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

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Abstract

We study how uncertainty propagates through production networks. First, we construct a highly disaggregated, forward-looking measure of industry-level uncertainty using option-implied volatility data for U.S. firms. Second, we identify the effects of sectoral uncertainty within industries, across supply chains, and at the aggregate level. We document a new empirical fact: Uncertainty shocks in upstream industries behave like supply shocks—raising prices and lowering employment across the production network—while those in downstream industries behave like demand shocks—lowering both prices and employment. As a result, the aggregate inflation response depends on where uncertainty originates. We develop a model that embeds sectoral uncertainty propagation into production networks to explain how the origins of uncertainty shape its transmission and macroeconomic consequences.

Keywords: uncertainty; production networks; shocks propagation; implied volatility.
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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 the transmission of these sector-specific shocks is well understood, much less is known about the role of supply chains in propagating uncertainty, including, for example, heightened volatility in commodity markets, trade tensions, financial instability, or regulatory changes affecting specific sectors. While previous literature has developed state-of-the-art methods to measure aggregate uncertainty and identify its macroeconomic effects, 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 uncertainty originates in the production network? This paper provides the first empirical and theoretical framework to study the dynamics of uncertainty shocks across industries.

Our results break new ground in two key areas. 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 effects of uncertainty depend 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. As a result, the aggregate inflation response depends on where uncertainty originates, with upstream uncertainty posing a greater challenge for central banks aiming to stabilize inflation and output fluctuations.

In the first part of the paper, we tackle the challenge of empirically estimating how heightened uncertainty propagates through the production network. This analysis requires disaggregated, industry-level measures of uncertainty that are not readily available. Moreover, identifying network effects requires sectoral uncertainty variation

that is uncorrelated to first-moment shocks and across industries. We address these challenges as follows.

First, we construct sectoral uncertainty measures using high-frequency, option-implied volatility data from publicly traded U.S. firms operating within a given NAICS 4-digit industry. This classification represents the most disaggregated level at which comprehensive data on employment, prices, and input-output relationships are consistently available.

The use of implied volatility from option 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 accurately.[1] Variations in implied volatility stem from uncertainty about future economic activity (e.g., expected cash flows) or 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, with the underlying option-issuing firms accounting for a significant share of sectoral output and employment on average. The average bilateral correlation across industries is positive but well below one, indicating the presence of significant idiosyncratic variation in sectoral uncertainty.

Next, we propose a novel approach to identifying sectoral uncertainty variation not explained by first-moment shocks or uncertainty shocks originating in other industries. We require that uncertainty shocks be orthogonal to realized volatility (which captures actual stock return volatility resulting from realized first-moment shocks), building on Berger et al. (2019). In addition, we leverage the high-frequency 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

[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).

firms within an industry and idiosyncratic uncertainty impacting large firms in the sector. Several 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.

Third, using panel local projections, we 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 or buy goods 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).

Sector-specific uncertainty shocks propagate through the supply chain. First, implied volatility rises in upstream and downstream industries, showing that uncertainty spreads to customer and supplier sectors. Second, network effects occur through changes in sectoral demand and relative prices. On one hand, employment and producer prices decline in supplier industries, consistent with weaker intermediate input demand from industries facing higher uncertainty. On the other hand, in customer industries, employment falls while producer prices rise, akin to a negative supply shock for downstream producers. Consistent with this sectoral propagation, we find that uncertainty shocks are contractionary at the aggregate level, while their impact on inflation depends on where they originate in the network. Uncertainty is inflationary when it increases in relatively upstream sectors in the production network.

What explains the network propagation of uncertainty shocks? In the remainder

[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.

of the paper, we show that a New Keynesian multi-sector model with input-output linkages and sector-specific time-varying volatility rationalizes the empirical findings. The results hold regardless of whether uncertainty arises from supply- or demand-side factors, such as sectoral productivity fluctuations or demand shocks. Two key model features—complementarity between labor and intermediates in production and imperfect sectoral labor mobility—drive the network propagation mechanism.

The key intuitions are the following. 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. Input-output linkages are essential to explaining the response of employment and prices across sectors, both qualitatively and quantitatively. Without production linkages, sectoral spillovers would solely reflect general equilibrium effects driven by households' precautionary saving, leading to counterfactual sectoral comovement–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 intermediate input usage. For an empirically plausible complementarity between labor and intermediate inputs, employment declines downstream. Consistent with the data, sectoral measures of implied volatility increase across the three sectors in the model. Finally, the model rationalizes the estimated response of aggregate output and inflation: uncertainty shocks are contractionary and become more inflationary the further upstream they originate.

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 identifying sector-specific uncertainty shocks and estimating their impact along the supply chain at business cycle frequencies.

While uncertainty may positively affect investment due to growth opportunities (e.g., Bloom, 2014), virtually all macroeconomic studies find that heightened uncertainty is recessionary. This research highlights three main channels for the contractionary effects of aggregate uncertainty: households' precautionary saving, which lowers aggregate demand (e.g., Basu and Bundick, 2017); firms' precautionary pricing, which raises markups and reduces production (e.g., Fernández-Villaverde and Guerrón-Quintana, 2020); and the real-option effect on hiring and investment, whereby firms postpone job creation and capital accumulation when uncertainty rises (e.g., Bloom, 2009). Our findings suggest that precautionary pricing and real-option effects also operate at the industry level and are central to understanding the supply chain propagation of uncertainty.

Our findings also contribute to a broad literature investigating how production networks transmit shocks and policies across 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). 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 work relates to recent work by Castelnuovo et al. (2022), who estimate a dynamic factor model on industrial production series to construct uncertainty indexes for durable and non-durable goods. Our analysis differs both in scope and methodology. First, our focus is estimating network propagation using disaggregated sectoral measures of uncertainty (capturing the sparsity of input-output tables). Second, using

[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

options data helps us address key empirical challenges in estimating network effects of uncertainty that would otherwise arise with macroeconomic time series data. Our analysis also relates to the recent literature on the effects of trade policy uncertainty (e.g., Steinberg, 2019; Caldara et al., 2020; Alessandria et al., 2019). This literature focuses on the aggregate effects of uncertainty arising in tradable sectors and does not focus on supply chain implications.

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 stock market data to measure uncertainty and its macroeconomic implications. Following Bloom (2009), a popular measure of aggregate uncertainty is the CBOE Volatility Index (VIX), which is constructed using options data using the prices of S&P 500 index options. The advantage of using implied volatility instead of realized volatility is that the former is a more accurate proxy for uncertainty (as highlighted in Berger et al., 2019). This is because realized volatility measures the magnitude of recent shocks, whereas implied volatility gauges the expected size of future shocks. Recently, Dew-Becker and Giglio (2023) have used options data (which also underlie the VIX) to construct a cross-sectional measure of uncertainty that captures the average variance of idiosyncratic firm-level shocks. Alfaro et al. (2023) emphasize the role of firm-level implied volatility in understanding uncertainty transmission and its macroeconomic effects. We also use options data to measure implied volatility at the security level. However, our focus and objectives differ. First, we aim to obtain industry-specific uncertainty measures rather than an aggregate measure of cross-sectional dispersion. Second, our goal is to study uncertainty propagation along the supply chain.

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 its exogenous variation. In this section we

describe the data that we use and our empirical strategy to identify exogenous variations 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-volatilities in OM are 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. We will consider other maturities for robustness.

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 over 14 million daily observations for 6,279 option issuers.

Our analysis focuses on issuers whose options are 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 125 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. See the Appendix for details.

2.2 Measuring Uncertainty

We first construct a daily measure of sector-level implied volatility as a weighted average of daily firm-level implied volatility for firms within a specific NAICS 4-digit industry:

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

where d indicate trading days, f indexes firms, i denotes industries. The firms' market capitalization share in its industry determines the weights $s_{f,i,d}$.

Our benchmark monthly measure of sectoral implied volatility, which we call $\sigma_{i,t}$, is constructed by averaging the daily measure using only the last 5 trading days of the month. As discussed in the next section, using a short time window to measure sectoral implied volatility allows us to better control for realized volatility, which captures first-moment shocks and implied volatility in customer and supplier industries. As an alternative, we also consider the average over all the trading days of the month.

Following Acemoglu et al. (2016) we construct measures that capture each industry's exposure to supplier and customer uncertainty. Supplier uncertainty for industry i is defined by

$$\sigma^U_{i,t} = \sum_k \omega_{ki} \sigma_{k,t}, \tag{2}$$

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

where ω_{ki} 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:

$$\sigma^D_{i,t} = \sum_k \tilde{\omega}_{ik}\sigma_{k,t}, \tag{3}$$

where $\tilde{\omega}_{jk}$ represents the fraction of i's output demanded by k-th sector in its Leontief Inverse form. The weights $\tilde{\omega}_{ik}$ and ω_{ki} are derived from the 2007 total-requirement input-output table.[7]

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

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

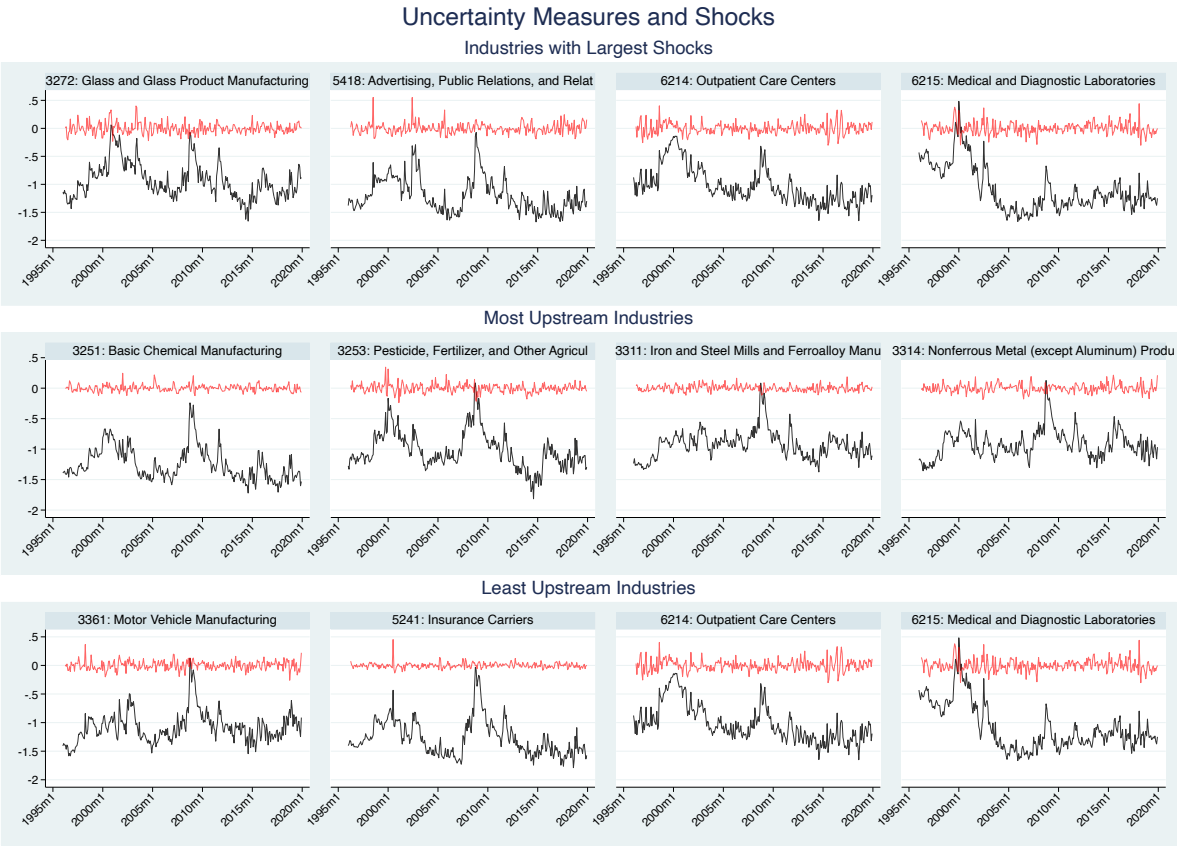
where $r_{f,i,d}$ denotes the stock return of firm f. We construct supplier and customer realized volatility, $RV^U_{i,t}$ and $RV^D_{i,t}$, analogously to equations (3) and (2). Finally, we construct aggregate monthly measures of realized and implied volatility using the monthly average of daily realized volatility of the $S\&P500$ index and the implied volatility of the same index. We denote these two variables by RV_t and σ_t.

Figure 1 shows in black the log of our benchmark measure of sectoral implied volatility, $\sigma_{i,t}$, for a selection of industries. To conserve space, we focus on NAICS 4-digit industries with the largest share of aggregate 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]

[7] 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.

[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 1: Sectoral Uncertainty and Uncertainty Shocks



Note: Log uncertainty (black) and uncertainty shocks (red).

The figure reveals substantial time variation in these time series. Some of this variation appears to be common across many series, particularly around the Great Recession. However, the series also exhibit numerous idiosyncratic spikes. As we now discuss, we leverage this idiosyncratic variation to identify uncertainty shocks suitable for estimating network effects.

2.3 Identification of Uncertainty Shocks

There are three main challenges to identifying industry-level uncertainty variations that are exogenous to other outcomes of interest within the same industry and along the production network. First, implied volatility is endogenous because it can fluctuate in response to sector-specific or aggregate first-moment shocks. 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 also 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, industry-level uncertainty may respond to aggregate uncertainty. Third, sectoral uncertainty may reflect changes in uncertainty originating in supplier and customer industries.

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:

$$\ln \sigma_{i,t} = \alpha_i + \sum_{\kappa=1}^{p_\sigma} \varphi_i^\kappa \ln \sigma_{i,t-\kappa} + \sum_{\kappa=0}^{p_\sigma} \psi_{\sigma_i}^\kappa \ln \sigma_{t-\kappa} + \sum_{\kappa=0}^{p_{RV}} \psi_{RV_i}^\kappa \ln RV_{t-\kappa} + \sum_{\kappa=0}^{p} \mathbf{\Psi}_i^\kappa \mathbf{Z}_{i,t-\kappa} + \nu_{i,t}, \quad (4)$$

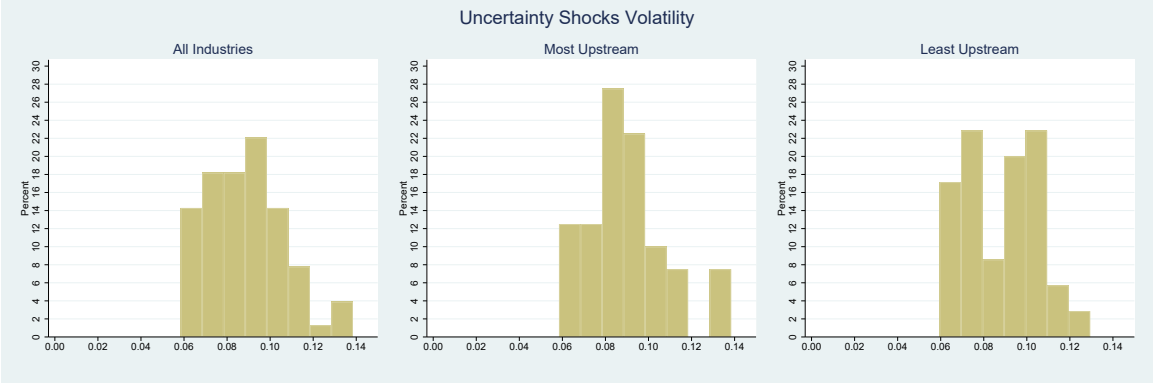
where $\mathbf{Z}_{i,t-\kappa}$ are contemporaneous and lagged sector-specific controls, and the left-hand side uncertainty measure is constructed by averaging daily sectoral implied volatility using the last 5 trading days of the month. The identified shocks correspond to the residuals of these industry-level regressions, $\nu_{i,t}$.

Regression (4) exploits two main assumptions. First, following the argument in Berger et al. (2019) we assume that first-moment shocks can affect contemporaneously realized volatility but, 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 causal impact effect of uncertainty shocks on realized volatility is nearly zero. We follow this rationale and control for contemporaneous and lagged realized volatility at the aggregate level ($\ln RV_{t-\kappa}$) (3 lags), industry level (3 lags), and in industries that are upstream and downstream relative to industry i (1 lag) ($RV_{i,t}^U$ and $RV_{i,t}^D$, included in $\mathbf{Z}_{i,t-\kappa}$). These controls purge the effects of (aggregate, industry-level, upstream and downstream) current and past first-moment shocks.

Second, we include in $\mathbf{Z}_{i,t-\kappa}$ measures of within-month implied volatility originating from upstream suppliers and downstream customers, $\sigma_{i,t}^U$ and $\sigma_{i,t}^D$, as previously described. Both measures are constructed using data from the first sixteen trading days of the month to ensure they capture information that does not overlap with the left-hand side variable.

We also assume that uncertainty in a given sector does not affect aggregate un-

Figure 2: Distribution of standard deviations of shocks



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

certainty, while the opposite is not true. This is motivated by the modest size of a NAICS 4-digit sector compared to the aggregate economy.[9] Consequently, we control for current and lagged implied volatility both at the aggregate level ($\ln \sigma_{t-\kappa}$) (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 $\ln \sigma_{i,t-\kappa}$.

As detailed in the next section, 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 5 days) or using only option-issuers that are always in sample (rather than for at least 10 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 only a small cross-industry correlation of 0.15. Figure 2 shows the distribution of the industry-level standard deviation of the estimated shocks for all industries and for industries in the top and bottom quartile of the upstreamness distribution. A comparison of the three panels shows that the distribution of shock sizes is relatively similar upstream and downstream. Table 1 confirms this finding by showing the top 5 industries with the largest standard devia-

[9] 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.

Table 1: Most and Least Upstream Industries with Largest Shocks

$\sigma(\nu_{i,t})$	NAICS4	Name
0.132	3351	Electric Lighting Equipment Manufacturing
0.107	3212	Veneer, Plywood, and Engineered Wood Product Manufacturing
0.097	3313	Alumina and Aluminum Production and Processing
0.096	5418	Advertising, Public Relations, and Related Services
0.093	4862	Pipeline Transportation of Natural Gas
0.153	5259	Other Investment Pools and Funds
0.128	6219	Other Ambulatory Health Care Services
0.113	4541	Electronic Shopping and Mail-Order Houses
0.102	4483	Jewelry, Luggage, and Leather Goods Stores
0.101	3122	Tobacco Manufacturing

Note: Top-5 standard deviation of estimated shocks in the first and last quartile of the upstreamness distribution.

tion of shocks. These standard deviations are comparable for the most upstream and least upstream industries.

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

The identified shocks capture unexpected changes in uncertainty affecting multiple firms within an industry or idiosyncratic uncertainty impacting large firms in the sector. Several shocks are associated with notable events that created uncertainty in specific sectors, such as regulatory changes, financial restructuring, technological transformations, and trade tensions. For instance, among the least upstream industries in Figure 1, the shocks series rose appreciably in the insurance industry (5241) in October 2004. This coincides with when an antifraud investigation by the NY attorney general led many insurance companies to announce they would stop paying contingent commissions to their agents, creating widespread uncertainty about the future profitability of the sector. In the outpatient care industry (6214), where a significant portion of the overall healthcare workforce is employed, we can see a series of large shocks in 2015. At this time, the Centers for Medicare & Medicaid Services began implementing value-based care initiatives, tying reimbursements to patient outcomes

rather than service volume. Outpatient care centers faced uncertainties in adapting to these new business models, which required care delivery, data reporting, and financial management changes. Uncertainty shocks in the motor vehicle manufacturing industry (3361) display an important spike in 1998. At this time, Daimler-Benz AG acquired Chrysler Corporation, forming DaimlerChrysler AG. This merger represented a major consolidation in the automotive industry, leading to uncertainty regarding management practices and potential impacts on the workforce. Upstream in the supply chain, industries closely tied to manufacturing experienced rising uncertainty during the late 2010 ' s as a result of the US-China escalating trade tensions. Correspondingly, the figure shows that ferrous and non-ferrous metal industries—such as 3311 and 3314—experienced significant shocks during this period. Finally, the advertising industry (5418) stands out among the industries exhibiting the largest uncertainty shocks. The estimated series captures key events that transformed the sector, including the digital shift of the late 1990s, the launch of Google AdWords in October 2000, and the emergence of YouTube in February 2005.

3 Uncertainty Propagation Along The Supply Chain

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

$$\ln X_{jt+h} - \ln X_{jt-1} = \alpha_{jh} + \beta_h^O \hat{v}_{jt} + \beta_h^D \hat{v}_{jt}^D + \beta_h^U \hat{v}_{jt}^U + \varpi_{t+h} + \sum_{\kappa=1}^{p_x} \mathbf{\Phi}_x^\kappa \mathbf{x}_{t-\kappa} + \epsilon_{jt+h}. \quad (5)$$

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 $\hat{v}_{j,t}$ as well as on the shocks of industries that are upstream or downstream relative to the industry in question. These shocks $\hat{v}_{j,t}^U$ and $\hat{v}_{j,t}^D$ 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 (3) and (2). The assumption is that

an increase in uncertainty in industry k is more important for industry j when the input/output share of sector k in j is higher. Our local projections also include a horizon-industry fixed effect, a time fixed effect, and lags of the outcome variable as controls ($x_{t-\kappa} \equiv \ln X_{j,t-\kappa} - \ln X_{j,t-\kappa-1}$).

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. The impulse responses for uncertainty, employment, and producer prices are displayed in Figures 3.

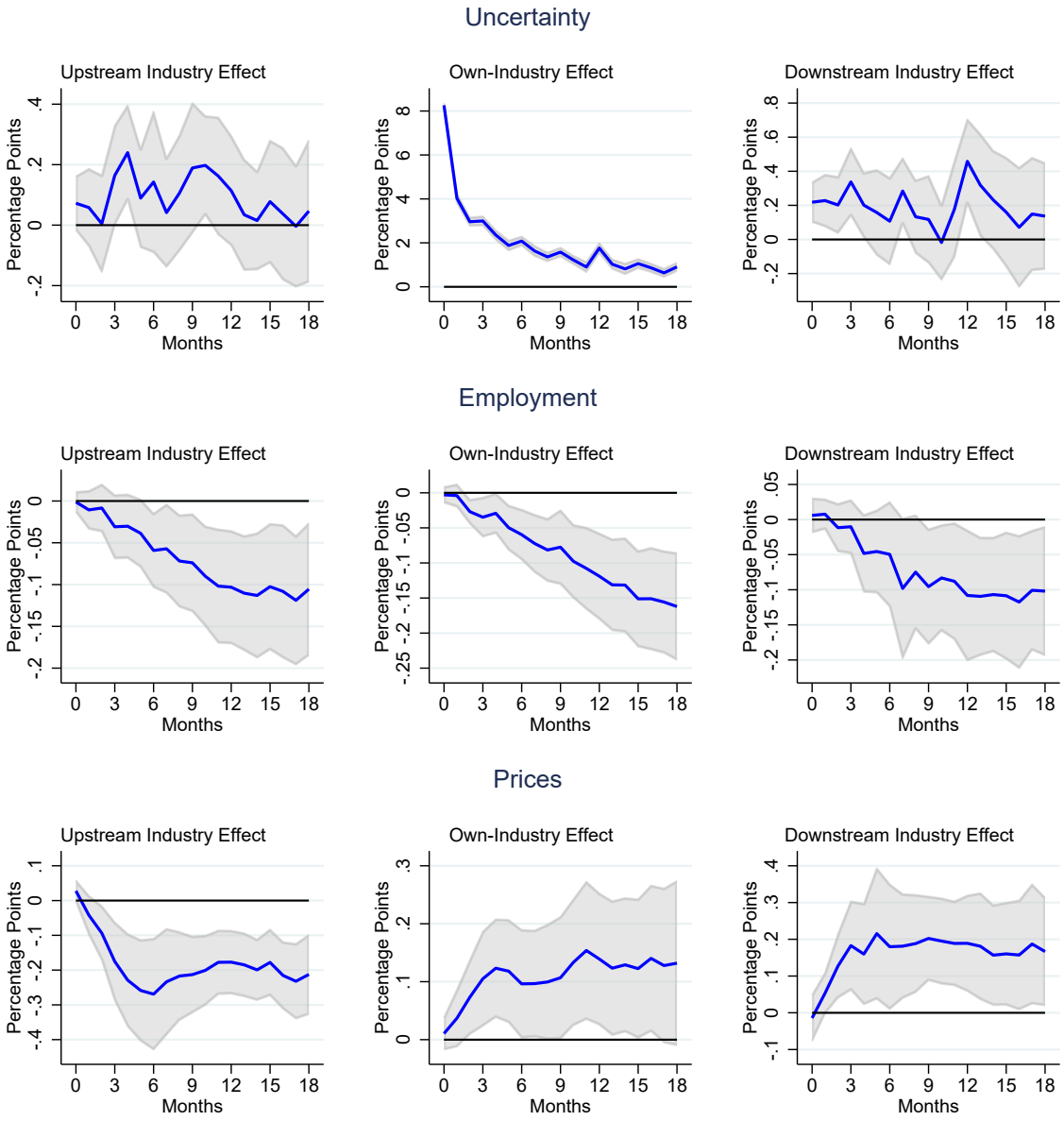
3.1 Industry-level Results

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 3, 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 upstream and downstream sectors albeit the effect is smaller and only significant for a few months. 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 (e.g., changes in prices and quantities in the industries facing higher uncertainty).

The second row of Figure 3 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 third row of Figure 3 depicts the response of producer prices to uncertainty 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

Figure 3: Impulse Responses to an Uncertainty Shock



Note: Estimated impulse response functions to uncertainty shocks. "Upstream effect" refers to the effect of a shock originating in downstream sectors relative to the industry in question. "Downstream effect" is symmetrically defined.

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).

Figure 3 shows 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 demand 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.

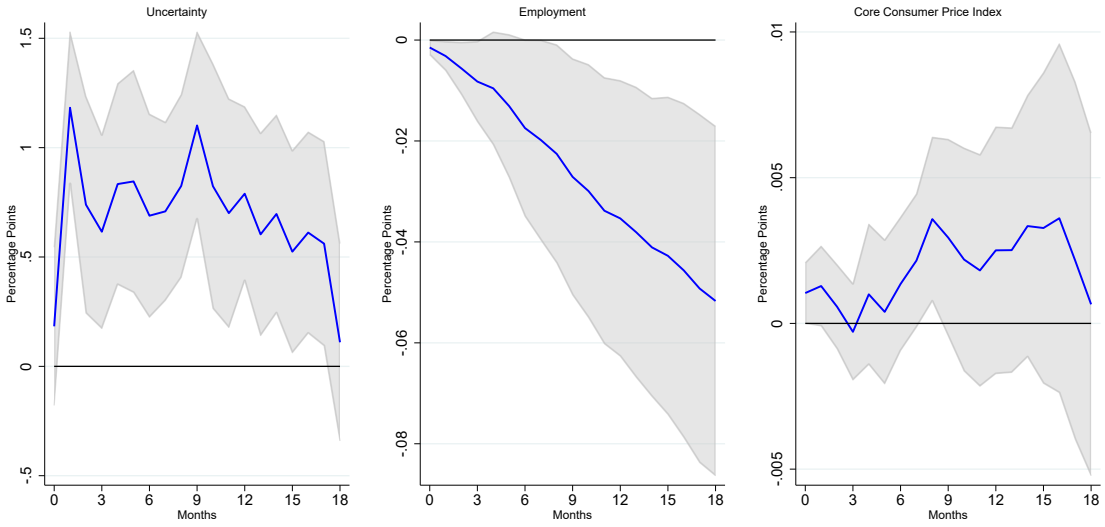
Our theoretical contribution in the next section is to show that a New Keynesian production network model can rationalize these empirical findings and explain the upstream and downstream propagation of uncertainty shocks. Central to network transmission is the fact that uncertainty raises prices in the 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 downstream production, 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 Aggregate Implications

The upstream and downstream propagation documented in Section 3.1 suggests the possibility that these sectoral uncertainty shocks may ultimately have aggregate con-

Figure 4: Impulse Responses of Aggregate Variables



Note: Estimated impulse response functions of aggregate variables to uncertainty shocks.

sequences. To study the aggregate implications of these shocks, we proceed as follows. First, we construct a time series of aggregate shocks by taking an average of sectoral shocks weighted by the market capitalization share of each sector :

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

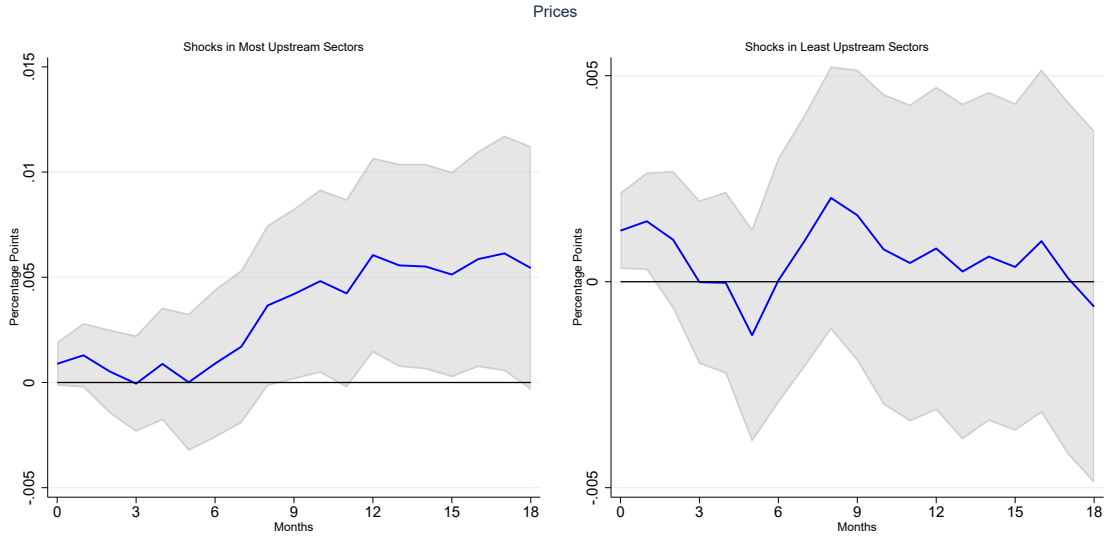
where s_{it} is industry i market capitalization share at time t. Therefore, this measure of aggregate shocks is sensitive to large shocks in a given industry or to shocks to industries with a large market capitalization. We then estimate the following series of aggregate local projections $h = 1, .., H$

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

where X is the outcome of interest and $\mathbf{x}_{t-\kappa}$ is a vector of aggregate controls that include lags of the dependent variable and of aggregate implied volatility, realized volatility, and of the shadow Federal Funds rate of Wu and Xia (2016). We use 6 lags of the shadow rate and 12 lags of the rest of the controls for monthly regressions.

Figure 4 shows the estimated impulse responses for aggregate implied volatility,

Figure 5: Response of core CPI - Shocks in Top (left) or Bottom (right) Upstreamness



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 4 also shows that core CPI does not respond significantly, although the point estimate tends to be positive throughout the horizon considered. To understand this result, recall that sectoral uncertainty shocks have inflationary effects in the sectors of origin and downstream, while they are deflationary for suppliers of industries affected. It would be erroneous to conclude that the aggregate effects just net out these sectoral effects as other general equilibrium forces, such as the response of aggregate demand, contribute to determining aggregate inflation. We will explore these forces in our general equilibrium model below.

Nevertheless, given the heterogenous sectoral response of producer price inflation previously documented, we now address whether shocks originating more upstream have different implications for aggregate inflation than those originating downstream. To answer these questions, 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 refined the shocks series as being either:

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

or

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

respectively.

Figure 5 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 4 where we were not conditioning on the sectoral origin of the shock. This result is consistent with the notion that when shocks originate upstream, aggregate CPI reflects mostly 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 show that the origin of uncertainty shocks matters for network propagation and aggregate dynamics. These findings imply that policymakers relying solely on aggregate tools (e.g., central banks) may need to tailor their responses to uncertainty-driven fluctuations based on the sectoral origins of such shocks.

4 Theoretical Insights

What explains the network propagation of uncertainty shocks? To address this question, we develop a multi-sector model with input-output linkages and sector-specific time-varying volatility. The model rationalizes the empirical findings and clarifies the economic forces driving the propagation of sectoral uncertainty along the supply chain and at the aggregate level.

We use the 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. While this section focuses on sector-specific productivity uncertainty, the Appendix shows that the intuition holds and the results remain robust when accounting for demand-driven uncertainty within a given industry. We illustrate the main results using a three-sector, linear network economy. As detailed below, the findings remain similar when considering a production network calibrated to U.S. data.

4.1 A Production Network Model with Sectoral Uncertainty Shocks

Here we describe the key ingredients of the model and refer the reader to the Appendix 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. 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 and Wholesalers. In each sector, a continuum of monopolistically competitive firms indexed by $j \in [0, 1]$ produce differentiated varieties of sectoral goods,

$Z^j_{s,t}$, by combining labor and intermediate inputs in the following production function:

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

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 elasticity of substitution between inputs χ_s is sector specific, as is the factor share α_s. Labor and intermediates cost $W_{s,t}$ and $Q_{s,t}$ in sector s.

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. Producers sell differentiated varieties to a competitive wholesale sector which bundles them into a single final sectoral good $Z_{s,t}$ using a CES production technology with elasticity of substitution ϵ:

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

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

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

where $H_{x,s,t}$ denotes the demand of retailers that produce the intermediate-good bundle used by sector x, and $C_{s,t}$ is consumption-good retailers' demand.

Retailers. The retail sector is perfectly competitive. Consumption good retailers aggregate sectoral goods to produce C_t using a Cobb-Douglas function :

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

where the $\omega_{C,s}$'s denote the sectoral shares that add up to one.

Similarly, in each sector s, intermediate-good retailers combine sectoral intermedi-

ate 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 for a generic sector s 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, which in our model coincides with GDP deflator inflation since the final goods resource constraint is $Y_t = C_t$.

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.[10]

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

[10] 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.

conditional volatility of the return on a claim to wholesale producers' cash flows, D_t^E:

$$D_{s,t}^E = P_{s,t}Y_{s,t} - W_{s,t}N_{s,t} - Q_{s,t}H_{s,t}, \tag{20}$$

$$R_{s,t+1}^E = \frac{D_{s,t+1}^E + P_{s,t+1}^E}{P_{s,t}^E} \tag{21}$$

$$V_{s,t}^E = 100 \times \sqrt{4 * VAR_t(R_{s,t+1}^E)} \tag{22}$$

Above, $R_{s,t+1}^E$ denotes the return and $V_{s,t}^E$ its conditional volatility. The measure of aggregate conditional volatility is analogously defined over the cashflows $D_t = \sum_{s \in S} D_{s,t}^E$. 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:

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

where M_{t+1} is the household's stochastic discount factor. Because our simple model abstracts from capital and leverage, claims on cashflows are quite stable, which implies that the average conditional volatility $\mathbb{E}[V_{s,t}^E]$ is too low compared to the data. To resolve this issue, we introduce more volatility in the price of risk by means of an exogenous financial shock in the Euler equation (23). Since the Modigliani and Miller (1958) theorem holds in our model, this shock only affects asset prices but not macroeconomic dynamics. We model ξ_t as an autoregressive process of order 1 in logs with persistence ρ_ξ and standard deviation σ_ξ.

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 an extended period in which the realizations of all shocks are identically zero to the counterfactual path in which a single one-standard-deviation shock to $\sigma_{s,t}^a$ is realized.

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 relative to that sector (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 consider elasticities of substitution between intermediate goods and labor of 1 and 0.4. The first value corresponds to a Cobb-Douglas production function and is close to the bound of empirical estimates, while the second value is on the lower end of empirical estimates (see discussion in Atalay, 2017). 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 sectoral productivity shocks' persistence and steady-state standard deviation at conventional values: $\rho_a = 0.95$ and $\sigma^a = 0.007$. We also set $\rho_\xi = 0.9$ and $\sigma_\xi = 0.9$ to match the empirical response of conditional volatility, $V^E_{s,t}$, to a one-standard-deviation increase in the second-moment or uncertainty shock, $\varepsilon^\sigma_{s,t}$. Finally, we calibrate the persistence and standard deviation of the sectoral uncertainty shock, σ_{σ_a}, to match the sectoral employment response relative to conditional returns' volatility following the same uncertainty shock. This requires setting $\rho_{\sigma^a} = 0.80$ and $\sigma_{\sigma_a} = 0.40$.

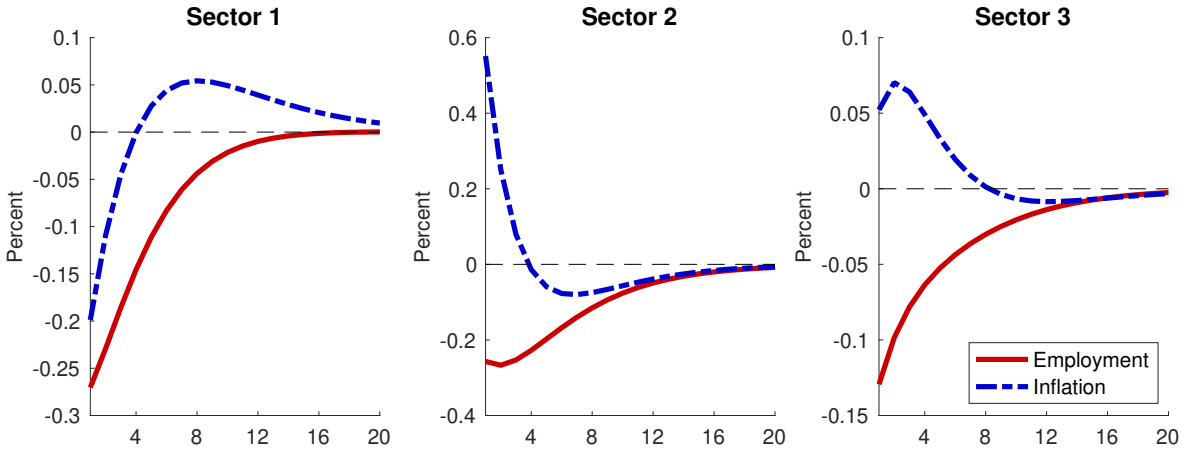
4.3 Propagation of uncertainty shocks

Figure 6a 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 6b considers instead an economy in which there are no

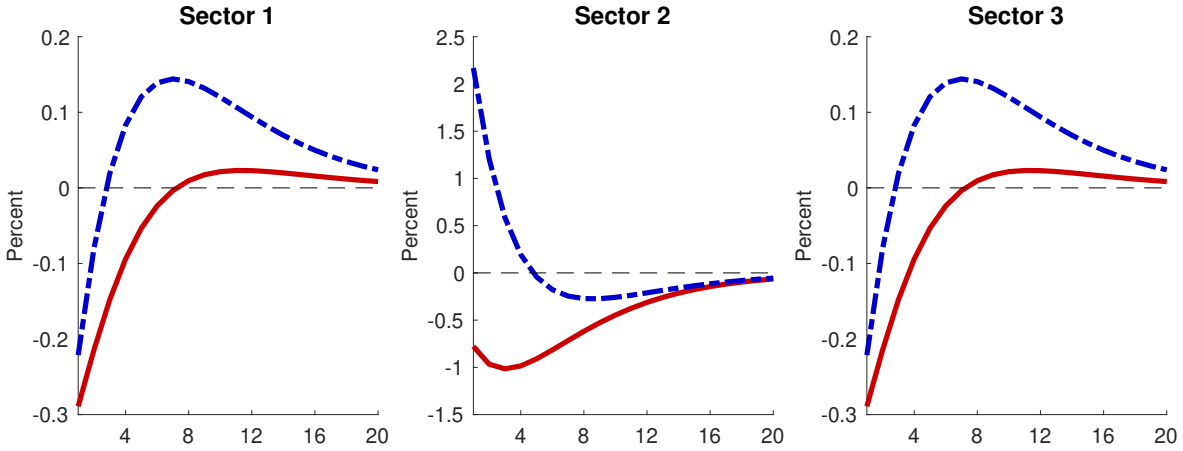
network linkages, i.e., every sector uses only output from its own sector as intermediate inputs ($\omega_{H,1,1} = 1$, $\omega_{H,2,2} = 1$, and $\omega_{H,3,3} = 1$.).

Figure 6: Impulse Responses to Sector 2 Uncertainty Shock

(a) Baseline Network



(b) No Network



To build intuition, consider first the no-network economy. Figure 6b shows that the uncertainty shock results in a persistent decrease in employment and output and in an increase in inflation in its own sector. The own-sector effect of this shock can be primarily understood in terms of the precautionary pricing motive that arises because of Calvo-style pricing frictions in our model (as discussed in Born and Pfeifer (2014); Fernández-Villaverde et al. (2015)). The idea is that when uncertainty about marginal cost increases, firms increase their prices (higher markups) to self-insure against being stuck with too low a price. The increase in markups results in a contraction of de-

mand and thus production, as well as an increase in inflation in the sector affected by the uncertainty shock. The lower demand for the industry output also reduces labor demand and employment in that sector.

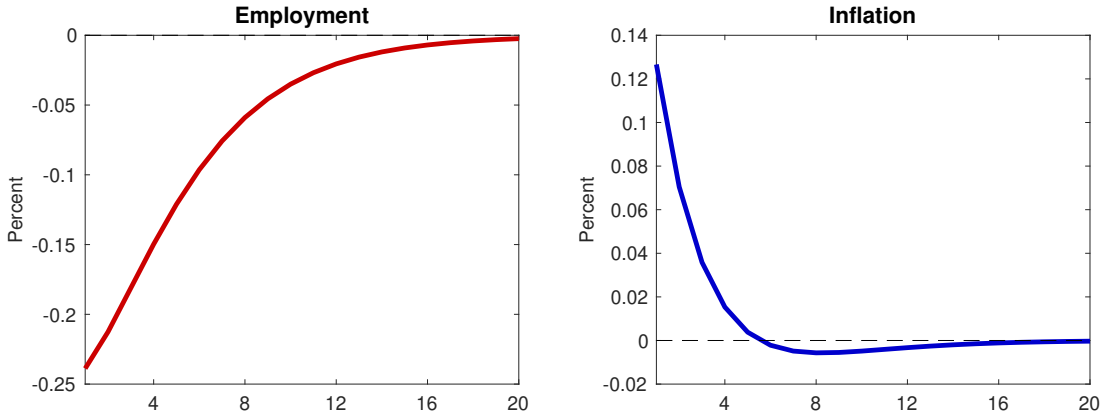
Despite the absence of sectoral production linkages, general equilibrium effects propagate the uncertainty shock to the other sectors of the economy. A first propagation mechanism is that the sectoral uncertainty shock generates precautionary savings, which results in a fall in households' final consumption demand and, therefore, deflationary pressure for all sectors of the economy. The response of quantities such as employment and output is also shaped by the response of labor supply in all the sectors of the economy, which may increase due to precautionary motives as discussed in Basu and Bundick (2017). In equilibrium, the aggregate demand channel dominates, explaining the fall in employment and output across all sectors.

Moving to the linear network economy, we emphasize the stronger propagation of uncertainty shocks on quantities in the other sectors of the economy and the heterogeneous response of sectoral inflation, all of which align with our empirical evidence. The linear production network adds further channels for uncertainty propagation. First, 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. This reinforces the negative demand shock that sector 1 experiences, now coming from final consumers and its customer industry. The result is a stronger contraction in employment and inflation in sector 1. Second, the increase in inflation in sector 2 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 reduces intermediate inputs demand and, to the extent that labor and intermediates are complement in production, further reduces labor demand relative to the no network case. This results in a stronger decline in employment and output in sector 3. Concerning the inflation dynamics, there are two competing forces: the aggregate demand channel tends to reduce inflation in the downstream sector, while the marginal cost channel tends to increase it. Figure 6b shows that for our illustrative calibration, the latter dominates, and the uncertainty shock is inflationary downstream.

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

Figure 7: Aggregate Responses to Sector 2 Uncertainty Shock

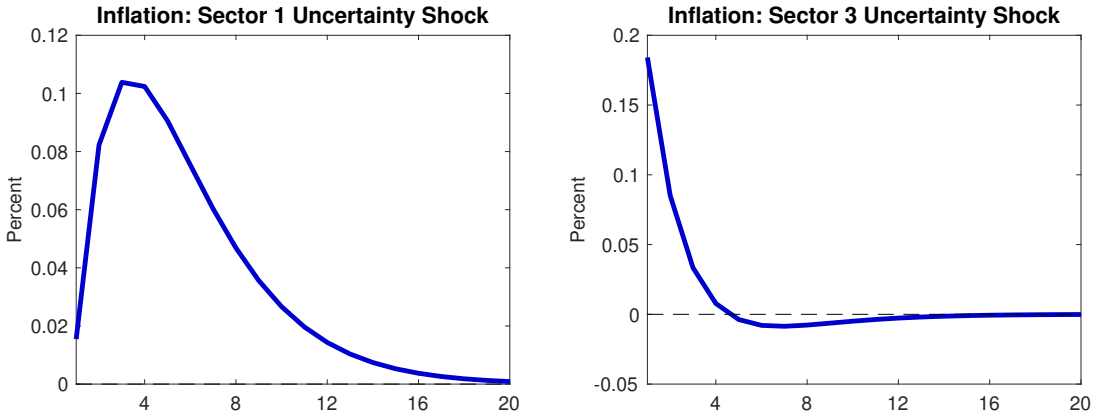


on where uncertainty originates in the production network. Figure 7 shows the impact of an uncertainty shock in sector 2 on aggregate employment and consumer price inflation. The shock is contractionary and leads to a very short-lived price increase. Figure 8 shows that the inflation increase becomes 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.

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 show that the previous results hold even under 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 up-

Figure 8: Heterogeneous Aggregate Inflation Response



stream broad sector corresponds to sector one in the model, while the least upstream broad sector maps into sector three. 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 heterogenous 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).

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.2 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.3 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 with $\chi = 0.5$. 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 empirical and theoretical results suggest that upstream uncertainty shocks pose a greater challenge for monetary policymakers seeking to stabilize aggregate activity and inflation. Understanding how uncertainty propagates through production networks is therefore essential for designing effective policy responses. A natural avenue for future research is to examine how the optimal policy response depends on the origin of uncertainty within the supply chain. Another important direction is to extend the analysis to study the transmission of uncertainty shocks along the global supply chain and explore their implications for international trade and cross-country spillovers.

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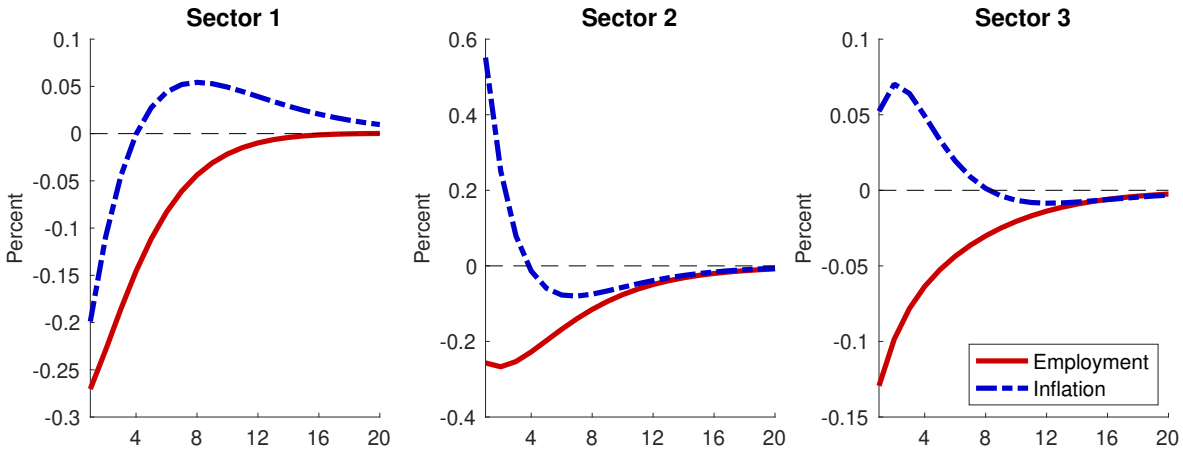
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Appendix

A Model Robustness

Figure A.1: Impulse Responses to Sector 2 Uncertainty Shock

(a) Baseline



(b) Empirical Network

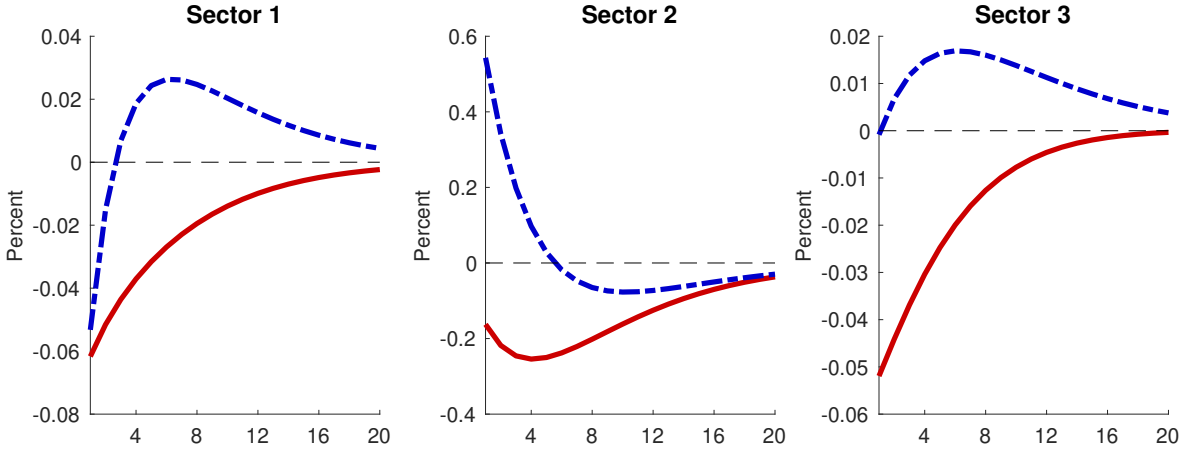
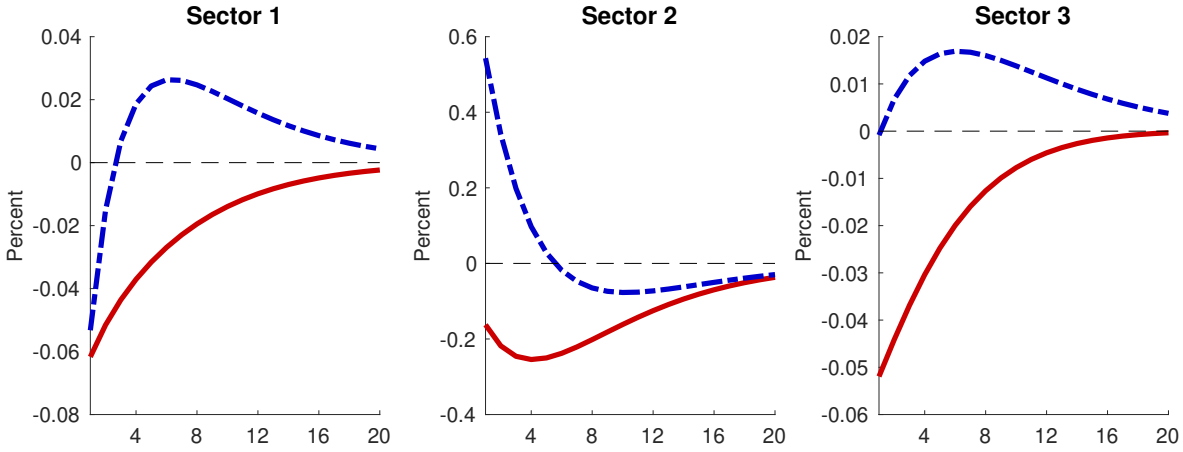


Figure A.2: Impulse Responses to Sector 2 Uncertainty Shock

(a) Empirical Network - Supply Uncertainty Shock



(b) Empirical Network - Demand Uncertainty Shock

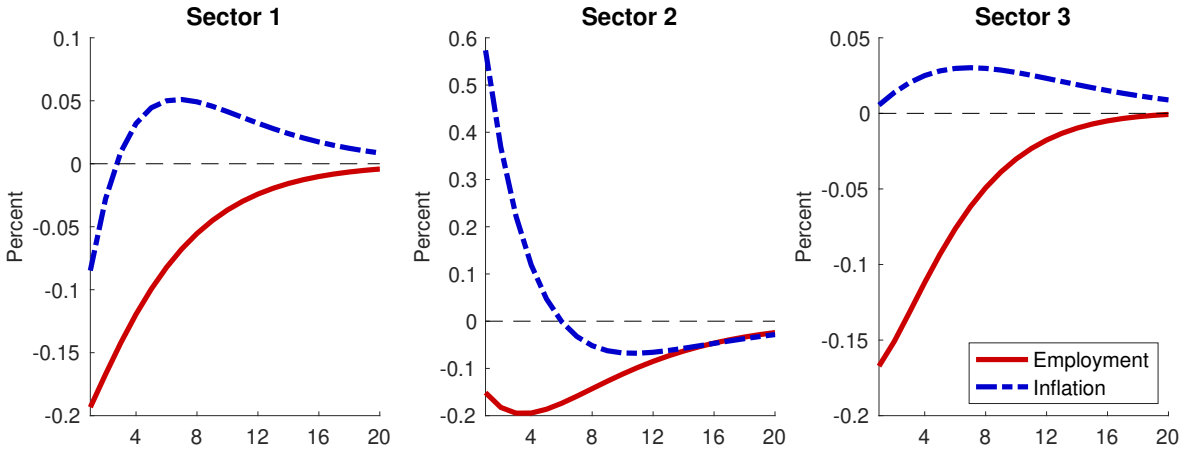
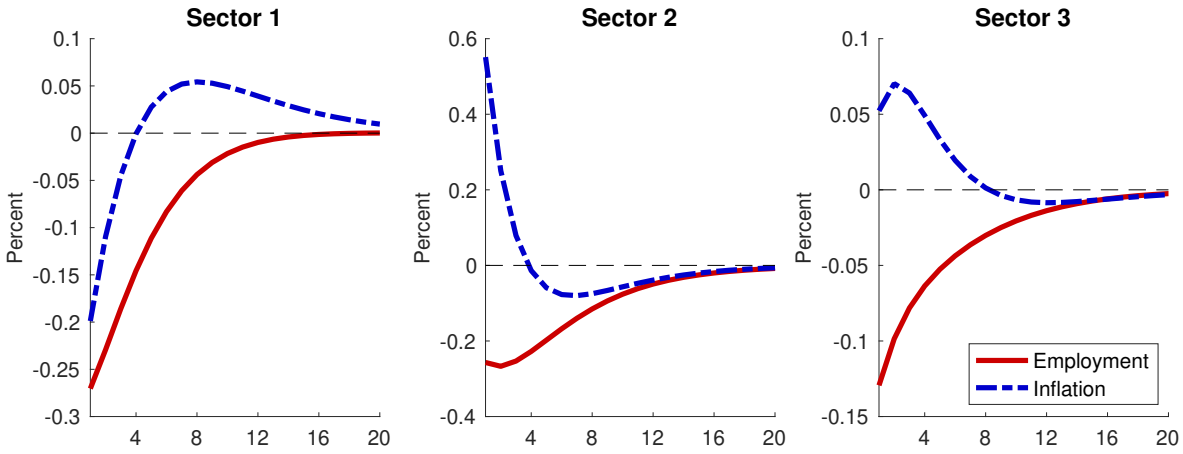


Figure A.3: Impulse Responses to Sector 2 Uncertainty Shock

(a) Baseline



(b) Cobb Douglas Production

