of a sectoral uncertainty shock on the industry of origin (positive) and its suppliers (negative).

Overall, these results demonstrate that the origin of uncertainty shocks has a significant impact on network propagation and aggregate dynamics.

4 Theoretical Insights

The empirical results from the previous section suggest that uncertainty shocks propagate to the supplier and customer industries by affecting the relative price and demand of intermediate inputs. To understand the mechanisms behind network transmission, we now develop a multi-sector model with input-output linkages and sector-specific time-varying volatility. The model rationalizes the empirical findings and illustrates the economic forces driving the propagation of sectoral uncertainty along the supply chain and at the aggregate level.

We use a minimal set of ingredients necessary to study the network propagation of uncertainty shocks. Building on recent literature (e.g., Bouakez et al., 2023), we develop a model with three key features: (i) nominal price rigidities, (ii) empirically plausible complementarity between labor and intermediate inputs in production, and (iii) imperfect sectoral labor mobility. To this relatively standard set of ingredients, we add sector-specific time-varying uncertainty. The baseline version of the model considers sector-specific productivity uncertainty. Appendix D demonstrates that the same intuition applies and that the results remain robust when considering demand-driven uncertainty. We illustrate the main results using a three-sector, linear network economy. As detailed below, the findings remain similar when considering a a non-linear production network calibrated to U.S. data. Saijo (2025) studies a related multisector model featuring sector-specific productivity uncertainty and capital accumulation, while abstracting from complementarity between labor and intermediates in production.

4.1 A Production Network Model with Sectoral Uncertainty Shocks

Here we describe the key ingredients of the model and refer the reader to Appendix B for further details. The economy is populated by a representative household, producers and wholesalers operating in the S sectors, retailers, and the government.

Household. The representative household chooses aggregate consumption, C_t, and leisure, $(1 - N_t)$, to maximize its expected lifetime utility given by

$$\mathbb{V}_t = \max \left[(1-\beta)(C_t^{\eta_l}(1-N_t)^{1-\eta_l})^{1-1/\psi} + \beta(\mathbb{E}_t \mathbb{V}_{t+1}^{1-\gamma})^{\frac{1-1/\psi}{1-\gamma}} \right]^{\frac{1}{1-1/\psi}}, \tag{10}$$

where β represents the time discount factor. The Epstein-Zin preferences in (10) decouple the intertemporal elasticity of substitution ψ from the risk aversion parameter γ, enabling quantitatively realistic comovements between macroeconomic variables and asset prices. To account for limited labor mobility across sectors, we assume labor is imperfectly substitutable across sectors (e.g., Bouakez et al., 2009). Specifically, labor provided by the household, N_t, is a Cobb-Douglas aggregate of the labor supplied to each sector:

$$N_t = \prod_{s \in S} N_{s,t}^{\omega_{N,s}}, \tag{11}$$

where we denote with $\omega_{N,s}$ the sector shares.

Producers. In each sector, a continuum of unit mass of monopolistically competitive firms, indexed by j, produce differentiated varieties of sectoral goods, $Z^j_{s,t}$, by combining labor and intermediate inputs in the following production function:

$$Z^j_{s,t} = \left[\alpha_s^{\frac{1}{\vartheta_s}} (A_{s,t} N^j_{s,t})^{\frac{\vartheta_s - 1}{\vartheta_s}} + (1 - \alpha_s)^{\frac{1}{\vartheta_s}} (H^j_{s,t})^{\frac{\vartheta_s - 1}{\vartheta_s}} \right]^{\frac{\vartheta_s}{\vartheta_s - 1}}, \tag{12}$$

where $N^j_{s,t}$ and $H^j_{s,t}$ denote labor and the intermediate input bundle used in sector s by producer j, and $A_{s,t}$ denotes sector s productivity. The parameter ϑ_s is the sector-specific elasticity of substitution between inputs, while α_s is the factor share. The producers in sector s hire labor and buy intermediate inputs at prices at prices $W_{s,t}$ and $P^H_{s,t}$, respectively.

Producers face Calvo-style price-setting frictions that result in price stickiness. These frictions introduce forward-looking behavior into the otherwise static producer problem, making them essential for capturing the real effects of uncertainty shocks. The probability of not changing prices in sector s is denoted by ϕ_s.

Wholesalers. Producers sell differentiated varieties to perfectly competitive wholesalers, who bundle them into a single final sectoral good, $Z_{s,t}$, using a CES production technology with elasticity of substitution ϵ:

$$Z_{s,t} = \left[\int_0^1 (Z^j_{s,t})^{\frac{\epsilon_s - 1}{\epsilon_s}} dj \right]^{\frac{\epsilon_s}{\epsilon_s - 1}}. \tag{13}$$

Wholesalers sell goods to perfectly competitive retailers, who assemble sectoral goods into bundles destined for consumption or intermediate input use. Consequently, the resource constraint for sector s is given by:

$$Z_{s,t} = C_{s,t} + \sum_{x=1}^{S} H_{x,s,t}, \tag{14}$$

where $H_{x,s,t}$ denotes the demand from retailers producing the intermediate-good bundle used by sector x, and $C_{s,t}$ represents the demand from consumption-good retailers.

Retailers. Perfectly competitive consumption-good retailers aggregate sectoral goods to produce C_t using a Cobb-Douglas production function:

$$C_t = \prod_{s \in S} C_{s,t}^{\omega_{c,s}}, \tag{15}$$

where $\omega_{c,s}$ denotes the sectoral share of good s, with $\sum_{s \in S} \omega_{c,s} = 1$.

Similarly, in each sector s, intermediate-good retailers combine sectoral intermediate inputs from the different x-sectors $H_{s,x,t}$ into an intermediate input bundle $H_{s,t}$ using a Cobb-Douglas aggregator:

$$H_{s,t} = \prod_{x=1}^{S} H_{s,x,t}^{\omega_{h,s,x}}. \tag{16}$$

The shares in the aggregator are sector-specific and denoted by $\omega_{H,s,x}$.

Government. The government consists of a monetary authority that follows a Taylor rule of the type:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_i} \left(\frac{\Pi_t}{\Pi}\right)^{(1-\rho_i)\psi_\pi}, \tag{17}$$

where i_t denotes the nominal interest rate and π_t is nominal consumer-price inflation.

Exogenous Processes. The economy is buffeted by sectoral first- and second-moment productivity shocks that follow the processes:

$$\log A_{s,t} = (1 - \rho_a) \log A_s + \rho_a \log A_{s,t-1} + \sigma^a_{s,t-1} \varepsilon^a_{s,t}, \tag{18}$$

$$\sigma^a_{s,t} = (1 - \rho_{\sigma_a}) \log \sigma^a + \rho_{\sigma_a} \log \sigma^s_{s,t-1} + \sigma_{\sigma_a} \varepsilon^\sigma_{s,t}, \tag{19}$$

where $\varepsilon^{a}_{s,t} \sim \mathcal{N}(0,1)$ is a first-moment shock that captures innovations to the level of the stochastic process for sectoral technology. We refer to $\varepsilon^{\sigma}_{s,t} \sim \mathcal{N}(0,1)$ a second-moment or uncertainty shock that captures innovations to the volatility of the stochastic process for sectoral technology.[14]

Conditional Sectoral Volatility To construct a model-based counterpart to the empirical measures of implied volatility studied in the first part of the paper, we define aggregate and sectoral conditional volatility of returns within our framework. Building on Basu and Bundick (2017), we define sectoral conditional volatility as the expected conditional volatility of the return on a claim to wholesale producers' cash flows, D^E_t:

$$D^E_{s,t} = P_{s,t}Y_{s,t} - W_{s,t}N_{s,t} - P^H_{s,t}H_{s,t}, \tag{20}$$

$$R^E_{s,t+1} = \frac{D^E_{s,t+1} + P^E_{s,t+1}}{P^E_{s,t}}, \tag{21}$$

$$V^E_{s,t} = 100 \times \sqrt{4 * VAR_t(R^E_{s,t+1})}. \tag{22}$$

Above, $R^E_{s,t+1}$ denotes the return and $V^E_{s,t}$ its conditional volatility. The measure of aggregate conditional volatility is analogously defined over the cashflows $D_t = \sum_{s\in S} D^E_{s,t}$. We assume that these equity claims are traded and held in equilibrium by the representative household. The following Euler equation determines the pricing of these claims:

$$E_t[M_{t+1}\xi_{t+1}R^E_{s,t+1}] = 1, \tag{23}$$

where M_{t+1} is the household's stochastic discount factor. ξ_{t+1} represents a financial shock that introduces realistic conditional returns' volatility $\mathbb{E}[V^E_{s,t}]$ in the stochastic steady state of the model despite the absence of capital and leverage. Since the Modigliani and Miller (1958) theorem holds, this shock only affects asset prices but not macroeconomic dynamics. Yet, its presence allows us to obtain a response of conditional returns' volatility to an uncertainty shock that aligns with the empirical evidence of section 3.1. We model ξ_t as an autoregressive process of order 1 with persistence ρ_ξ and standard deviation σ_ξ.

[14] We assume that sector-specific volatility is exogenous since the estimated response of upstream and downstream implied volatility is relatively small compared to the size of the average shock. Modelling the correlation of sectoral uncertainty across sectors would not alter any of the main results; it would strengthen the role of precautionary pricing in network transmission.

Solution Method. Since we focus on the dynamic effect of uncertainty shocks, we solve the model using a third-order approximation of the policy function of the model around the steady state. We compute impulse responses by comparing the path of the economy over $5,000$ periods in which the realizations of all shocks are zero to the alternative path in which a single one-standard-deviation shock to $\sigma^a_{s,t}$ is realized in period $4,500$.

4.2 Calibration

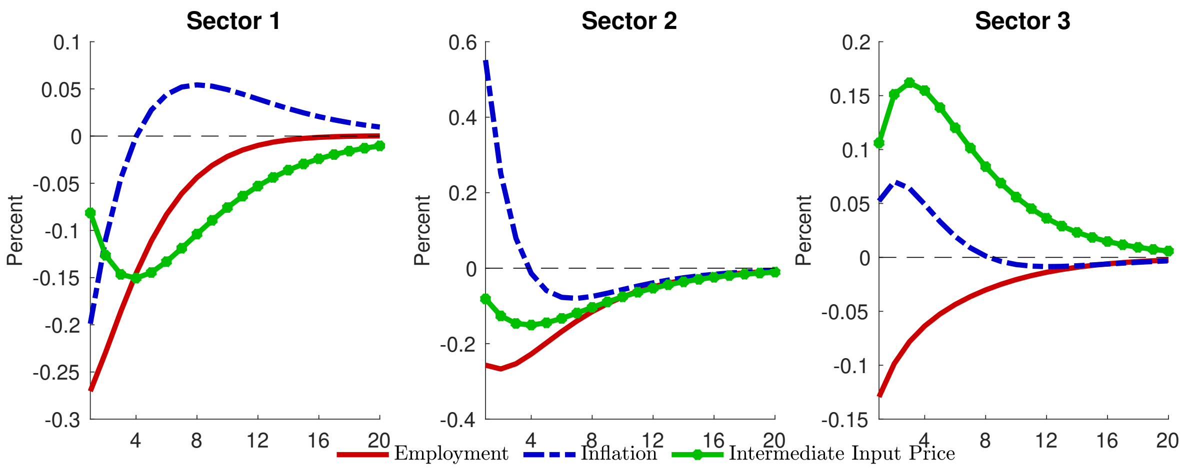
We consider a monthly calibration of the model. To illustrate the main intuitions transparently, we first focus on a linear production network such that $\omega_{H,1,1} = 1$, $\omega_{H,2,1} = 1$, and $\omega_{H,3,2} = 1$. Thus, each sector uses as intermediate inputs only output produced from sectors that are immediately upstream (in practice, sector 3 uses inputs from sector 2, and sector 2 uses inputs from sector 1). We also assume symmetric price stickiness and consumption shares across sectors. In the next subsection, we extend the analysis to an empirically calibrated production network, also incorporating sectoral heterogeneity in price stickiness and consumption shares.

We set $\beta = 0.9967$ corresponding to a steady-state annual real interest rate of 4%. We fix the intertemporal elasticity of substitution to 2 and follow Basu and Bundick (2017) in setting the risk aversion parameter γ to 80. The value of η_l to chosen to obtain a Frisch elasticity of labor supply of 2.25. The elasticity of substitution across different product varieties in a sector, ϵ, is set to 6, which implies a steady-state markup of 33%. The Taylor rule parameters take standard values: the smoothing coefficient is $\rho_i = 0.80$, and the reaction coefficient to inflation is $\psi_\pi = 1.5$. We calibrate the production function parameter α_s to 0.4, close to the average of the sectoral employees' compensation share in value added. We set the elasticity of substitution between intermediate goods and labor, ϑ, to 0.5, which is in the range of empirical estimates (see discussion in Atalay, 2017). For robustness, we will consider setting $\vartheta = 1$, which corresponds to a Cobb-Douglas production function. When considering a symmetric degree of price stickiness across sectors, we set $\phi_s = \phi = 0.7$. We divide the economy into three broad sectors ($S = 3$) and set the consumption weights such that $\omega_{C,1} = \omega_{C,2} = 0.3$.

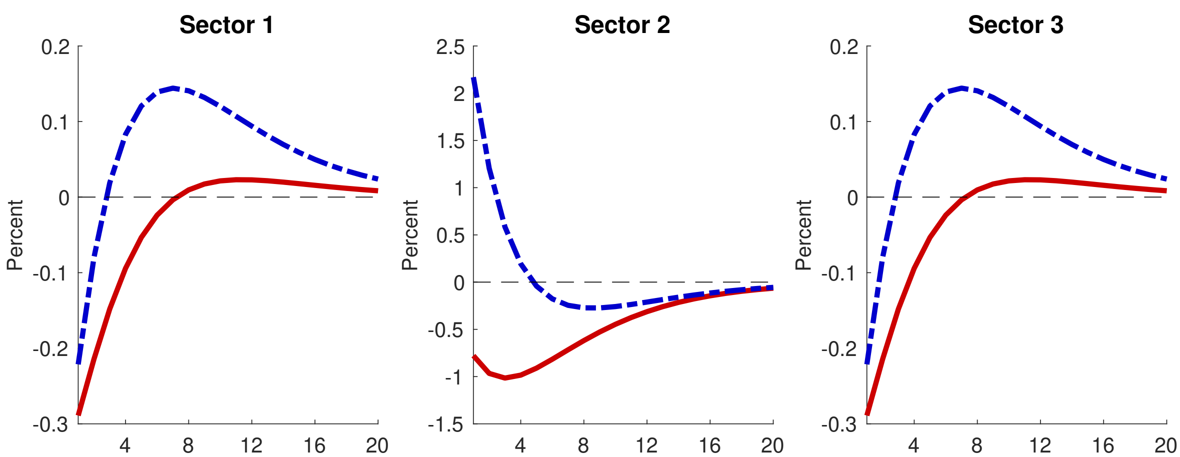
We set the persistence and steady-state standard deviation of sectoral productivity shocks at conventional values: $\rho_a = 0.95$ and $\sigma^a = 0.007$. We calibrate the persistence and standard deviation of the sectoral uncertainty shock, $\sigma^a_{s,t}$, to match the sectoral

Figure 8: Impulse Responses to Sector 2 Uncertainty Shock

(a) Baseline Network



(b) No Network



Note: Model sectoral impulse response functions to a one-standard-deviation sectoral uncertainty shock in sector 2 ($\varepsilon^{\sigma}_{2,t}$).

employment response relative to conditional returns' volatility in sector 2. This requires setting $\rho_{\sigma^a} = 0.80$ and $\sigma_{\sigma_a} = 0.40$. To match the absolute response of conditional returns' volatility, we set $\rho_{\xi} = 0.90$ and its standard deviation $\sigma_{\xi} = 0.0025$.

4.3 Propagation of uncertainty shocks

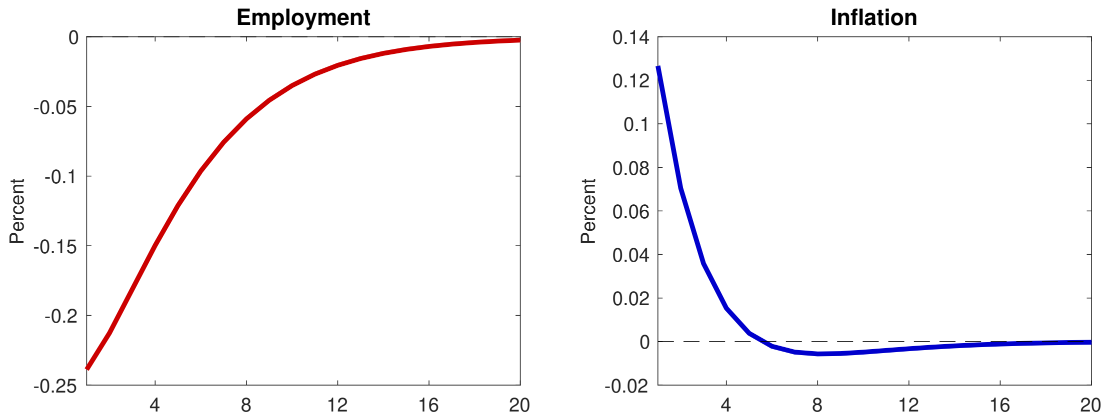
Figure 8a presents impulse responses to a one-standard-deviation sectoral uncertainty shock in the linear network economy. We shock sector 2 so that we can easily see the effects on the sector where the shock originates but also in sectors upstream (sector 1) and downstream (sector 3). To understand how the production network propagates uncertainty shocks, Figure 8b considers instead an economy in which there are no network linkages, i.e., every sector uses only output from its own sector as intermediate inputs ($\omega_{H,1,1} = 1$, $\omega_{H,2,2} = 1$, and $\omega_{H,3,3} = 1$).

To build intuition, consider first the no-network economy. Figure 8b shows that a sectoral uncertainty shock leads to a persistent decline in employment and output, alongside a rise in inflation within the affected sector. These own-sector responses reflect a precautionary pricing motive arising from Calvo-style pricing frictions (as in Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015). Specifically, when uncertainty about future marginal costs increases, firms raise prices (i.e., increase markups) to self-insure against being locked into prices that may prove too low. This rise in markups reduces demand and production, resulting in lower employment and higher inflation in the shocked sector.

Despite the absence of sectoral production linkages, general equilibrium effects propagate the uncertainty shock to other sectors of the economy. However, the resulting comovement in sectoral prices is inconsistent with the empirical evidence. The shock induces households to increase precautionary savings, which reduces final consumption demand and generates deflationary pressure in both upstream and downstream sectors. Additionally, aggregate labor supply rises due to precautionary motives, as discussed in Basu and Bundick (2017). In equilibrium, the aggregate demand channel dominates, leading to declines in employment and output across all sectors.

Moving to the network economy, production linkages add further channels for uncertainty propagation, which ultimately are central to rationalize the price dynamics across sectors documented empirically: the fact that prices decrease upstream and increase downstream in response to higher uncertainty. First, the increase in sector 2 prices due to the precautionary pricing motive, now results in an increase in the marginal cost of sector 3, which uses sector 2's output as an intermediate input. This increase in marginal cost creates inflationary pressure in sector 3. Figure 8b shows that cost pass-through more than offsets the deflationary effect of lower aggregate demand for downstream goods. As shown in Appendix D, this result obtains also when considering a non-linear, empirically calibrated network. The increase in sector 3's marginal cost reduces intermediate inputs demand and, to the extent that labor and intermediates are complements in production, further reduces labor demand relative

Figure 9: Aggregate Responses to Sector 2 Uncertainty Shock



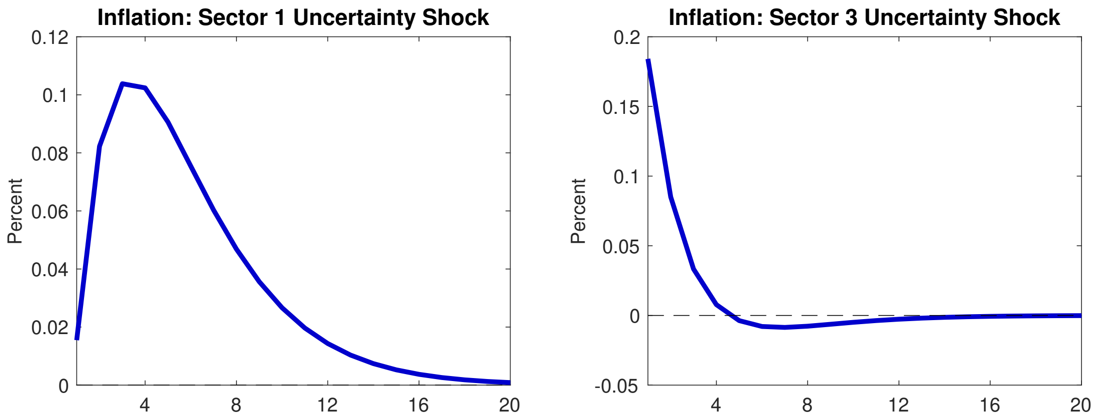
Note: Model aggregate responses to a one-standard-deviation sectoral uncertainty shock in sector 2 ($\varepsilon^{\sigma}_{2,t}$).

to the no network case. This results in a stronger decline in employment and output in sector 3.[15]

Second, the fall in labor demand of sector 2 also comes with a fall in intermediate input demand from the upstream sector, i.e. sector 1, which adds to deflationary pressure and further contracts employment in that sector.

Overall, these results demonstrate that not only do production linkages alter sectoral price dynamics, but they also magnify the contractionary effects of uncertainty. To conclude, we note that the network propagation of sector-specific uncertainty differs from the effects of an aggregate uncertainty shock—that is, an increase in uncertainty common across all sectors. As shown in Appendix C, aggregate uncertainty results in higher prices across all sectors, including upstream producers (sector 1). This finding demonstrates that the identified effects of sectoral uncertainty shocks cannot be rationalized by a uniform increase in uncertainty across all sectors, as the resulting price comovement would not be asymmetric. A second implication is that price dispersion across sectors during periods of heightened uncertainty is more likely to reflect sector-specific rather than aggregate second-moment shocks.

Figure 10: Heterogeneous Aggregate Inflation Response



Note: Model response of aggregate inflation to a one-standard-deviation sectoral uncertainty shock in sector 1 ($\varepsilon^{\sigma}_{1,t}$, left) and sector 3 ($\varepsilon^{\sigma}_{3,t}$, right).

4.4 Aggregate effects

We now examine the aggregate effects of uncertainty shocks and ask whether these effects are network-dependent—that is, whether the macroeconomic impact depends on where uncertainty originates in the production network. Figure 9 shows the impact of an uncertainty shock in sector 2 on aggregate employment and consumer price inflation. The shock is contractionary and leads to a very short-lived price increase. Figure 10 shows that the inflation increase becomes larger and much more persistent when uncertainty originates upstream in the network (sector 1), consistent with our empirical results in Section 3. As previously discussed, this result stems from the fact that precautionary pricing and the marginal cost channel dominate the aggregate demand channel, and the more upstream uncertainty arises, the more upstream uncertainty shocks propagate downstream like a negative supply shock. The network-dependent aggregate effects of uncertainty raise important policy questions and potential challenges. Indeed, to the extent that the central bank seeks to stabilize aggregate employment or output and aggregate inflation, our results suggest that upstream uncertainty shocks imply a more challenging aggregate stabilization trade-off than downstream uncertainty shocks.

[15] As shown in Appendix D, if labor and intermediate inputs are not complements in production, the increase in intermediate input prices implies that firms substitute towards labor, which ultimately dampens the contraction in employment relative to the no-network economy.

4.5 Model Robustness

For illustrative purposes, the baseline parametrization focuses on a linear production network and assumes a symmetric degree of price stickiness across sectors and uniform consumption shares. We now consider an empirically calibrated version of these three model features. To obtain an empirically-based calibration of the model production network, we collapse the 57 NAICS 3-digit industries considered in Bouakez et al. (2023) into three broad sectors based on their upstreamness (again using the classification in Antràs and Chor, 2013). The most upstream broad sector corresponds to sector 1 in the model, while the least upstream broad sector maps into sector 3. For each sector, we then set the $\omega_{H,s,x}$'s at the within-sector average use of intermediate inputs from other industries, based on the Input-Output matrices of the BEA averaged from 1995-2015. We similarly set the consumption shares $\omega_{C,s}$'s to the average contribution to aggregate consumption of the industries in each of the three sectors. Finally, we allow for heterogeneous price stickiness, calibrating the parameters ϕ_s to match the average frequency of price changes in our three sectors using data from Pastén, Schoenle, and Weber (2024). Figure A.6b shows that the qualitative patterns remain the same, although in sector 3 the inflation response is more hump-shaped than in the baseline.

In an additional robustness exercise, we look at the response to demand-side uncertainty by augmenting our model with sectoral government spending, driven by exogenous processes analogous to those for productivity in (18) - (19). Figure A.7 shows that our results do not depend on whether we consider supply- or demand-side uncertainty shocks under the empirically relevant calibration described just above.

Finally, we consider whether our results depend on the degree of complementarity in production between intermediate inputs and labor. Figure A.8 shows that under an alternative calibration of the linear network economy with Cobb-Douglas production, results are qualitatively similar, but the response of employment in sector 3 is significantly smaller and less persistent than under our baseline. Therefore complementarity in production between labor and intermediate inputs is important for the downstream propagation to be quantitatively realistic.

5 Conclusions

We have studied the propagation of uncertainty shocks along the supply chain. To do so, we constructed a disaggregated measure of sectoral uncertainty using the option-implied volatility of U.S. firms. Leveraging this novel measure of industry-level uncertainty, we estimated the dynamic effects of uncertainty within and across sectors, as well as at the aggregate level. Our findings indicate that uncertainty shocks are contractionary and inflationary in the industry in which they originate. Moreover, these shocks are significantly transmitted along the supply chain. In particular, uncertainty propagates upstream like a negative demand shock and downstream like a negative supply shock. At the aggregate level, the inflation response depends on where uncertainty originates, while employment unambiguously declines.

We have also demonstrated that a New Keynesian production network featuring sector-specific uncertainty shocks rationalizes the empirical findings, both qualitatively and quantitatively. The model underscores the central role of input-output linkages in shaping the transmission of uncertainty across sectors and influencing macroeconomic dynamics.

Our findings suggest that macroeconomic policy should adopt a more granular approach to uncertainty. When shocks originate in upstream sectors, they can propagate inflationary pressure even as aggregate activity declines—a combination that complicates the standard policy playbook. Recognizing the network transmission of uncertainty, therefore, has first-order implications for the design of stabilization policy. We leave to future research the task of understanding these implications.

References

Acemoglu, D., U. Akcigit, and W. Kerr (2016). Networks and the macroeconomy: An empirical exploration. *Nber macroeconomics annual 30*(1), 273–335.

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012). The network origins of aggregate fluctuations. *Econometrica 80*(5), 1977–2016.

Alfaro, I., N. Bloom, and X. Lin (2023). The finance uncertainty multiplier. *Journal of Political Economy 0*(0), 000–000.

Andreasen, M. M., G. Caggiano, E. Castelnuovo, and G. Pellegrino (2024). Does risk matter more in recessions than in expansions? implications for monetary policy. *Journal of Monetary Economics 143*, 103533.

Antràs, P. and D. Chor (2013). Organizing the global value chain. *Econometrica 81*(6), 2127–2204.

Atalay, E. (2017, October). How important are sectoral shocks? *American Economic Journal: Macroeconomics 9*(4), 254–80.

Bachmann, R., S. Elstner, and E. R. Sims (2013, April). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics 5*(2), 217–49.

Baqaee, D. R. and E. Farhi (2019a). The macroeconomic impact of microeconomic shocks: Beyond hulten's theorem. *Econometrica 87*(4), 1155–1203.

Baqaee, D. R. and E. Farhi (2019b, 09). Productivity and misallocation in general equilibrium*. *The Quarterly Journal of Economics 135*(1), 105–163.

Barattieri, A. and M. Cacciatore (2023). Self-harming trade policy? protectionism and production networks. *American Economic Journal: Macroeconomics 15*(2), 97–128.

Barattieri, A., M. Cacciatore, and N. Traum (2023). Estimating the effects of government spending through the production network. Technical report, National Bureau of Economic Research.

Barrot, J.-N. and J. Sauvagnat (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics 131*(3), 1543–1592.

Basu, S. and B. Bundick (2017). Uncertainty shocks in a model of effective demand. *Econometrica 85*(3), 937–958.

Basu, S., G. Candian, R. Chahrour, and R. Valchev (2021). Risky business cycles. Technical report, National Bureau of Economic Research.

Berger, D., I. Dew-Becker, and S. Giglio (2019, 04). Uncertainty Shocks as Second-Moment News Shocks. *The Review of Economic Studies 87*(1), 40–76.

Bernanke, B. and O. Blanchard (2024). What caused the us pandemic-era inflation? *American Economic Journal: Macroeconomics forthcoming*.

Black, F. and M. Scholes (1973). The pricing of options and corporate liabilities. *Journal of Political Economy 81*(3), 637–654.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica 77*(3), 623–685.

Bloom, N., P. Bunn, S. Chen, P. Mizen, P. Smietanka, G. Thwaites, and G. Young (2018). Brexit and uncertainty: insights from the decision maker panel. *Fiscal Studies 39*(4), 555–580.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2018). Really uncertain business cycles. *Econometrica 86*(3), 1031–1065.

Boehm, C. E., A. Flaaen, and N. Pandalai-Nayar (2019). Input linkages and the transmission of shocks: Firm-level evidence from the 2011 tōhoku earthquake. *The Review of Economics and Statistics 101*(1), 60–75.

Born, B. and J. Pfeifer (2014). Policy risk and the business cycle. *Journal of Monetary Economics 68*, 68–85.

Bouakez, H., E. Cardia, and F. J. Ruge-Murcia (2009). The transmission of monetary policy in a multisector economy. *International Economic Review 50*(4), 1243–1266.

Bouakez, H., O. Rachedi, and E. Santoro (2023, January). The government spending multiplier in a multisector economy. *American Economic Journal: Macroeconomics 15*(1), 209–39.

Caggiano, G., E. Castelnuovo, and G. Nodari (2022). Uncertainty and monetary policy in good and bad times: A replication of the vector autoregressive investigation by bloom (2009). *Journal of Applied Econometrics 37*(1), 210–217.

Carvalho, V. M. and B. Grassi (2019). Large firm dynamics and the business cycle. *American Economic Review 109*(4), 1375–1425.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi (2020, 12). Supply chain disruptions: Evidence from the great east japan earthquake*. *The Quarterly Journal of Economics 136*(2), 1255–1321.

Cascaldi-Garcia, D., C. Sarisoy, J. M. Londono, B. Sun, D. D. Datta, T. Ferreira, O. Grishchenko, M. R. Jahan-Parvar, F. Loria, S. Ma, M. Rodriguez, I. Zer, and J. Rogers (2023, June). What is certain about uncertainty? *Journal of Economic Literature 61*(2), 624–54.

Castelnuovo, E., K. Tuzcuoglu, and L. Uzeda (2022). Sectoral uncertainty.

Cesa-Bianchi, A., M. H. Pesaran, and A. Rebucci (2020). Uncertainty and economic activity: A multicountry perspective. *The Review of Financial Studies 33*(8), 3393–3445.

Christiano, L., R. Motto, and M. Rostagno (2014). Risk shocks. *American Economic Review 104*(1), 27–65.

Cremers, M. and D. Weinbaum (2010). Deviations from put-call parity and stock return predictability. *Journal of Financial and Quantitative Analysis 45*(2), 335–367.

Dew-Becker, I. and S. Giglio (2023, April). Cross-sectional uncertainty and the business cycle: Evidence from 40 years of options data. *American Economic Journal: Macroeconomics 15*(2), 65–96.

Fajgelbaum, P. D., E. Schaal, and M. Taschereau-Dumouchel (2017). Uncertainty traps. *Quarterly Journal of Economics 132*(4), 1641–1692.

Fernández-Villaverde, J., P. Guerrón-Quintana, K. Kuester, and J. Rubio-Ramírez (2015, November). Fiscal volatility shocks and economic activity. *American Economic Review 105*(11), 3352–84.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica 79*(3), 733–772.

Gilchrist, S., R. Schoenle, J. Sim, and E. Zakrajšek (2017, March). Inflation dynamics during the financial crisis. *American Economic Review 107*(3), 785–823.

Grigoris, F. and G. Segal (2021). Investment under up-and downstream uncertainty. *Unpublished working paper. Indiana University*.

Herskovic, B., B. Kelly, H. Lustig, and S. Van Nieuwerburgh (2016). The common factor in idiosyncratic volatility: Quantitative asset pricing implications. *Journal of Financial Economics 119*(2), 249–283.

Herskovic, B., B. Kelly, H. Lustig, and S. Van Nieuwerburgh (2020). Firm volatility in granular networks. *Journal of Political Economy 128*(11), 4097–4162.

Jordà, O. (2005, March). Estimation and inference of impulse responses by local projections. *American Economic Review 95*(1), 161–182.

Jurado, K., S. C. Ludvigson, and S. Ng (2015). Measuring uncertainty. *American Economic Review 105*(3), 1177–1216.

Kopytov, A., B. Mishra, K. Nimark, and M. Taschereau-Dumouchel (2024). Endogenous production networks under supply chain uncertainty. *Econometrica 92*(5), 1621–1659.

Krogh, M. and G. Pellegrino (2025). Real activity and uncertainty shocks: The long and the short of it. Technical report.

Leduc, S. and Z. Liu (2016). Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics 82*, 20–35.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance 29*(2), 449–470.

Modigliani, F. and M. H. Miller (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review 48*(3), 261–297.

Nieuwerburgh, S. V. and L. Veldkamp (2006). Learning asymmetries in real business cycles. *Journal of Monetary Economics 53*(4), 753–772.

Pan, J. and A. M. Poteshman (2006, 02). The information in option volume for future stock prices. *The Review of Financial Studies 19*(3), 871–908.

Pastén, E., R. Schoenle, and M. Weber (2024, April). Sectoral heterogeneity in nominal price rigidity and the origin of aggregate fluctuations. *American Economic Journal: Macroeconomics 16*(2), 318–52.

Saijo, H. (2025). Volatility shocks in networks.

Wu, J. C. and F. D. Xia (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking 48*(2-3), 253–291.

Appendix

A Industry-Level Analysis: Robustness

Figure A.1 presents the response of employment and producer prices when daily sectoral uncertainty is constructed using previous-year firm sales relative to industry sales as weights $s_{f,i,d}$ (see equation (1)). Figure A.2 refers to the case in which NAICS 4-digit implied volatility, $\sigma_{i,t}$, is measured using only the common component of firm-level volatility within a month, $\beta_{i,t}$. As discussed in the main text, we estimate the following fixed-effects regression:

$$\ln(\sigma_{f,i,t}) = \alpha_f + \beta_{i,t} + \varepsilon_{f,i,t}. \tag{A.1}$$

We then estimate the first-stage regression in equation (2) using $\beta_{i,t}$ as the left-hand-side variable.

Figure A.3 presents results using options traded for at least 5 years (instead of 10 years). Finally, Figure A.4 considers a simpler first-stage regression that excludes controls for upstream and downstream implied volatility. In this case, we use all trading days within a month to measure NAICS 4-digit implied volatility, $\sigma_{i,t}$.

Figure A.1: Responses to an Uncertainty Shock - Sales Weights

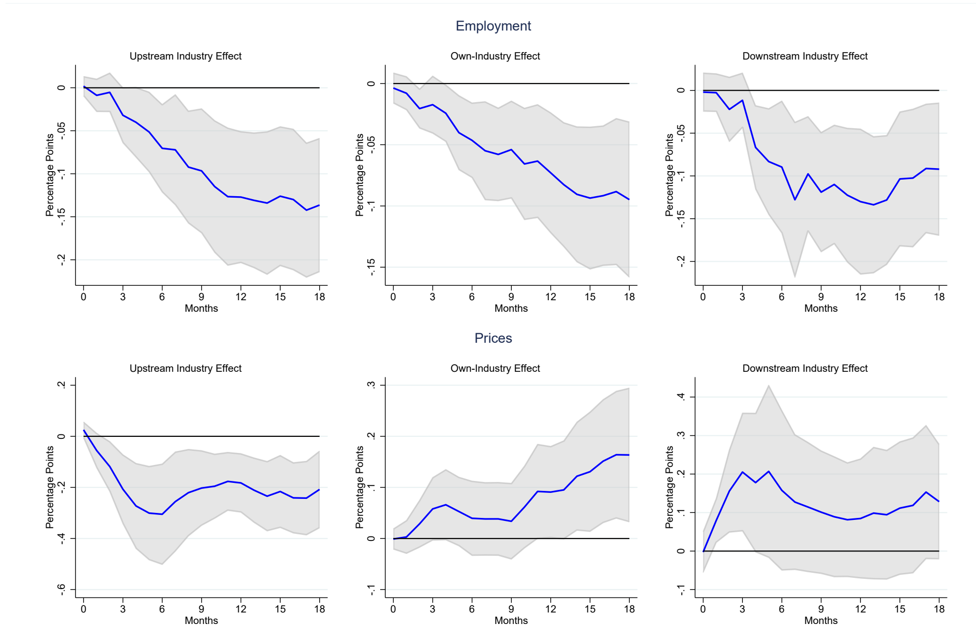


Figure A.2: Responses to an Uncertainty Shock - Fixed Effect

Note: "Own industry" effect is the effect of a shock originating in that same industry ($\hat{\nu}_{i,t}$). "Upstream effect" refers to the effect of a shock originating in downstream sectors relative to the industry in question ($\hat{\nu}^D_{i,t}$). "Downstream effect" is symmetrically defined.

Figure A.3: Responses to an Uncertainty Shock - Options Traded 5 Years or More

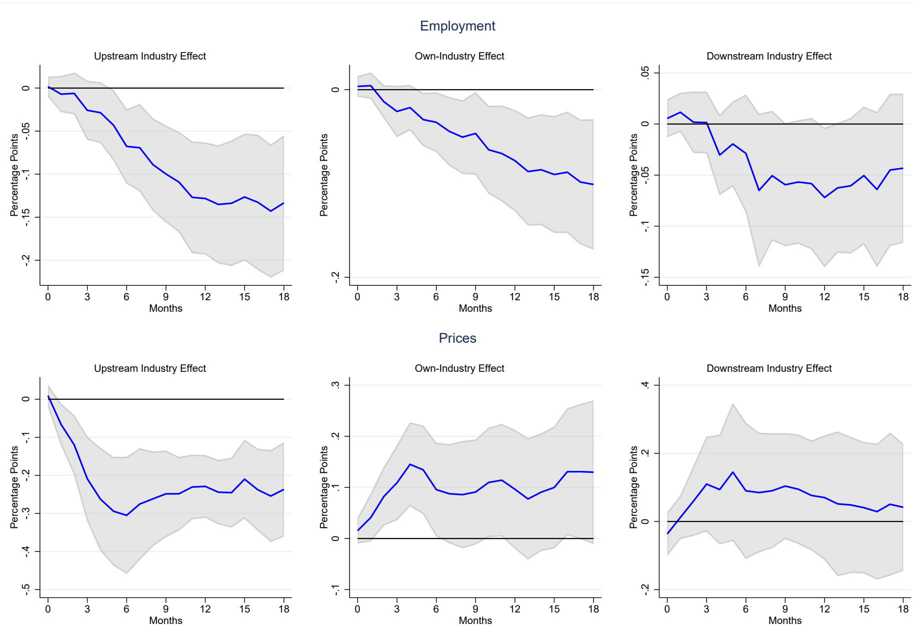
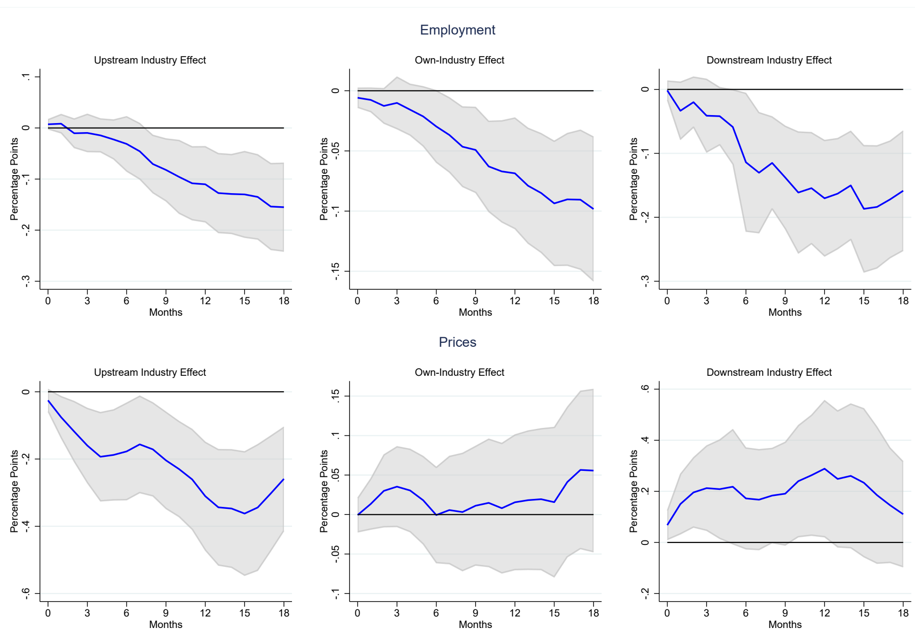


Figure A.4: Responses to an Uncertainty Shock - Simple First Stage



Note: "Own industry" effect is the effect of a shock originating in that same industry ($\hat{\nu}_{i,t}$). "Upstream effect" refers to the effect of a shock originating in downstream sectors relative to the industry in question ($\hat{\nu}^{D}_{i,t}$). "Downstream effect" is symmetrically defined.

B Model

We here present a full description of the model environment.

B.1 Households

An infinitely-lived representative houehold maximizes the following lifetime utility function:

$$\mathbb{V}_t = \max\left[(1-\beta)(C_t^{\eta_l}(1-N_t)^{1-\eta_l})^{1-1/\psi} + \beta(\mathbb{E}_t \mathbb{V}_{t+1}^{1-\gamma})^{\frac{1-1/\psi}{1-\gamma}}\right]^{\frac{1}{1-1/\psi}}, \tag{A.2}$$

where β represents the time discount factor. The parameter ψ is the intertemporal elasticity of substitution, while γ parameterizes risk aversion. In the utility function, C_t represents final consumption goods, which the household purchases at price $P_{c,t}$, and N_t denotes aggregate labor, which pays an aggregate wage W_t.

Each period t, the household trades one-period nominal bonds B_t, which pay a gross nominal return of R_t in period $t+1$. The household also pays a nominal lump-sum tax T_t and receives nominal profits from firms in all sectors, $D_{s,t}$. The budget constraint in nominal terms as follows:

$$P_{c,t}C_t + B_t + T_t = W_t N_t + B_{t-1}R_{t-1} + \sum_{s\in S} D_{s,t}. \tag{A.3}$$

Maximization of equation (A.2), subject to the budget constraint (A.3), results in the following first-order conditions:

$$\mathbb{E}_t\left[M_{t+1}\frac{R_t}{\pi_{t+1}}\right] = 1, \tag{A.4}$$

$$\frac{1-\eta_l}{\eta_l}\frac{C_t}{1-N_t} = \frac{W_t}{P_{c,t}}, \tag{A.5}$$

$$M_{t+1} = \beta\left(\frac{C_{t+1}^{\eta_l}(1-N_{t+1})^{1-\eta_l}}{C_t^{\eta_l}(1-N_t)^{1-\eta_l}}\right)^{-1/\psi}\frac{C_{t+1}^{\eta_l-1}(1-N_{t+1})^{1-\eta_l}}{C_t^{\eta_l-1}(1-N_t)^{1-\eta_l}}\left(\frac{\mathbb{V}_{t+1}}{(\mathbb{E}_t\mathbb{V}_{t+1}^{1-\gamma})^{\frac{1}{1-\gamma}}}\right)^{1/\psi-\gamma}. \tag{A.6}$$

Labor provided by the household, N_t, is a Cobb-Douglas aggregate of the labor supplied to each sector:

$$N_t = \prod_{s \in S} N_{s,t}^{\omega_{N,s}}. \tag{A.7}$$

The weights $\omega_{N,s}$ are such that $\sum_{s=1}^{S} \omega_{N,s} = 1$. The aggregate wage is given by:

$$W_t = \left[\sum_{s=1}^{S} \omega_{n,s} W_{s,t}^{1+\nu_n} \right]^{\frac{1}{1+\nu_n}}. \tag{A.8}$$

The household chooses $N_{s,t}$ to maximize:

$$\max W_t N_t - \sum_{s=1}^{S} W_{s,t} N_{s,t}, \tag{A.9}$$

subject to equation (A.5). The first-order condition implies:

$$N_{s,t} = \omega_{n,s} \left(\frac{W_{s,t}}{W_t} \right) N_t. \tag{A.10}$$

B.2 Differentiated Goods Producers

In each sector, a continuum of unit mass of monopolistically competitive firms, indexed by j, produce differentiated varieties of sectoral goods, $Z_{s,t}^{j}$, by combining labor and intermediate inputs in the following production function:

$$Z_{s,t}^{j} = \left[\alpha_s^{\frac{1}{\vartheta_s}} (A_{s,t} N_{s,t}^{j})^{\frac{\vartheta_s - 1}{\vartheta_s}} + (1 - \alpha_s)^{\frac{1}{\vartheta_s}} (H_{s,t}^{j})^{\frac{\vartheta_s - 1}{\vartheta_s}} \right]^{\frac{\vartheta_s}{\vartheta_s - 1}}, \tag{A.11}$$

where $N_{s,t}^{j}$ and $H_{s,t}^{j}$ denote labor and the intermediate input bundle used in sector s by producer j, and $A_{s,t}$ denotes sector s productivity. The parameter ϑ_s is the sector-specific elasticity of substitution between inputs, while α_s is the factor share. These producers is sector s hire labor and buy intermediate inputs at prices at prices $W_{s,t}$ and $P_{s,t}^{H}$ respectively. Producers choose inputs to minimize costs, subject to producing enough goods to meet demand. The first-order conditions for the associated cost minimization problem are:

$$W_{s,t} = MC_{s,t}\alpha_{n,s}^{\frac{1}{\vartheta_s}}A_{s,t}(A_{s,t}N_{s,t}^{j})^{\frac{-1}{\vartheta_s}}(Z_{s,t}^{j})^{\frac{1}{\vartheta_s}}, \tag{A.12}$$

$$P_{s,t}^{H} = MC_{s,t}(1-\alpha_{n,s})^{\frac{1}{\vartheta_s}}(H_{s,t}^{j})^{\frac{-1}{\vartheta_s}}(Z_{s,t}^{j})^{\frac{1}{\vartheta_s}}. \tag{A.13}$$

Since all producers in a sector are subject to the same factor costs, they all choose the same intermediate-labor ratio, which is also equal to the aggregate intermediate-labor ratio. Thus, all producers face the same nominal marginal costs $MC_{s,t}$.

The producer j sells its good at the price $P_{s,t}^{j}$ to wholesalers. Producers are subject to Calvo-pricing, where the probability that the price remains fixed from one period to another is constant and identical for all producers within a sector. The probability can differ across sectors to allow for differential levels of price rigidities. We denote this probability by ϕ_s. Since average and marginal costs coincide, the firm chooses $P_{s,t}^{j}$ to maximize the following present discounted value of real profits:

$$\max_{P_{s,t}^{j}} E_t \sum_{k=0}^{\infty}(\beta\phi_s)^k \frac{\lambda_{t+k}}{\lambda_t}\left[\left(P_{s,t}^{j}\right)^{1-\epsilon_s} {P_{s,t+k}}^{\epsilon_s}\frac{Z_{s,t+k}}{P_{t+k}} - mc_{s,t+k}\left(\frac{P_{s,t}^{j}}{P_{s,t+k}}\right)^{-\epsilon_s} Z_{s,t+k}\right]. \tag{A.14}$$

The first-order condition is

$$\begin{aligned}&(1-\epsilon_s)(P_{s,t}^{j})^{-\epsilon_s}E_t\sum_{k=0}^{\infty}(\beta\phi_s)^k\frac{\lambda_{t+k}}{\lambda_t}P_{s,t+k}^{\epsilon_s}P_{t+k}^{-1}Z_{s,t+k}\\ &+\epsilon_s(P_{s,t}^{j})^{-\epsilon_s-1}E_t\sum_{k=0}^{\infty}(\beta\phi_s)^k\frac{\lambda_{t+k}}{\lambda_t}mc_{s,t+k}P_{s,t+k}^{\epsilon_s}Z_{s,t+k} = 0\end{aligned} \tag{A.15}$$

where $mc_{s,t} \equiv MC_{s,t}/P_{c,t}$ denotes the real marginal cost.

B.3 Wholesale Producers

In each sector, perfectly competitive firms aggregate the differentiated varieties into a final good. The wholesaler sells this good to both final consumption and intermediate input retailers. The production function is:

$$Z_{s,t} = \left[\int_0^1 (Z_{s,t}^{j})^{\frac{\epsilon_s-1}{\epsilon_s}}dj\right]^{\frac{\epsilon_s}{\epsilon_s-1}}. \tag{A.16}$$

The price of the bundled sector s good is

$$P_{s,t} = \left[\int_0^1 (P^j_{s,t})^{1-\epsilon_s} dj \right]^{\frac{1}{1-\epsilon_s}}. \tag{A.17}$$

The wholesaler maximizes

$$\max P_{s,t} Z_{s,t} - \int_0^1 P^j_{s,t} Z^j_{s,t} dj, \tag{A.18}$$

subject to

$$Z_{s,t} \leq \left[\int_0^1 (Z^j_{s,t})^{\frac{\epsilon_s - 1}{\epsilon_s}} dj \right]^{\frac{\epsilon_s}{\epsilon_s - 1}}. \tag{A.19}$$

The first-order condition gives the demand function:

$$Z^j_{s,t} = \left(\frac{P^j_{s,t}}{P_{s,t}} \right)^{-\epsilon_s} Z_{s,t}. \tag{A.20}$$

Sectoral market clearing implies

$$Z_{s,t} = C_{s,t} + \sum_{x=1}^{S} H_{x,s,t}. \tag{A.21}$$

B.4 Intermediate-Input Retailers

The sectoral intermediate input, $H_{s,t}$, is produced by a perfectly-competitive intermediate-input retailer using the following technology:

$$H_{s,t} = \prod_{x=1}^{S} H_{s,x,t}^{\omega_{h,s,x}}, \tag{A.22}$$

where $H_{s,x,t}$ is purchased at price $P_{x,t}$ from wholesale producers in sector x. $\omega_{h,s,x}$, such that $\sum_{x=1}^{S} \omega_{h,s,x} = 1$, gives the weight of good x in the intermediate-input bundle for sector s, and ν_h is the elasticity of substitution of intermediate inputs across sectors. The price of the intermediate-input bundle is:

$$P_{h,s,t} = \prod_{x=1}^{S} P_{x,t}^{\omega_{h,s,x}}. \tag{A.23}$$

The intermediate input retailer maximizes

$$\max P_{h,s,t} H_{s,t} - \sum_{x=1}^{S} P_{x,t} H_{s,x,t}, \tag{A.24}$$

subject to equation (A.22). The first-order condition leads to the demand function

$$H_{s,x,t} = \omega_{h,s,x} \left(\frac{P_{x,t}}{P_{h,s,t}} \right)^{-1} H_{s,t}. \tag{A.25}$$

B.5 Final Consumption Retailers

A perfectly competitive retailer produces the final consumption good, C_t, using the following technology:

$$C_t = \prod_{s \in S} C_{s,t}^{\omega_{c,s}}, \tag{A.26}$$

where $C_{s,t}$ is purchased at price $P_{s,t}$ from wholesale producers in sector s. $\omega_{c,s}$, such that $\sum_{s=1}^{S} \omega_{c,s} = 1$, gives the weight of good s in the consumption bundle and ν_c is the elasticity of substitution of consumption across sectors. The price of the consumption good is:

$$P_{c,t} = \prod_{s \in S} P_{s,t}^{\omega_{c,s}}. \tag{A.27}$$

The consumption retailer maximizes

$$\max P_{c,t} C_t - \sum_{s=1}^{S} P_{s,t} C_{s,t}, \tag{A.28}$$

subject to equation (A.26). The first-order condition leads to the demand function

$$C_{s,t} = \omega_{c,s} \left(\frac{P_{s,t}}{P_{c,t}} \right)^{-1} C_t. \tag{A.29}$$

B.6 Monetary Policy

The monetary authority sets the nominal interest rate according to a Taylor rule:

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R} \right)^{\rho_i} \left(\frac{\Pi_t}{\Pi} \right)^{(1-\rho_i)\psi_\pi}, \tag{A.30}$$

where R_t denotes the nominal interest rate, and Π_t is consumer-price inflation. The latter coincides with the GDP deflator inflation since the final goods resource constraint is $Y_t = C_t$.

B.7 Aggregation

Market clearing implies $N_{s,t} = \int_0^1 N_{s,t}^j dj$ and $H_{s,t} = \int_0^1 H_{s,t}^j dj$. The aggregate production function is

$$\int_0^1 Z_{s,t}^j dj = Z_{s,t} \int_0^1 \left(\frac{P_{s,t}^j}{P_{s,t}} \right)^{-\epsilon_s} dj = Z_{s,t} v_{s,t}, \tag{A.31}$$

where $v_{s,t} \equiv \int_0^1 \left(\frac{P_{s,t}^j}{P_{s,t}} \right)^{-\epsilon_s} dj$ measures sectoral price dispersion. The sectoral price dispersion can be written recursively as:

$$\begin{aligned} v_{s,t} &= (1-\phi_s) \left(\frac{P_{s,t}^j}{P_{s,t}} \right)^{-\epsilon_s} + \phi_s \pi_{s,t}^{\epsilon_s} v_{s,t-1} \\ &= (1-\phi_s) \left(\pi_{s,t}^* \right)^{-\epsilon_s} \pi_{s,t}{}^{\epsilon_s} + \phi_s \pi_{s,t}^{\epsilon_s} v_{s,t-1}. \end{aligned} \tag{A.32}$$

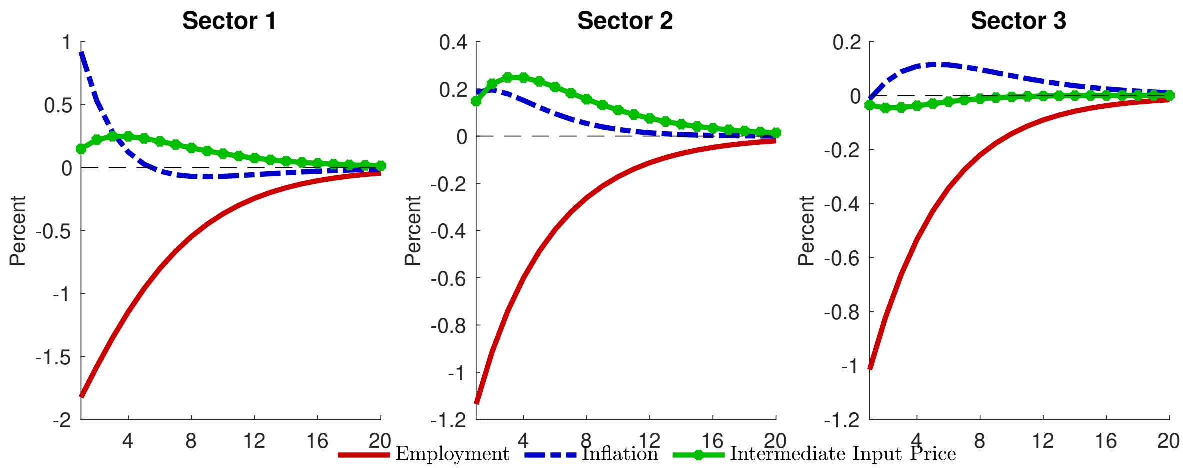
The aggregate sectoral production function is

$$Y_{s,t} \equiv \left[\alpha_{n,s}^{\frac{1}{\vartheta_s}} (A_{s,t} N_{s,t})^{\frac{\vartheta_s - 1}{\vartheta_s}} + (1-\alpha_{n,s})^{\frac{1}{\vartheta_s}} (H_{s,t})^{\frac{\vartheta_s - 1}{\vartheta_s}} \right]^{\frac{\vartheta_s}{\vartheta_s - 1}} = Z_{s,t} v_{s,t}. \tag{A.33}$$

C The Effects of Aggregate Uncertainty Shocks

Figure A.5 shows the responses of sectoral output an inflation to a positive one-standard-deviation increase in productivity uncertainty in all sectors of the economy. As the figure shows an increase in aggregate uncertainty lowers employment and increases inflation across the entire production network, resulting in positive sectoral comovement of both quantities and prices.

Figure A.5: Aggregate Uncertainty Shock



Note: Model responses to a one-standard-deviation productivity uncertainty shock common to all sectors.

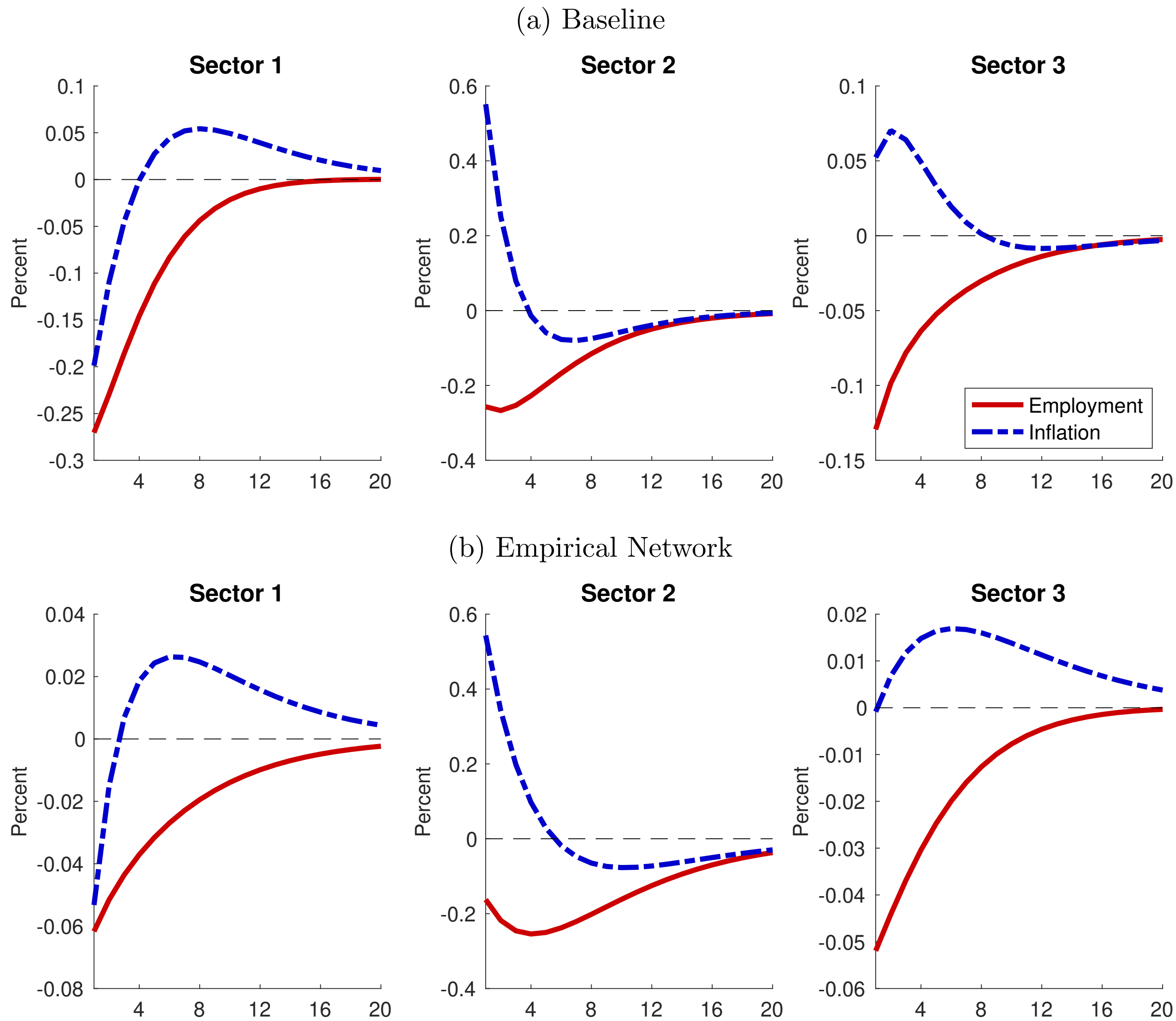
D Model Sensitivity Analysis

We here examine the sensitivity of the model's impulse responses to sectoral uncertainty shocks to different parameterizations and modeling assumptions. We first consider an empirically based calibration of the three sector model, as described in main text. Figure A.6 compares the responses of sectoral employment and inflation to a one-standard-deviation productivity uncertainty shock in sector 2 in our baseline linear-network economy (panel a) to this empirically calibrated version (panel b). As can be seen in the Figure, the qualitative patterns remain the same, although in sector 3 the positive inflation response is more hump-shaped than in the baseline.

Second, we consider the sensitivity of the models' responses to the source of sectoral uncertainty shocks, differentiating between supply and demand uncertainty. To introduce demand uncertainty shocks, we modify the model as follows. Wholesalers now sell their goods to the consumption and intermediate input retailers (as before), as well as the government. Therefore, the market clearing conditions (A.21) become

$$Z_{s,t} = G_{s,t} + C_{s,t} + \sum_{x=1}^{S} H_{x,s,t}. \tag{A.34}$$

Figure A.6: Impulse Responses to Sector 2 Uncertainty Shock



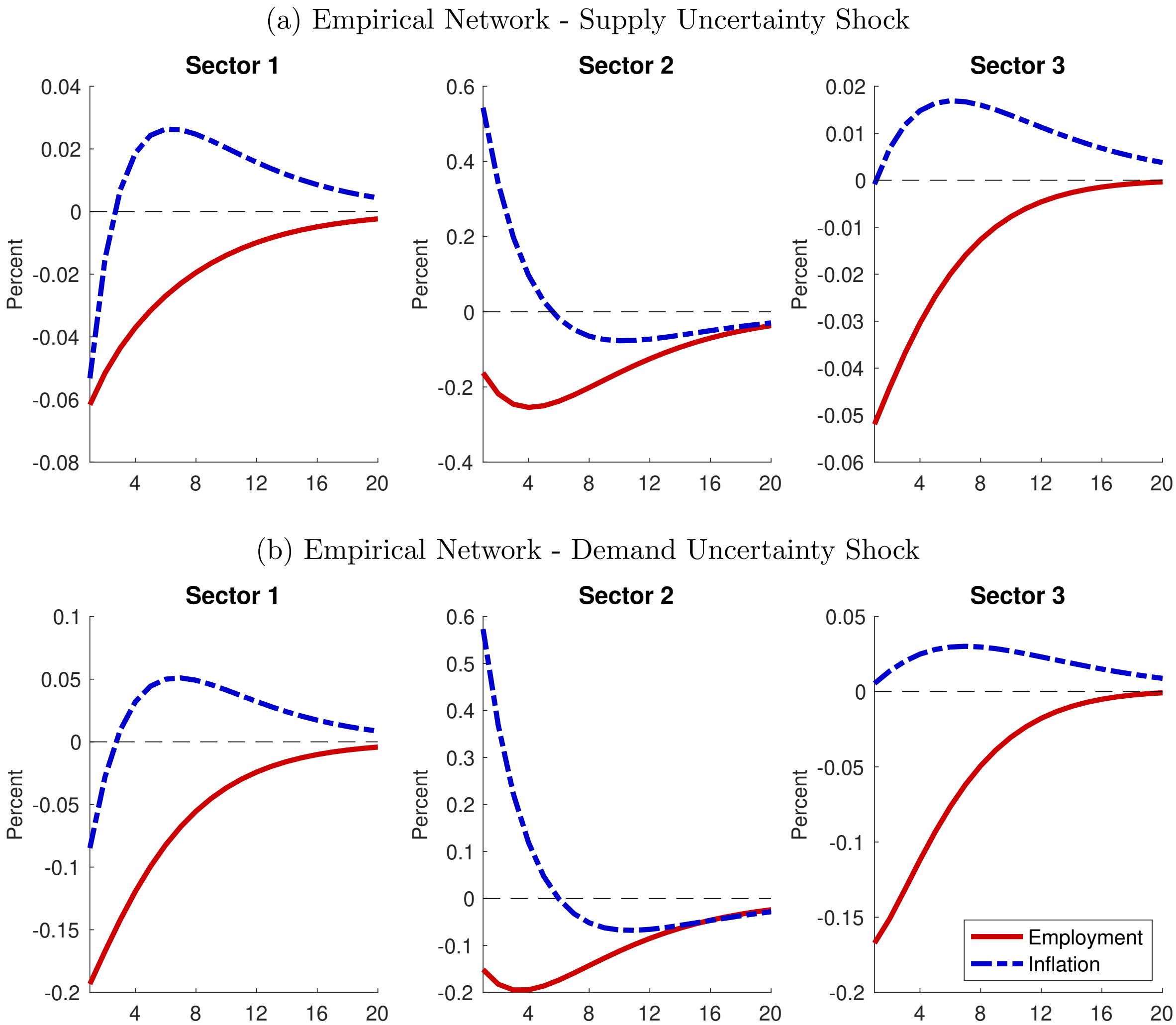
Note: Model sectoral impulse response functions to a one-standard-deviation sectoral uncertainty shock in sector 2 ($\varepsilon^{\sigma}_{2,t}$).

We assume that government purchases for each sector s follow the AR(1) process:

$$\log G_{s,t} = (1 - \rho_g) \log G_s + \rho_g \log G_{s,t-1} + \sigma^g_{s,t-1} \varepsilon^g_{s,t}, \tag{A.35}$$

with $\varepsilon^g_{s,t} \sim \mathcal{N}(0, 1)$. The government purchases these goods from wholesalers at the price $P_{s,t}$. Government spending is assumed to be wasteful and financed through lump-

Figure A.7: Impulse Responses to Sector 2 Uncertainty Shock



Note: Model sectoral impulse response functions to a one-standard-deviation sectoral uncertainty shock in sector 2 ($\varepsilon^{\sigma}_{2,t}$).

sum taxes T_t. The government's budget constraint is

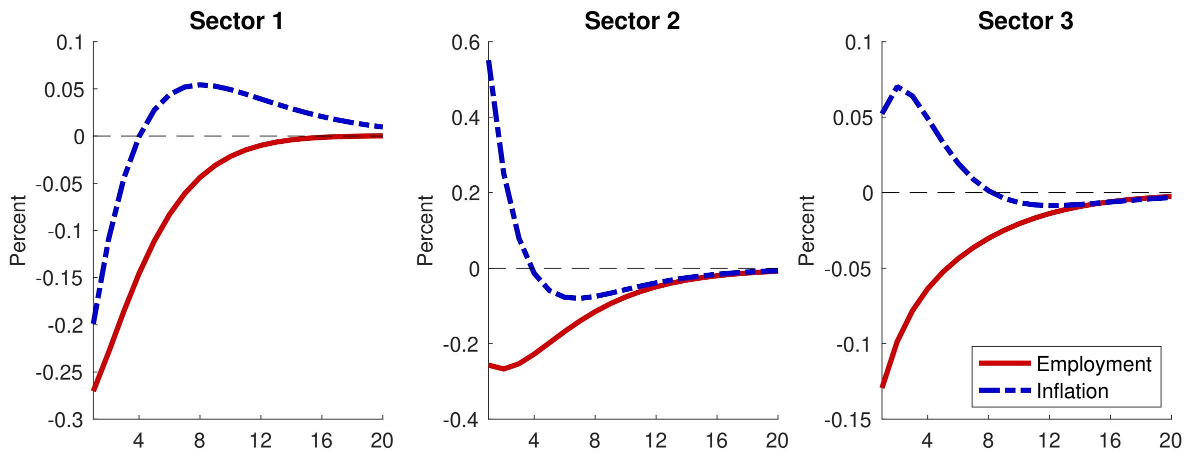
$$\sum_{s \in S} P_{s,t} G_{s,t} = T_t. \tag{A.36}$$

The standard deviation of government spending in every sector s is time-varying and follows the process:

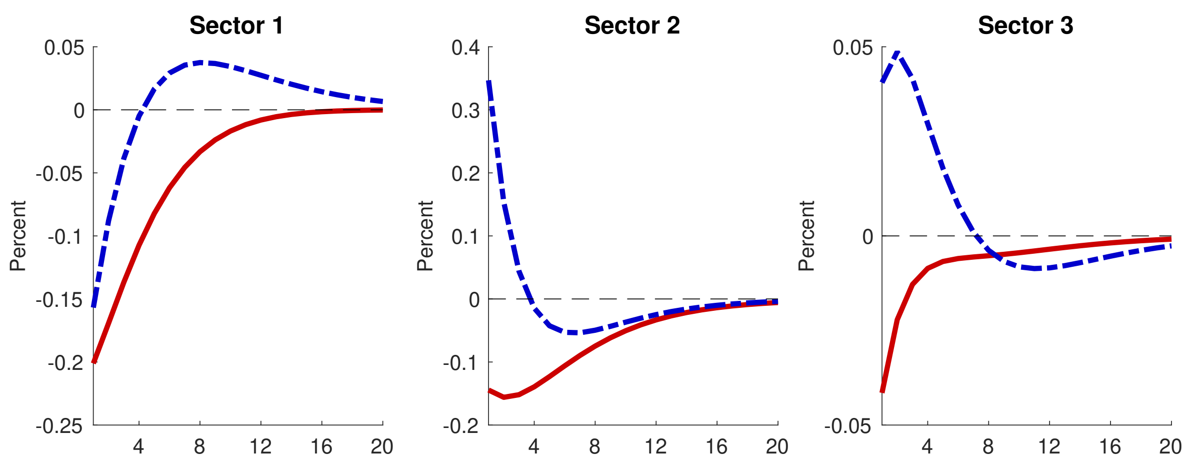
$$\sigma^{g}_{s,t} = (1 - \rho_{\sigma_g}) \log \sigma^{g} + \rho_{\sigma_g} \log \sigma^{g}_{s,t-1} + \sigma_{\sigma_g} \varepsilon^{\sigma,g}_{s,t}. \tag{A.37}$$

Figure A.8: Impulse Responses to Sector 2 Uncertainty Shock

(a) Baseline



(b) Cobb Douglas Production



Note: Model sectoral impulse response functions to a one-standard-deviation sectoral uncertainty shock in sector 2 ($\varepsilon^{\sigma}_{2,t}$).

We refer to $\varepsilon^{\sigma,g}_{s,t} \sim \mathcal{N}(0,1)$ as a sectoral demand uncertainty shock as it captures innovations to the volatility of the stochastic process for sectoral government spending.

Figure A.7 compares the responses of sectoral employment and inflation to a one-standard-deviation supply uncertainty shock (panel a) to a demand uncertainty shock (panel b) in sector 2 under our empirically based calibration. As the Figure shows, the source of uncertainty does not affect the qualitative patterns of the responses in the three sectors. Compared to supply uncertainty, however, demand uncertainty has a stronger effect in sector 1 and 3 relative to sector 2.

Finally, we consider the sensitivity of the model to different assumptions about the complementarity between labor and intermediate inputs in production. Figure A.8 compares our baseline economy with complementarity in production ($\vartheta = 0.4$) in panel a to an economy with Cobb-Douglas production function ($\vartheta \to 1$) in panel b. More substitutability in production does not alter the qualitative patterns but reduces the size and the persistence of the drop in employment in the downstream sector (sector 3) in response to the sectoral productivity uncertainty shock.