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Dynamic industry uncertainty networks and the business cycle ☆

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ABSTRACT

This paper identifies smoothly varying industry uncertainty networks from option prices that contain valuable information about business cycles, especially in terms of forecasting. Such information is stronger when the network is formed on uncertainty hubs, firms identified as the main contributors to uncertainty shocks. The stronger predictive ability of the hubs-based network is robust to a wide range of checks, the inclusion of a large set of controls, and is also confirmed out-of-sample.

1. Introduction

Throughout history, the industrial structure has witnessed influential economic and financial cycles, marking the ebb and flow of different sectors taking a leading role.[1] Understanding the differences in the behaviour and performance of firms within different industrial sectors of an economy provides important insights into the economy as a whole. At the same time, modern economies are dominated by large firms, and thus idiosyncratic shocks to these firms can contribute significantly to economic fluctuations (Gabaix, 2011; Acemoglu et al., 2012), and industry-level shocks account for a large proportion of the variation in aggregate output growth (Atalay, 2017).[2] A shock to uncertainty in a given sector, especially of large firms within that sector, can in turn increase uncertainty

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[1] The rise of technology and telecommunications is a notable recent example. The fast-growing internet sector accounted for $2.1 trillion of the US economy in 2018, or about 10% of the country's gross domestic product (GDP).

[2] For example, for the United States, the sales of the top 100 firms average 29% of GDP. The top 100 firms thus represent a large part of macroeconomic activity, so understanding their actions provides a good insight into the overall economy. As another example, in December 2004, a one-time $24 billion dividend from Microsoft boosted personal income growth from 0.6% to 3.7% (Bureau of Economic Analysis, 31 January 2005).

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in other (smaller) firms within the sector through a cascading effect, and adequately capture the uncertainty dynamics and fluctuations that occur in that sector, which can spill over to other sectors and the economy as a whole.[3] Fluctuations in performance, valuation and interconnectedness are hence critical not only for financial market volatility, but also for the real economy and business cycle forecasting. Despite the increasing interconnectedness of economic activities across industries, we do not fully understand the impact of such networks on the real economy. Against this background, we develop dynamic forward-looking measures of industry uncertainty networks derived from the time evolution of industry-specific shocks to option investors' expectations. We examine how these industry uncertainty networks provide novel insights to improve our understanding of macroeconomic activity as reflected in business cycle markers.

To infer such information, we collect an extensive sample of option prices to extract option-based uncertainty measures for a large sample of firms across the US industrial landscape. We construct aggregate uncertainty measures for each industry at a daily frequency covering three recession periods (including the recent Covid-19 crisis). Based on the time-varying parameter approximation models, we then construct a measure of the ex-ante industry uncertainty network that reflects investors' expectations of future uncertainty relevant to each industry. Our approach incorporates the argument that time-varying variance decompositions well characterise how shocks to uncertainty create dynamic networks (e.g. Diebold and Yılmaz, 2014; Barunik and Ellington, 2020).[4] We assess the different role of industries in driving shocks to business cycle uncertainty. Our analysis then naturally leads to the question of how useful such uncertainty network measures are in predicting economic activity.[5] In short, the paper answers the following questions: *How does the network of industry uncertainty evolve over time, which industries are the main drivers of the network of industry uncertainty, and what is the relationship between these network measures and the business cycle.*

The main findings of our paper are as follows. First, we identify industries that show a stronger (as opposed to weaker) contribution of shocks to uncertainty and its propagation, and thus play an essential role within the aggregate industrial uncertainty network. Specifically, we uncover an uncertainty hub role for communications, financials and IT, which appears to be largely time-invariant. In contrast, industrials, materials and utilities are classified as non-hub sectors. In line with the intuition underlying our framework, our data show evidence of an enhanced contribution to uncertainty propagation in the system associated with the uncertainty hubs, which is not limited to a specific business cycle.

Second, we have a number of other findings relevant to the time series perspective. We find that the ex-ante industry network increases sharply during the dot-com bubble and the GFC, and rises steadily thereafter. We also find an increasing importance of hub-specific shocks over the last decade, implying that shocks to hubs account for most of the aggregate fluctuations after the GFC, driven mainly by the communications and IT industries.

Third, our empirical exercise shows that the ex-ante industry uncertainty network generates an important channel through which sector-specific shocks propagate. Moreover, the industry uncertainty network shows significant utility as a leading predictor of business cycles up to one year ahead. Changes in business cycle indicators occur in line with changes in the comovement of uncertainty across industries, and business cycle turning points appear to be particularly consistent with changes in the network connectedness of uncertainty hubs. Sectoral shocks to hubs drive aggregate shocks to the whole system, while the response of aggregate economic trends to uncertainty shocks in non-hubs is marginal. The stronger predictive ability of the hub-based network is also confirmed out-of-sample. Our results are robust to a wide range of controls and to the inclusion of a large set of control variables.

The essence of our contribution relates to two relatively recent strands of literature. The first strand deals with uncertainty and risk measures and their relationship with the real economy and business cycle fluctuations (e.g. Bloom, 2009, 2014; Jurado et al., 2015; Arellano et al., 2019; Ludvigson et al., 2020).[6] The second strand focuses on the role of sectoral or firm-level linkages in microeconomic shocks and their relationship to the aggregate economy and changes in business conditions (see, e.g. Gabaix, 2011; Acemoglu et al., 2012; Carvalho and Gabaix, 2013; Barrot and Sauvagnat, 2016; Acemoglu et al., 2017; Baqaee and Farhi, 2019; Carvalho and Tahbaz-Salehi, 2019).[7] In contrast to this literature on the importance of network effects in macroeconomics (see Acemoglu et al., 2012; Carvalho and Gabaix, 2013; Gabaix, 2016; Barrot and Sauvagnat, 2016; Acemoglu et al., 2017; Baqaee and Farhi, 2019; Acemoglu and Azar, 2020), we identify a network that fluctuates over time from data on market expectations. Specifically, we focus on the shocks to expectations about industry fluctuations that generate fluctuations in other industries and, in turn, influence fluctuations in business cycles.

To capture uncertainty associated with industrial structures, one can rely on information about volatility or uncertainty shocks, exploiting the importance of network measures to capture the propagation of volatility mechanisms (see Acemoglu et al., 2012; Carvalho and Gabaix, 2013; Gabaix, 2016; Acemoglu et al., 2017; Baqaee and Farhi, 2019; Herskovic et al., 2020). Financial uncertainty shocks and risk fluctuations have been identified as one of the main drivers of the US business cycle (e.g. Bloom, 2009; Christiano et al., 2014; Bloom et al., 2018; Ludvigson et al., 2020; Fernández-Villaverde and Guerrón-Quintana, 2020).[8] The novelty

[3] In our context, the advantage of looking at a set of large firms also stems from the availability of options data, which is key for us to extract forward-looking idiosyncratic measures of uncertainty at the firm level.

[4] Our approach is closely related to the network node degrees, mean degrees and connectedness measures of Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012).

[5] Significant aggregate fluctuations may arise from firm-specific or industry-level shocks due to linkages between different firms and industries, acting as a potential propagation mechanism of idiosyncratic shocks throughout the economy (e.g. Acemoglu et al., 2012; Atalay, 2017).

[6] See also Bachmann and Bayer (2014), Christiano et al. (2014), Popp and Zhang (2016), Basu and Bundick (2017), Bloom et al. (2018) and Görtz and Yeromonahos (2022).

[7] On the importance of industry factors and industry risk see Griffin and Karolyi (1998) and Griffin et al. (2003).

[8] For a comprehensive literature review on uncertainty shocks and business cycle research, see Fernández-Villaverde and Guerrón-Quintana (2020).

of our approach lies in proposing an ex-ante approach that derives information from the option prices of individual firms that, after industry aggregation, reflects investors' expectations in terms of industry-related "fears". We argue that such information provides a reliable description of the prospective risk and performance of industries and the firms within them.

While we build our market data-driven approach to network measurement on the previous literature (Diebold and Yılmaz, 2014; Baruník et al., 2022), our novelty lies in quantifying network linkages based on shocks to ex-ante expectations about future industry fluctuations, which moreover change smoothly over time. In contrast, Diebold and Yılmaz (2014) measures uncertainty ex-post and does not allow the network to change smoothly over time. Using implied measures of uncertainty provides access to better information that reflects market participants' expectations of future movements in the underlying asset price compared to ex-post measures of uncertainty (see Christensen and Prabhala, 1998). We are interested in capturing shocks to the ex-ante uncertainty of industry j that are transmitted to future expectations about the uncertainty of industry k. Moreover, our framework timely translates industry uncertainty shocks into fluctuations in macroeconomic aggregates.

Notably, several authors also examine the role of production networks as a transmission mechanism from individual firms and/or industries to the real economy.[9] We also refer to the strand of the literature that proposes uncertainty as a cause of lower economic growth through i) the real options effects of uncertainty (e.g. Bernanke, 1983), ii) uncertainty affecting financing constraints (e.g. Arellano et al., 2019), and iii) precautionary saving (e.g. Basu and Bundick, 2017; Leduc and Liu, 2016; Fernández-Villaverde et al., 2011).

According to (e.g. Bloom, 2009), firms hire and invest only when business conditions are sufficiently good, and fire and disinvest when they are sufficiently bad. Therefore, when business conditions are profitable for that particular sector, investors expect stock returns to be higher and uncertainty to be lower, and vice versa. We argue that this can be inferred from option prices, as shocks to uncertainty, as measured by ex-ante expectations of return fluctuations, are transmitted across industries and have direct consequences for the broader economy and business cycles. Using purely market-based networks as a mechanism to dynamically study the propagation of industry uncertainty shocks to the real economy, we argue that industry-based uncertainty networks represent more informative (leading) channels that are highly relevant for predicting business cycles.

Moreover, by identifying "islands" or "investment hubs", Garin et al. (2018) and Vom Lehn and Winberry (2022) show that sector-specific shocks have become more volatile relative to aggregate shocks. Extending the definition of "hubs" from the input-output network literature, we characterise critical "uncertainty hubs" as industries that largely transmit and/or receive uncertainty over the business cycle, while "non-hubs" are those industries that are (largely) neutral over the business cycle. It is important to note that the role of industries changes dynamically over time, and thus our classification is specific to the period under study. We identify industries that are uncertainty hubs according to their actual role in dynamically transmitting and receiving uncertainty shocks over the business cycle. In general, our methods can be used for such classification in real time, providing hubs specific to a daily, monthly or business cycle period of interest. To show the information content of uncertainty hubs and non-hubs for business cycle predictability, we take an average contribution of uncertainty in our sample and define hubs as those above this threshold and non-hubs as those below.

We hypothesise that hubs are created by industries that are more connected to the economy and business conditions. Uncertainty shocks in hubs can affect production, employment and growth within the hub, but they can also generate larger uncertainty spillovers and changes in prices, growth and production in other industries in the system, ultimately affecting the broader economy (e.g. Kozeniauskas et al., 2018).[10] Therefore, we believe that the industry network constructed from uncertainty hubs can play a more prominent role in signalling phases of the business cycle compared to the non-hubs uncertainty network.

The rest of this paper is organised as follows. Section 2 describes the data and sampling used in our study. Section 3 presents the essence of the TVP-VAR network connectedness method applied to our chosen industry setting. Section 4 examines the dynamic aggregate uncertainty network connectedness, and section 5 presents the results for the dynamic idiosyncratic uncertainty network connectedness over the business cycle. Section 6 examines the predictive ability of the networks for the real economy. Section 7 concludes the paper. Additional results are relegated to the online appendix of the paper.

2. Industry uncertainty, investor beliefs and option prices

To study the dynamic uncertainty network, we develop a forward-looking measure of uncertainty that reflects investor beliefs. It is derived from industry-level option price data and is closely related to the VIX methodology. The VIX index (often referred to as the "fear index"), introduced by the Chicago Board Options Exchange (CBOE), is a model-free forward-looking measure implied by option prices that reflects investors' expectations of uncertainty in the stock market.

The VIX is a common proxy for uncertainty used in the financial economics literature (see Bloom, 2009; Duan and Yeh, 2010; Bekaert et al., 2013; Leduc and Liu, 2016; Kozeniauskas et al., 2018) that is able to assist policymakers in real time. At the same time, it is a proxy for aggregate fears. Uncertainty about outcomes due to changes in idiosyncratic variables faced by firms is usually more difficult to measure, as data on firm-specific beliefs are scarce (see Kozeniauskas et al., 2018).

Since we measure uncertainty from the cross section of firms (and then aggregate it to the industry level), a single firm VIX measure can be a valid proxy for both macroeconomic and firm level uncertainty, capturing both aggregate volatility and the

[9] For an incomplete list, see e.g. Foerster et al. (2011); Di Giovanni et al. (2014); Atalay (2017); Garin et al. (2018); Dessertaine et al. (2022); Vom Lehn and Winberry (2022).

[10] Some theories assume that higher uncertainty is generated directly in the process of technological innovation, which subsequently causes a decline in real activity (e.g. Bloom, 2009; Justiniano et al., 2010; Bloom et al., 2018).

dispersion of firm-specific outcomes. In addition, option-based measures of uncertainty also contain information about investor sentiment and fears about future firm and macroeconomic outcomes, and they can provide an upper bound proxy for uncertainty above measures that are strictly related to fundamentals. Finally, option-based measures of risk are superior to historical measures of volatility in terms of both predictive power and information content (e.g. Christensen and Prabhala, 1998; Santa-Clara and Yan, 2010; Baruník et al., 2022).

2.1. Extracting model-free industry uncertainty from option prices

We first derive VIX measures from the uncertainty of individual firms drawn from the major US industries.[11] For each selected firm in our sample, we compute a model-free industry VIX using all available option prices.[12] This measure hence reflects investors' expectations of uncertainty about the individual firm over the next 30 days. We then aggregate the individual firm information to construct an industry level measure of ex-ante uncertainty.

More formally, the ex-ante industry uncertainty measure $\mathrm{IVIX}_t^{(\mathrm{Ind})}$ is constructed by taking the time-varying weighted average of all the stocks in each industry and at each point in time through our sample period as:

$$\mathrm{IVIX}_t^{(\mathrm{Ind})} = \sum_{s \in N^{(\mathrm{Ind})}} \mathcal{W}_t^{(s)} \mathrm{VIX}_t^{(s)} \tag{1}$$

where $\mathrm{Ind} \in \{1, \dots, 11\}$ represents the industry we consider, s is an index for one of the $N^{(\mathrm{Ind})}$ firms included in the given industry at time t, $\mathrm{VIX}_t^{(s)}$ is the implied volatility for an individual stock s, and $\mathcal{W}_t^{(s)}$ is the time-varying market capitalization weight of stock s computed as the ratio between the time-varying market capitalization of stock s and the total market capitalization of all stocks included in that specific industry.[13]

We adopt a market capitalization-weighted average since big companies intuitively have a greater influence compared to smaller firms (e.g. mid-cap firms). The U.S. stock market large firms and the industries to which they belong are what matter the most when studying these as economic and business cycle drivers (e.g. Gabaix (2011)).[14] As a robustness check, we alternatively adopt a volume-weighted construction and the main substance of the findings (reported in the online appendix) are qualitatively the same.

2.2. Data

We use a dataset of options data from OptionMetrics to compute daily individual stock VIX measures from January 2000 to December 2020.[15] We include stocks from the time of their IPO and listing, stocks with data available in OptionMetrics, stocks with good options data coverage, stocks with data over a long period (more than 5 years of continuous data). Conversely, we exclude stocks from the dataset at the time of their bankruptcy, delisting, M&A or index restructuring.[16] Following our selection criteria, we end up with a database containing a wide range of options on more than 700 US stocks at a daily frequency over the last two decades. We apply common procedures in the literature to further exclude stocks with a low number of available contracts on a given day, less than 3 contracts after standard options filters to remove options with i) missing deltas, ii) missing implied volatility, iii) bid prices equal to 0 or after two consecutive 0 bids, and that iv) violate arbitrage conditions (see e.g. Bakshi et al., 1997, 2003; Carr and Wu, 2011). We use call and put option prices around the next 30 days, taking into account all available strike prices for each individual stock option, as detailed in the online appendix, section A. In total, we end up with a sample of 535 stocks. About 90% of these are classified as big cap stocks and 10% as mid cap stocks. The majority of these stocks have been included in the S&P 500 over the last 20 years. Additional stocks included in our dataset are some large- and mid-cap stocks included in the Russell 1000 for which we have good data coverage.

We also obtain forward prices from OptionMetrics for each stock in our sample that matches the stock ticker and option expiration in the database.[17] The other financial information, such as share price, market capitalisation and trading volume for each stock, is obtained from Bloomberg. We eliminate duplicates and keep the VIX measure with the closest 30-day values (see also the VIX methodology in the online appendix, section B). At almost 90%, we cover a very high percentage of the total market capitalisation of US public companies.[18] As such, this comprehensive and extensive dataset overcomes concerns about survival/selection bias in our analysis.

Our analysis focuses on the 11 main US industries: Consumer Discretionary (CD), Communications (CM), Consumer Staples (CS), Energy (E), Financials (F), Health Care (HC), Industrials (IN), Information Technology (IT), Materials (M), Real Estate (RE) and

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[11] Composition of US industries is detailed in the online appendix, section A.

[12] The details can be found in the online appendix, section B.

[13] See also Bekaert et al. (2012) for a similar value weighted variance measure.

[14] Gabaix (2011) states that macroeconomic questions can be clarified by looking at the behaviour of large firms. He adopts a sample including annual U.S. Compustat data for the largest 100 firms as of 2007.

[15] Prior to 2000, there is insufficient data available to compute the individual stock VIX for a significant number of companies.

[16] Examples of bankruptcies are General Motors, Lehman Brothers and Merrill Lynch; examples of M&A are Raytheon and United Technologies, Dow Chemical and DuPont, and Walt Disney Company and 21st Century Fox.

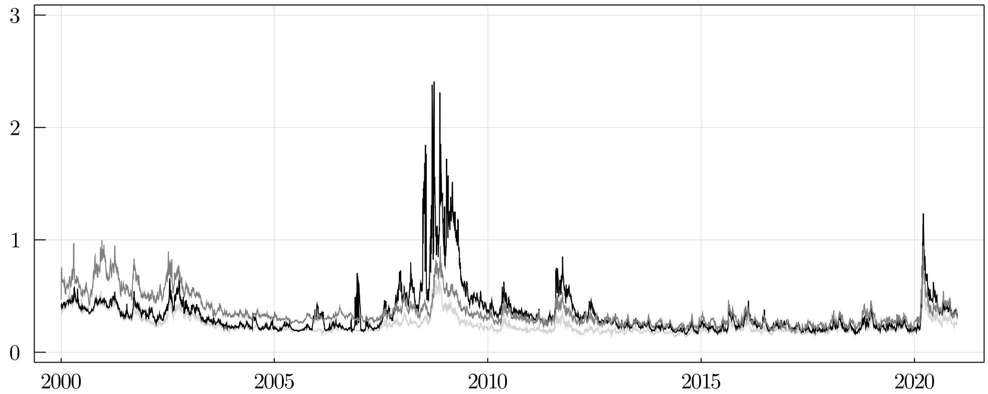
[17] The forward prices are available from OptionMetrics in a separate file that is merged with the options file.

[18] As of December 2020, the total market capitalisation of the S&P 500 was around 33.4 trillion and that of the entire US public market around 40.7 trillion, making the S&P 500 about 82% of total US market capitalisation. By adding other large and mid-cap companies that are not currently included in the S&P 500 but are included in the Russell 1000, our final sample covers approximately 89% of total US market capitalisation.

Table 1
Industry uncertainty $IVIX_t^{(Ind)}$ descriptive statistics.

Ind	CD	CM	CS	E	F	HC	IN	IT	M	RE	U
Mean	0.331	0.327	0.245	0.312	0.348	0.298	0.307	0.362	0.307	0.303	0.270
Standard Dev.	0.106	0.113	0.082	0.111	0.221	0.083	0.116	0.141	0.125	0.178	0.120
Min	0.159	0.147	0.137	0.170	0.161	0.179	0.175	0.175	0.187	0.106	0.123
Max	1.058	0.946	0.840	1.390	2.411	0.917	1.103	0.996	1.230	1.758	0.979
Skewness	1.544	1.596	1.922	2.822	3.752	1.934	2.302	1.549	1.854	2.288	1.925
Kurtosis	3.288	2.938	4.508	13.216	19.238	6.098	7.323	1.958	5.641	8.486	4.392

Notes: This table reports the descriptive statistics for the industry uncertainty $IVIX_t^{(Ind)}$ of 11 industries: consumer discretionary (CD), communications (CM), consumer staples (CS), energy (E), financials (F), health care (HC), industrials (IN), information technology (IT), materials (M), real estate (RE) and utilities (U). The time period is from 03-01-2000 to 31-12-2020, at a daily frequency.



Notes: This figure shows $IVIX_t^{(Ind)}$ series for financials (black), IT (grey) and consumer staples (light grey) covering the period 03-01-2000 to 31-12-2020 at a daily frequency.

Fig. 1. Industry uncertainty.

Utilities (U). Table B1 in the online appendix shows the included stocks within each industry and the available time period. Figure B1 in the online appendix shows an example of individual firm uncertainty $VIX^{(i)}$.[19]

We report descriptive statistics for the industry uncertainty measures in Table 1. We observe high mean values for the Information Technology and Financials industry uncertainty measures, while Consumer Staples and Utilities have the lowest mean values. Uncertainty in financials and real estate has the highest standard deviation, while financials and energy have the highest skewness. On the other hand, consumer staples and health care uncertainties are much less volatile. Communications and information technology show lower skewness and kurtosis compared to the other industry uncertainty measures. The minimum values of the industry uncertainty range between 10.6% and 18.7%, while the maximum values show a wider range, with financials and real estate reaching the highest values among the uncertainty measures.

As an example, we plot the uncertainty measures for financials, IT and consumer staples in Fig. 1. We observe that IT uncertainty dominates the other two during the dotcom bubble and technology boom in the early 2000s. Financial uncertainty shows a dominant role during the GFC in 2008 and the eurozone debt crisis in 2010 and 2011. Interestingly, more recently, the IT sector has shown greater uncertainty than financials, indicating that investors may be aware of potential risks from technological developments and related disruptions. Consumer Staples shows peaks in the early 2000s and during the GFC, but its level of uncertainty is always lower than the other two series and low overall throughout the sample period. All three measures of uncertainty increased in line with the Covid-19 pandemic in March 2020. Financials and IT increased more in the midst of the Covid-19 crisis, while consumer staples were less affected by the pandemic.

3. Measurement of dynamic industry uncertainty networks

Industries are directly linked through counterparty risk, contractual obligations or other general business conditions of the constituent firms, which also change over time. Option prices, measured at high frequencies, reflect the decisions of many agents assessing the risks arising from the existing linkages. Therefore, unlike other network techniques, the purely market-based approach we use allows us to monitor the network on a daily basis and exploit its slowly changing and forward-looking strength with minimal assumptions.

[19] The CBOE has introduced stock market VIX series for a few stocks in the U.S. Comparing our calculations with the CBOE counterparts for the available period shows an average correlation of more than 94%. This slight divergence is probably due to the interpolation between the two closest 30-day expirations used in the CBOE methodology.

By considering how a shock to the expected uncertainty of a firm j is transmitted to future expectations about the uncertainty of a firm k at a given time, we define weighted and directed networks. Aggregating information across such networks provides industry-level uncertainty characteristics that measure how strongly investors' expectations are related. Importantly, we focus on the time variation of such networks.

Note that the measures we use are closely related to modern network theory. Algebraically, the adjacency matrix, which captures information about network linkages, carries all the information about the network, and any credible measure must be related to it. As noted by Diebold and Yılmaz (2014), a variance decomposition matrix, which defines the network adjacency matrix, is then easily used as a network feature, which is related to the network node degrees and the mean degree. To identify the dynamic network measures, we use a concept of locally stationary processes.

3.1. Locally stationary processes

One of our key issues is how to capture the dynamics of shock propagation underlying industrial networks. Looking at the data discussed in the previous section, one quickly questions the stationarity required by standard time series methods. While stationarity plays an important role in time series analysis over decades due to the availability of natural linear Gaussian modelling frameworks, most economic relationships and data, including those we wish to study, are not stationary in the longer run. The behaviour of agents is highly dynamic and the assumption of time-invariant mechanisms generating the data is unrealistic.

A more general non-stationary process can be one that is locally close to a stationary process at any point in time, but whose properties gradually change in a non-specific way over time. The idea that the process can only be stationary for a limited period of time and that the process is still valid for estimation is not new. So-called locally stationary processes were introduced in Dahlhaus (1996) and have been used in volatility modelling and forecasting (Stărică and Granger, 2005). The concept of locally stationary processes will be useful for us to establish theoretical quantities, as it allows the networks to change smoothly over time.

More formally, assume that the industry uncertainty constructed in the previous section is underpinned by a non-stationary process IVIX_t that depends on a time-varying parameter model. In this framework, we replace IVIX_t by a triangular array of observations $(\mathrm{IVIX}_{t,T}; t = 1, \ldots, T)$, where T is the sample size, and we assume that we observe $\mathrm{IVIX}_{t,T}$ at times $t = 1, \ldots, T$. Such a non-stationary process $\mathrm{IVIX}_{t,T}$ can be locally approximated (Dahlhaus, 1996) around each rescaled and fixed time $u \approx t/T$ such that $u \in [0,1]$, by a stationary process $\mathrm{IVIX}_t(u)$. In other words, under some suitable regularity conditions, $\left|\mathrm{IVIX}_{t,T} - \mathrm{IVIX}_t(u)\right| = \mathcal{O}_p\left(\left|\frac{t}{T} - u\right| + \frac{1}{T}\right)$. While stationary approximations vary smoothly over time as $u \mapsto \mathrm{IVIX}_t(u)$, locally stationary processes can be interpreted as processes that change their (approximate) stationary properties smoothly over time. The main properties of $\mathrm{IVIX}_{t,T}$ are therefore encoded in the stationary approximations, and hence in estimation we will focus on quantities $\mathbb{E}\left[g(\mathrm{IVIX}_t(u), \mathrm{IVIX}_{t-1}(u), \ldots)\right]$ with some function $g(.)$ as a natural approximation of $\mathbb{E}\left[g(\mathrm{IVIX}_{t,T}, \mathrm{IVIX}_{t-1,T}, \ldots)\right]$.

3.2. Construction of dynamic uncertainty network

We construct a dynamic network of industry uncertainty from the industry-implied volatilities computed for the major US industries and interpret the TVP-VAR model that approximates their dynamics as a dynamic network, following the work of Barunik and Ellington (2020). In particular, we consider a time-varying parameter autoregressive (TVP-VAR) model of lag order p, which describes the dynamics of industry uncertainty as

$$\mathbf{IVIX}_{t,T} = \mathbf{\Phi}_1(t/T)\mathbf{IVIX}_{t-1,T} + \ldots + \mathbf{\Phi}_p(t/T)\mathbf{IVIX}_{t-p,T} + \epsilon_{t,T}, \tag{2}$$

where $\mathbf{IVIX}_{t,T} = \left(\mathrm{IVIX}^{(1)}_{t,T}, \ldots, \mathrm{IVIX}^{(\mathrm{N})}_{t,T}\right)^{\top}$ is a doubly indexed N-variate time series of industry uncertainties, $\epsilon_{t,T} = \sum^{-1/2}(t/T)\eta_{t,T}$ with $\eta_{t,T} \sim NID(0, I_M)$, and $\mathbf{\Phi}(t/T) = \left(\mathbf{\Phi}_1(t/T), \ldots., \mathbf{\Phi}_p(t/T)\right)^T$ are the time-varying autoregressive coefficients. Then $\mathbf{IVIX}_{t,T}$ can be locally approximated by a stationary process $\mathbf{IVIX}_{t,T} \approx \mathbf{IVIX}(u)$ for a given $t/T \approx u$ with $\mathbf{\Phi}_i(t/T) \approx \mathbf{\Phi}_i(u)$. Rescaling time so that the continuous parameter $u \approx t/T$ is a local approximation of the weakly stationary time series (Dahlhaus, 1996), we approximate $\mathbf{IVIX}_{t,T}$ in a neighbourhood of a fixed time $u_0 = t_0/T$ by a stationary process $\widetilde{\mathbf{IVIX}}_t(u_0)$ as

$$\widetilde{\mathbf{IVIX}}_t(u_0) = \mathbf{\Phi}_1(u_0)\widetilde{\mathbf{IVIX}}_{t-1}(u_0) \ldots + \mathbf{\Phi}_p(u_0)\widetilde{\mathbf{IVIX}}_{t-p}(u_0) + \epsilon_t. \tag{3}$$

Crucially, a locally stationary process $\mathbf{IVIX}_{t,T}$ can be represented by a time varying vector moving average VMA(∞) representation (Dahlhaus et al., 2009; Roueff and Sanchez-Perez, 2016)

$$\mathbf{IVIX}_{t,T} = \sum_{h=-\infty}^{\infty} \mathbf{\Psi}_{t,T,h}\epsilon_{t-h} \tag{4}$$

where the parameter vector $\mathbf{\Psi}_{t,T,h}$ can be approximated, under certain smoothness assumptions (Dahlhaus, 1996), by coefficient functions $\mathbf{\Psi}_{t,T,h} \approx \mathbf{\Psi}_h(t/T)$, which is a time-varying impulse response function characterised by a bounded stochastic process.[20] The construction with $\mathbf{\Psi}_{t,T,h}$ and $\mathbf{\Psi}_h(t/T)$ looks complicated at first glance, but a function $\mathbf{\Psi}_h(u)$ is needed for rescaling and to

[20] As $\mathbf{\Psi}_{t,T,h}$ contains an infinite number of lags, we approximate the moving average coefficients at $h = 1, \ldots, H$ horizons.

impose smoothness conditions, while the additional use of $\mathbf{\Psi}_{t,T,h}$ makes the class rich enough to cover autoregressive models (see Theorem 2). 3. in Dahlhaus (1996)), which we are interested in later.

The connectedness measures rely on variance decompositions, which are transformations of the information in $\mathbf{\Psi}_{t,T,h}$ that allow measuring the contribution of shocks to the system. Since a shock to a variable in the model does not necessarily occur in isolation, an identification scheme is crucial for computing variance decompositions. We adapt the generalised identification scheme in Pesaran and Shin (1998) to locally stationary processes.

The following proposition establishes a time-varying representation of the variance decomposition of shocks from asset j to asset k. It is central to the development of dynamic network measures because it constitutes a dynamic adjacency matrix.

Proposition 1 *(Dynamic adjacency matrix).* [21] *Suppose* $\mathbf{IVIX}_{t,T}$ *is a locally stationary process, then the time-varying generalized variance decomposition of the* j*th variable at a rescaled time* $u = t_0/T$ *due to shocks in the* k*th variable forming a dynamic adjacency matrix of a network is*

$$\left[\theta^H(u)\right]_{j,k} = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H} \left(\left[\mathbf{\Psi}_h(u) \mathbf{\Sigma}(u) \right]_{j,k} \right)^2}{\sum_{h=0}^{H} \left[\mathbf{\Psi}_h(u) \mathbf{\Sigma}(u) \mathbf{\Psi}_h^\top(u) \right]_{j,j}} \tag{5}$$

where $\mathbf{\Psi}_h(u)$ *is a time-varying impulse response function.*

Proof. See Online Appendix C. □

It is important to note that the Proposition 1 fully defines the dynamic network. Of course, our adjacency matrix is filled with weighted links, showing the strength of the links over time. The links are directional, meaning that the link from j to k is not necessarily the same as the link from k to j. Therefore, the adjacency matrix is asymmetric.

To characterise network uncertainty, we define the total dynamic network connectedness measure in the spirit of Diebold and Yılmaz (2014); Barunik and Ellington (2020) as the ratio of the off-diagonal elements to the sum of the entire matrix.

$$C^H(u) = 100 \times \sum_{\substack{j,k=1 \\ j \neq k}}^{N} \left[\widetilde{\theta}^H(u)\right]_{j,k} \Bigg/ \sum_{j,k=1}^{N} \left[\widetilde{\theta}^H(u)\right]_{j,k} \tag{6}$$

where $\left[\widetilde{\theta}^H(u)\right]$ is a θ normalised by the row sum. This measures the contribution of the forecast error variance attributable to all shocks in the system, minus the contribution of own shocks. Similar to the aggregate network connectedness measure, which infers the system-wide strength of connections, we define measures that indicate when an industry is a transmitter or receiver of uncertainty shocks in the system. We use these measures to proxy for dynamic network uncertainty. The dynamic directional connectedness, which measures how much of each industry's j variance is due to shocks in other industries $j \neq k$ in the economy, is given by

$$C^H_{j\leftarrow\bullet}(u) = 100 \times \sum_{\substack{k=1 \\ k \neq j}}^{N} \left[\widetilde{\theta}^H(u)\right]_{j,k} \Bigg/ \sum_{j,k=1}^{N} \left[\widetilde{\theta}^H(u)\right]_{j,k}, \tag{7}$$

which defines the so-called FROM connectedness. Note that this quantity can be interpreted precisely as dynamic from-degrees (or out-degrees in the network literature) associated with the nodes of the weighted directed network, which we represent by the dynamic variance decomposition matrix. Similarly, the contribution of asset j to the variances of other variables is

$$C^H_{j\rightarrow\bullet}(u) = 100 \times \sum_{\substack{k=1 \\ k \neq j}}^{N} \left[\widetilde{\theta}^H(u)\right]_{k,j} \Bigg/ \sum_{k,j=1}^{N} \left[\widetilde{\theta}^H(u)\right]_{k,j} \tag{8}$$

and is the so-called TO connectedness. Again, this can be interpreted as the dynamic to-degrees (or in-degrees in the network literature) associated with the nodes of the weighted directed network that we represent by the variance decomposition matrix. These two measures show how other industries contribute to the uncertainty of industry j and how industry j contributes to the uncertainty of others, respectively, in a time-varying manner. Furthermore, the NET dynamic connectedness, which shows whether an industry generates more uncertainty than it receives from other industries in the system, can be calculated as the difference between TO and FROM as $C^H_{j,\mathrm{NET}}(u) = C^H_{j\rightarrow\bullet}(u) - C^H_{j\leftarrow\bullet}(u)$ and the AGG connectedness measure as $C^H_{j,\mathrm{AGG}}(u) = C^H_{j\rightarrow\bullet}(u) + C^H_{j\leftarrow\bullet}(u)$.

[21] Note to notation: $[\boldsymbol{A}]_{j,k}$ denotes the jth row and kth column of matrix $\boldsymbol{A}$ denoted in bold. $[\boldsymbol{A}]_{j,\cdot}$ denotes the full jth row; this is similar for the columns. A $\sum A$, where A is a matrix that denotes the sum of all elements of the matrix A.

3.3. Obtaining network measures

Time-varying parameter models, and in particular TVP-VAR models, have recently received a great deal of attention in the macroeconomic literature because it is implausible to assume that relationships between economic variables remain fixed. Two common approaches to estimating TVP-VAR use state-space methods (Primiceri, 2005; Cogley and Sargent, 2005) and non-parametric, frequentist estimators (Giraitis et al., 2014). Neither of these can accommodate large dimensional systems in the presence of time-varying parameters. This is particularly relevant when considering a model that is richly parameterised even for a small number of endogenous variables and lags, and consequently overfits the data. To overcome this problem, we use Petrova (2019), who propose to combine existing nonparametric approaches with Bayesian methods and establish a quasi-Bayesian local likelihood (QBLL) estimation methodology for a general multivariate model with time-varying parameters.

The QBLL approach has several advantages over the widely used state-space methods. The time variation of the parameters is entered non-parametrically, reducing the risk of invalid inference due to misspecification of the state space equation. It does not suffer from dimensionality problems, as the combination of the closed-form quasi-posterior expressions with Minnesota-type priors specified directly on the drifting parameters allows the number of variables in the VAR to be very large, while facilitating parameter drift.

The availability of analytic expressions for the quasi-posterior density in the Gaussian VAR case further alleviates the computational burden of Markov Chain Monte Carlo (MCMC) algorithms used to estimate TVP VARs by state-space methods, making the quasi-Bayesian procedure of Petrova (2019) computationally efficient. Another advantage is the inverted Wishart property of the time-varying covariance matrix, which ensures symmetric positive definiteness of the resulting estimators without the need for further restrictions (e.g. triangularisation) commonly imposed in the state-space literature; the absence of such restrictions ensures that the ordering of the variables in the VAR system does not affect the estimation of the reduced-form covariance matrix.

To obtain the time-varying coefficient estimates and the time-varying covariance matrices at a fixed time $u = t_0/T$, $\mathbf{\Phi}_1(u), ..., \mathbf{\Phi}_p(u)$ $\mathbf{\Sigma}(u)$, we estimate the approximate model in (2) using Quasi-Bayesian Local-Likelihood (QBLL) methods (Petrova, 2019). Specifically, we use a kernel weighting function that gives larger weights to observations surrounding the period whose coefficient and covariance matrices are of interest. Using conjugate priors, the (quasi-) posterior distribution of the model parameters is available analytically. This reduces the need to use a Markov Chain Monte Carlo (MCMC) simulation algorithm and allows the use of parallel computing. Note also that by using (quasi) Bayesian estimation methods, we obtain a distribution of parameters that we use to construct network measures that provide confidence bands for inference. The estimation algorithm is described in detail in the online appendix, section D.

To estimate the elements of the dynamic adjacency matrix, we must first truncate the infinite VMA(∞) representation of the approximation model with a choice of finite horizon H. Next, the estimation of dynamic network measures requires the user to choose a kernel and its bandwidth. Typically, the larger the bandwidth, the smoother the time evolution of our dynamic network measures. Therefore, before tracking dynamic network connections, it is important that the user considers the time series properties of their data. For example, if common peaks (troughs) in the time series occur frequently and are transient, then a smaller bandwidth may be necessary. Conversely, if you are tracking network connections between data that changes gradually over time, such as interest rates, a larger bandwidth may be more appropriate.

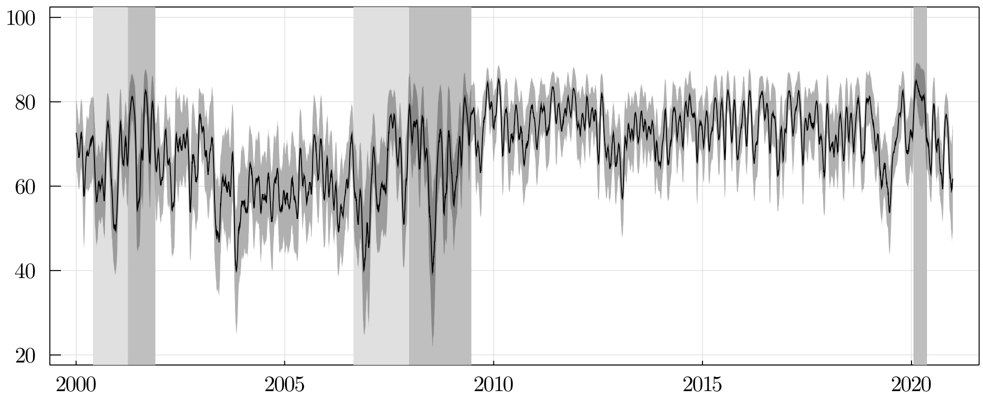
It is worth noting that the choice of a two-sided kernel may come at a cost, especially if one wishes to use network measures for forecasting purposes. In these cases, one may wish to: i) estimate the dynamic network recursively through time, so that the normal kernel truncates to use only past values at the time of estimation T; or ii) choose a one-sided kernel, as in Hahn et al. (2001); Barigozzi et al. (2020). In the context of our study, we use a normal kernel with variance-optimising bandwidth in a recursive estimation. Note that we also experimented with different kernels and sizes and the results did not change significantly.

4. The dynamics of the network connectedness of industry uncertainties

With the TVP VAR model and the estimated network measures in hand, we study the industry uncertainties dynamics over the business cycles. Being able to temporally characterize the industry-based network dynamics is crucial given that industries can swiftly change their characteristics and macro-economic roles. The technological and housing market bubbles, the commodity crash, and the Covid-19 pandemic are a few major examples showing how a dramatic increase in uncertainty and different investors' expectations can rise sharply from alternative industries.

We compute the dynamic aggregate network connectedness through equation (6) and present its dynamics in Fig. 2. We identify several cycles mainly driven by key events that took place in our sample such as the dot com bubble in the early 2000s, the housing market bubble, the 2007–2009 GFC, and the most recent Covid-19 crisis. Some events might be described as bursts that rapidly subside, others might be characterized by a more continuous pattern and trend. We also partition our full sample period into one of the three cycle phases: inversions, recessions and expansions. Specifically, inversions are marked between July 2000 and March 2001 and between September 2006 and December 2007, based on an inverted US yield curve (10-year-to-3-month Treasury spread).[22] The

[22] An inverted yield curve, taken as the difference between short-term interest rates (3-month T-bills) and long-term interest rates (10-year Treasury bonds), is often a harbinger of recession (see Estrella and Hardouvelis, 1991; Estrella, 2005; Adrian and Estrella, 2008). Over our sample period, every occurrence of an inverted yield curve has been followed by recession as declared by the NBER business cycle dating committee. September 2006 is identified as the end of the tightening cycle because during that month the one-month fed futures rate went from higher than the spot rate to lower Adrian and Estrella (2008).



Notes: This figure shows the dynamic uncertainty network connectedness with respect to the 11 U.S. industries estimated during the 03-01-2000–31-12-2020 period, at a daily frequency. Inversions (light grey area) are marked between July 2000 and March 2001 and between September 2006 and December 2007. The recessions (grey area) are marked between April 2001 and November 2001, between January 2008 and June 2009, and between February 2020 until April 2020, while the other years are marked as expansions. Note the network connectedness is plotted with two standard deviation percentiles of the measure.

Fig. 2. Dynamic network connectedness of industry uncertainties.

recessions are marked between April 2001 and November 2001, between January 2008 and June 2009, and between February 2020 until April 2020, while the other years are marked as expansions.[23]

We document the system to be strongly connected with values fluctuating around 70% in the first half of 2000. The first cycle starts with the burst of the tech bubble in 2000 with the network measure climbing from about 60% to 75%. It then increased up to about 82% in the second half of 2001 as a response to the dot com bubble strengthening the U.S. industries' uncertainty connections via shocks to uncertainty from the technology industry. The index recovers to the initial level until 2004, hitting one of the minimum values in our sample in 2004 before spiking again. After that, uncertainty network connectedness presents a new lower average level, fluctuating around 60% until the second half of 2007, except for a peak at the end of 2005 which might be due to the U.S. housing bubble showing a connectedness level up to 70%.

The index records a significant upward movement from the beginning of 2007 to 2009 reaching a level close to 80%, in response to the high uncertainty during the 2007–2009 GFC spreading from the financials industry to other industries. Several cycles can be detected during the 2007–2009 GFC: the first between the first quarter of 2007 and August 2007 reflecting the U.S. credit crunch; the second in January–March 2008 (panic in stock and foreign exchange markets, and Bear Stearns' takeover by JP Morgan), the collapse of Lehman Brothers in September 2008 showing a spike from 55% to 78% in our network connectedness, and lastly in the first half of 2009, after a big drop, when the financial crisis started to propagate towards all other industries increasing the average network connectedness level.

Uncertainty connectedness spikes again in line with the two phases of the European sovereign debt crisis, in 2010 and the second half of 2011, reaching one of the highest levels in our sample breaching the 80% level. We then observe a quite flat period from 2012 to mid-2013 with the index however presenting a higher average level compared to the pre-GFC period. The connectedness spikes again at the end of 2013, likely due to trade wars and energy turmoil reaching levels above 80%, at the end of 2014, in mid-2015, and in correspondence with Brexit in 2016, and again at the end of 2017. Eventually, the index spiked again reaching one of its all-time maximum values in March 2020 (a level of 83%), due to the coronavirus outbreak and signalling the beginning of the Covid-19 crisis. This reflects the tight connectedness among all industries in the coronavirus period since almost all industries have been severely affected.[24]

The fluctuations of the aggregate uncertainty network across crises, market downturns and expansions invite a further investigation of the role of each industry uncertainty network characteristic. The U.S. industries appear to be more connected after the GFC and even more with the most recent Covid-19 crisis. For instance, when we consider the largest five increases and decreases of the network uncertainty index within a quarter (3-month window), we find that these are most of the time in proximity or associated with inversion and recession periods. In only a few exceptions these are found to be in an expansion period which may be due to a specific industry shock (e.g. real estate bubble in 2004 or the commodity crash in 2005). This evidence calls for a more in-depth analysis of the specific industry networks as well as the main drivers of the network uncertainty indicators across business cycles. The next sections aim to clarify these points exploiting the precise time-varying estimation of the uncertainty network and its forward-looking properties.

[23] Due to the unprecedented causes of the pandemic recession in 2020, this has resulted in a downturn with different characteristics and dynamics than prior recessions. Hence, we are unable to establish an inversion period for the Covid-19 crisis that we signal only as a recession from February 2020. The NBER stated that the Covid-19 recession ended in April 2020. That makes the two-month downturn the shortest in U.S. history. See also the NBER website: https://www.nber.org/cycles.html. The same dates are documented in the Chicago Fed National Activity Index description (see section 6 for more information).

[24] While literature documents increased correlations in crisis periods (e.g. King and Wadhwani, 1990), the results we document are controlled for the correlation in the system.

Table 2
Aggregate C_{NET} and C_{AGG} across business cycles.

	Inversion			Recession			Expansion			Total Period		
	NET	AGG	AGG %	NET	AGG	AGG %	NET	AGG	AGG %	NET	AGG	AGG %
CD	2.46	23.48	11.7	2.88	25.27	9.6	2.31	20.26	9.4	1.01	21.64	9.5
CM	-1.02	20.67	10.3	1.69	29.05	11.0	0.96	22.90	10.6	1.13	24.89	11.0
CS	-0.31	18.80	9.4	-3.34	23.76	9.0	-1.30	22.42	10.3	-1.97	21.86	9.5
E	-2.79	19.33	9.6	-0.40	24.02	9.1	-0.19	19.41	8.9	-0.82	20.37	8.9
F	2.24	28.17	14.1	3.74	36.66	13.9	0.37	23.62	10.9	2.64	28.04	12.4
HC	-2.02	16.15	8.1	-3.94	22.16	8.4	-2.05	19.62	9.1	-2.61	19.89	8.7
IN	-0.98	12.36	6.1	1.78	22.75	8.7	-0.90	17.10	7.9	-0.79	16.75	7.3
IT	3.20	24.35	12.1	-0.83	26.29	10.0	-1.46	22.20	10.3	0.96	24.33	10.8
M	-1.23	11.46	5.7	-1.21	16.58	6.3	-1.62	14.80	6.8	-1.98	15.08	6.6
RE	1.23	15.80	7.9	-0.25	22.83	8.7	4.24	22.75	10.4	3.32	23.78	10.4
U	-0.75	10.11	5.1	-0.11	12.69	4.8	-0.35	10.75	4.9	-0.89	11.17	4.9

Notes: The table shows the average NET and AGG values with respect to the 11 U.S. industries' uncertainty network: consumer discretionary (CD), communications (CM), consumer staples (CS), energy (E), financials (F), health care (HC), industrials (IN), information technology (IT), materials (M), real estate (RE) and utilities (U). When the NET measure is positive an industry can be classified as a NET marginal transmitter, while, when negative, it can be classified as a NET marginal receiver. The highest values of the AGG network statistics are associated with uncertainty hubs, while the lowest with uncertainty non-hubs. The statistics are reported for the business cycle main phases, namely inversion, recession, expansion, aggregated, and also for the total period, namely from 03-01-2000 to 31-12-2020.

5. Uncertainty networks across the business cycles

We can classify each industry based on their expected contribution to shocks to uncertainty in the system across different phases of the business cycle. More specifically, we identify transmitters, receivers as well as industries being considered hubs of uncertainty. To this end, we classify industries according to the C^H_{NET} and C^H_{AGG} characteristics of dynamic uncertainty network. A specific shock to uncertainty related to any industry, especially when the most influential industries are affected, can trigger major consequences for the other industries generating an aggregate impact on the whole network, tightening or weakening the uncertainty network, as well as being ultimately transmitted to the real economy. For instance, a tightening in the industry network may be connected to drops in real activity, representing a timely monitoring tool for immediate interventions by the Federal Reserve to sustain the business cycle.

5.1. Uncertainty hubs, non-hubs and business cycles

With regard to the NET measure, computed as TO (equation (8)) minus FROM (equation (7)) values, an industry is deemed to be an uncertainty *transmitter* (*receiver*) if this difference takes a positive (negative) value. An industry transmitting or receiving shocks to uncertainty at an intermediate level can be classified as a *moderate* transmitter or receiver, respectively, contributing to the uncertainty propagation in the system in a relatively mild manner.

An industry showing high values of both directional measures reflected by high AGG values is playing an active role in the transmission of uncertainty shocks and is, therefore, deemed an *uncertainty hub*. As reflected by the existence of these strong bidirectional forces of uncertainty propagation, such uncertainty hub industries contribute the most to uncertainty shocks within the network. Conversely, a *neutral* industry shows low AGG values and is deemed an *uncertainty non-hub*.

Industries can contribute differently to shocks to uncertainty depending on the specific economic cycle thereby seeing them change their network roles and classification. Accordingly, to accommodate this potential for dynamism conditioned on cycle state, we average the network characteristics across each of the three business cycle phases (inversions, recessions and expansions) as well as over the total period. Table 2 provides the details.

The highest values for financials and IT during the inversion and recession periods identify these two as uncertainty hubs. This reflects the sensitive role played by these two industries in the dot com and GFC, respectively. Also, the consumer discretionary and communications can be classified as uncertainty hubs during these inversion and recession phases. The IT and financials show a relatively high percentage of contribution to uncertainty shocks also in expansion periods (10.3% and 10.9%, respectively) however in this case sharing the hub role also with the real estate, communications and consumer discretionary industries. The IT, financials and communications industries are consistently found to be the main uncertainty hubs during almost all cycles, showing a time-invariant role as key industries in terms of the contribution of shocks to uncertainty.

Hence, the communications, financials, and IT industries are classified as the main uncertainty hubs within our total sample given their greatest contribution to shocks to uncertainty within the system as measured by the AGG value. This finding echoes the important role that the information and communication technology (ICT) industries have played in the last two decades in the system (e.g. Jorgenson, 2001; Bloom et al., 2012).[25]

[25] Bloom et al. (2012) show that a large fraction of the recent growth occurred in IT-producing sectors or intensive IT-user sectors. For example, according to Jorgenson (2001), the (IT) sector has produced a fundamental change in the U.S. economy, leading to an improvement in growth prospects. Similarly, Stiroh (2002) presents evidence that ICT production and use are associated with faster productivity growth in U.S. industries.

Notably, the financials industry uncertainty has been transmitting differently within market settings, and mainly during inversions and recessions, but it is overall classified as an uncertainty hub. Previous studies have also documented how the financial and banking sector may represent a major channel in transmitting the shocks across markets during crises (e.g. Kaminsky and Reinhart, 1999; Baur, 2012). Also, the real estate industry is classified as a main uncertainty hub given its high AGG value in the total period, but especially during expansion phases of the business cycle.

In sharp contrast, when we look at the total period, industrials, materials, and utilities present the smallest AGG values and, therefore, are classified as uncertainty non-hubs within our system. For instance, Table 2 reveals that the IT industry, the main uncertainty hub, with a 12.4% AGG measure contributes to the network connectedness characteristics around double the magnitude of materials (6.6%) and utilities (4.9%).

5.2. Shocks to uncertainty in specific business cycles

In this subsection, we briefly discuss a more granular classification of industries for each specific cycle in our sample (e.g. expansion after the dot-com bubble, GFC, Covid-19 crisis) to further emphasize the usefulness and flexibility of our methodology in this context. The results are reported in Table E1 in the online appendix.

For instance, let's consider the IT industry. It can be clearly classified as one of the main uncertainty hubs during both the inversion and recession phases related to the dot com bubble (from 2000 to mid-2002), contributing to the crisis and therefore to the spread of uncertainty within the whole system. It is detected as an uncertainty transmitter given the high NET value equal to 10.57. Its role in spreading uncertainty diminished during the GFC-related inversion and recession, becoming dominant again in the post-GFC and Covid-19 expansions.

The financials uncertainty show a predominant role during the GFC inversion and recession periods, contributing almost 20% to the total shocks to uncertainty in the system. The financials industry takes on the main role as a NET uncertainty transmitter with values of 7.47 and, more than double, 15.79, during the GFC inversion and recession, respectively. After the GFC, the U.S. economy is characterized by a long recovery period during which the financials industry was not seen as the main propagator of uncertainty: it presents a lower AGG value compared to the pre-GFC and it even takes the role as an uncertainty receiver during the Covid-19 crisis. This finding may reflect the ability of authorities to influence the U.S. financials sector in the aftermath of the GFC through accommodative and unconventional monetary policies. To some, such policy interventions aimed at restoring the functioning of the financials sector during the Great Recession might have been key to avoiding a second Great Depression.[26] This has also been accompanied by stronger harmonization of financial regulatory standards (e.g. the Basel capital framework). The financials sector has seen one of the most-pronounced stock market booms on record during 2009–2018. It is therefore not surprising that there has been a lower level of uncertainty contribution from the financials industry in the post-GFC.

Overall, by looking at a more granular business cycles structure, we confirm the uncertainty hub roles for the communications, financials and IT industries that seem largely time-invariant. Further, industrials, materials and utilities continue to show a persistent much smaller uncertainty contribution. Other industries behave in a more time-varying manner. For example, while the energy industry is found to be neutral for a great part of the sample period, it shows a greater AGG value in the post dot com and GFC expansions, as well as in the Covid-19 recession. This can be due to a combination of events throughout these time periods, which impacted the energy industry uncertainty, and are also reflected in the aggregate network's spikes between June 2014 and February 2015 associated with the global commodity price crash and oil price drop (see Fig. 2).

Another example of an event specific hub is the real estate industry. It is classified as uncertainty hub in the expansion after the dot com bubble since this period corresponds to the U.S. housing market bubble, for many identified as the preamble of the GFC. The bursting of the real estate bubble is precisely identified by the dynamic network at the end of 2005 (see Fig. 2). The real estate industry also assumes an uncertainty hub role during the GFC and in the most recent years leading us to classify it as one of the overall uncertainty hubs in our system.

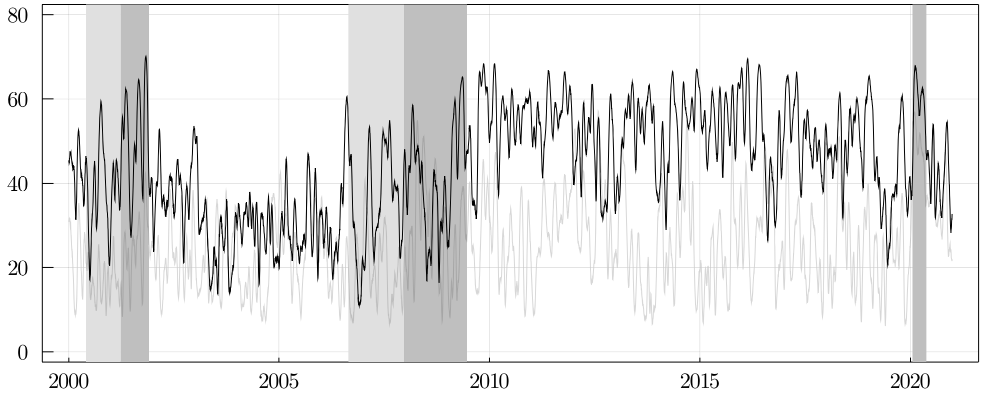
This more granular analysis further highlights the usefulness of the methodology when applied to construct an industry uncertainty network that is truly dynamic, time-varying, and more specifically uncovers the role of industries in contributing to shocks to uncertainty across business cycles. We could rank industry uncertainties in shorter time horizons (e.g. months), therefore providing a powerful tool for regulators and policy makers to monitor the shaping of the uncertainty networks within industries in a timely and flexible manner.

5.3. Uncertainty hub and non-hub networks

In this subsection, we report separate forward-looking networks extracted from uncertainty hubs only, $\text{IVIX}_t^{(\text{Ind})}$ of hubs only (communications, financials, IT, and real estate) and of non-hubs only (industrials, materials and utilities) in the network model in equation (6).

Fig. 3 plots the dynamics of both network connectedness characteristics. We observe that the uncertainty network extracted from hubs shows a higher degree of integration compared to the ones extracted from non-hubs. The difference in uncertainty produced by hubs versus non-hubs becomes stronger in the post-GFC and more recent years, implying that shocks in hubs such as, especially

[26] To note that The IMF October 2017 Global Financial Stability Report (GFSR) finds that the global financial system continues to strengthen in response to extraordinary policy support, regulatory enhancements, and the cyclical upturn in growth.



Notes: This figure shows the network connectedness measures extracted from uncertainty hubs (black line) and non-hubs (grey line) from 03-01-2000 to 31-12-2020 at a daily frequency. Inversions (light grey area) are marked between July 2000 and March 2001 and between September 2006 and December 2007. The recessions (grey area) are marked between April 2001 and November 2001, between January 2008 and June 2009, and between February 2020 and April 2020, while the other years are marked as expansions.

Fig. 3. Uncertainty hubs and non-hubs networks.

ICT and financials have played a key role increasingly contributing to shocks to uncertainty within the system generating aggregate fluctuations over time. This finding is consistent with the development of ICT in recent decades. Such hubs are in fact industries providing services to other industries, sharing a role in propagating uncertainty shocks to other sectors (see Bloom et al., 2012). This channel can also be because uncertainty hubs are sectors likely to have financial importance such as financials and real estate as well as large and fast-growing market capitalization (e.g. ICT firms).

Some theories presume that higher uncertainty generates directly in the process of technological innovation, which subsequently causes a decline in real activity (e.g. Bloom, 2009; Justiniano et al., 2010; Bloom et al., 2018). An uncertainty shock can affect production, employment and growth within the hub, it can also generate larger uncertainty spillovers, changes in prices, growth and production of other sectors in the system, affecting the broader economy (e.g. Kozeniauskas et al., 2018). As an example of a few possible mechanisms, Vom Lehn and Winberry (2022) state that a positive shock to an investment hub directly increases production and employment in that hub; because the shock also raises the supply of investment goods, other sectors increase employment to produce more intermediate inputs for the hub. In contrast, a shock in a non-hub has a small effect on investment supply generating smaller spillovers to the rest of the economy. Further, according to the islands' framework in Garin et al. (2018), a shock that simultaneously affects both hubs and non-hubs (both islands) is significantly weaker compared to shocks in both islands separately, this is due to a reallocative shock mechanism.

In our context, this would directly translate into an increase in uncertainty of both islands (hubs and non-hubs) with the difference that non-hubs receive shocks to uncertainty, while hubs (mainly providers of services cross-sectorally) both receive and transmit shocks to uncertainty to a much larger extent (captured by a higher AGG statistic in our model). The uncertainty transmitted or received by hubs is found to be approximately almost half of the total uncertainty in the system and more than twice the one transmitted by non-hubs.[27]

Thus, shocks to uncertainty hubs generate larger effects within the network of industries and may spread their impact to the real economy. One possible channel at work is the following: investor beliefs generate shocks to uncertainty in hubs, which reflect value-added growth in the hub industries, leading to future price increases or losses that affect their future outcomes, which may ultimately trigger economic booms or downturns to a greater extent than in non-hubs.

Therefore, the hub-based network measure is intuitively a better leading indicator of business cycles than non-hubs, which is further explored in the next section. Note that while in this study we focus on industry networks stemming from uncertainty shocks,[28] we also checked whether the inter-firm linkages and their relationship with economic fluctuations can be related to a first moment microfoundation. Building the network from shocks to realized returns identifies the same hub and non-hub structure, but is not informative for the future.

6. Industry uncertainty networks and business cycle predictability

In this section, we study whether the information extracted from options of a large sample of U.S. firms and aggregated into ex-ante industry uncertainty networks contributes to the predictability of U.S. business cycle indicators. While we draw from an extensive

[27] Let's try to draw a rationale for this mechanism. On a given horizon, the uncertainty of a firm k increases or decreases following a shock. The specific firm k VIX will reflect this variation which will, in turn, be also reflected in the industry VIX ($IVIX^{(I)}$)-j including that firm k, leading to an increase in the industry j uncertainty measure. This will represent a shock to uncertainty reflected in the overall uncertainty network, being greater at the hubs level since these are the most active industries in terms of uncertainty contribution.

[28] See the literature discussing the importance of second moment shocks over first moment shocks in relation to economic conditions and business cycles, (Bloom, 2009; Carvalho and Gabaix, 2013; Basu and Bundick, 2017; Bloom et al., 2018; Herskovic et al., 2020; Ludvigson et al., 2020; Fernández-Villaverde and Guerrón-Quintana, 2020).

previous literature on the role of aggregated sector-level or firm-level networks of shocks to uncertainty and their relationship with the aggregate economy and business conditions (e.g. Gabaix, 2011; Acemoglu et al., 2012; Carvalho and Gabaix, 2013; Barrot and Sauvagnat, 2016; Atalay, 2017; Vom Lehn and Winberry, 2022), we are interested in exploiting the forward-looking aspect of our network to predict future business cycles in advance. We hypothesize that our network measure represents an even more timely and forward-looking predictor of business cycle indicators given its ex-ante characteristics from the options market. It might therefore represent both a good predictor of coincident and leading indicators and it can be also classified as a leading monitoring tool of the business cycle itself. This would provide researchers, policy-makers and the public with an even more timely indicator than the ones already available.

6.1. The predictability of business cycle coincident and leading indicators

Berge and Jordà (2011) provides an exhaustive summary of the different measures available that provide reliable signals about the current state of the business cycle. Among those, we select the Chicago Fed National Activity Index (CFNAI).[29] Specifically, we adopt the 3-month moving average of the Chicago FED National Activity Index (CFNAI-MA3) as the main business cycle coincident indicator in our study (see, e.g. Berge and Jordà, 2011; Chava et al., 2020).[30]

We aggregate the network connectedness measure at a monthly frequency to match the frequency of the business cycle indicators and we run the following predictive regression:

$$\mathcal{Y}^{(\ell)}_{t+h} = \beta_0 + \beta_C\, C_t + \sum_{i=1}^{N} \beta_{X,i}\, X_{t,i} + \epsilon_t \tag{9}$$

where $\mathcal{Y}^{(\ell)}_{t+h}$ is one of the business cycle indicators we select (or their components) with the predictive horizon $h \in 1, 3, 6, 9, 12$ months. The C_t is the industry uncertainty network measure (note we drop index H here for the ease of notation), $X_{t,i}$ is a set of control variables including both traditional predictors of business cycles such as oil price changes (OIL), term-spread as 10-year bond rate minus the 3-month bond rate (TS), unemployment rate (UR), (see also Gabaix, 2011), and also a potential leading indicator extracted from the financial markets, namely the CBOE VIX index being a common proxy for macro uncertainty in the U.S. (VIX), the $S\&P500$ price index (SPX), the Bloomberg Commodity price index (COMM) and the S&P Case-Shiller Home price (CSHP).[31] Therefore, $X_{t,i}$ is indexed for i up to $N = 7$, the number of controls that we select, with $i \in$ (OIL, TS, UR, VIX, SPX, COMM, CSHP).

Table 3 reports the predictive results. From Panel A, we observe that the uncertainty network is a strong predictor of the aggregate CFNAI-MA3 indicator of the business cycle from 3 months up to 12 months in advance (excluding the 6-month horizon). The coefficient associated with our independent predictor is negative suggesting that a tighter network of industry uncertainties would lead to a contraction in the business cycle in the future horizons. The network is therefore found to behave counter-cyclically, a finding that is both intuitively appealing and in line with previous studies relating uncertainty measures with the business cycles (e.g. Bloom et al., 2018). The performance of the models measured by the adjusted-R^2 is found to be around 37% at the 1-month horizon, reaching 47.3% for the 3-month horizon, then decreasing to around 18% at the longer horizons (9 and 12 months).

Due to its forward-looking nature, we argue that the uncertainty network connectedness could also potentially serve as a good predictor of business cycle leading indicators, and, indeed, be considered a leading indicator itself. Hence, we check the predictive ability of this index for two business cycle leading indicators: the U.S. composite leading indicator (CLI) by the OECD,[32] and the U.S. leading indicator (U.S.LI) computed by the Economic Cycle Research Institute (ECRI).[33] U.S.LI is available at a weekly frequency and aggregated here at a monthly frequency, and we take the growth rate of the indicator. We repeat the same predictive exercise of the previous subsection, by running equation (9) where now the dependent variable is either CLI or U.S.LI. From Panels B and C in Table 3, we observe that the predictability of uncertainty network connectedness is even stronger for the business cycle leading indicators, spanning from 1-month up to one year (3-month excluded) and from 1-month up to 9-month horizons, for CLI and U.S.LI, respectively. The coefficients are still found to be negative confirming our previous findings, namely that an uncertainty network intensification would prompt a contraction in the business cycle leading indicators.

[29] The CFNAI is a monthly index that tracks the overall economic activity and the inflationary pressure. It is computed as the first principal component of 85 series drawn from four broad categories of data all adjusted for inflation. A zero value for the monthly index has been associated with the national economy expanding at its historical trend (average) rate of growth; negative values with below-average growth; positive values with above-average growth. Methodologically, the CFNAI is similar to the index of economic activity developed in Stock and Watson (1999). For more information see https://www.chicagofed.org/publications/cfnai/index.

[30] Note the raw monthly CFNAI is very volatile due to the volatilities in the underlying data series. On the other hand, the three-month moving average of the CFNAI (the CFNAI-MA3) smooths the volatility in the monthly data while more accurately identifying turning points in U.S. business cycles, periods of sustained increasing inflation, and better track economic expansions and contractions than the monthly version. In fact, the CFNAI-MA3 business cycle indicator can also be disentangled into proxies of expansions and recessions following the approach by Berge and Jordà (2011). To focus on the persistent rather than transitory component of the index, the three-month moving average of the CFNAI, the CFNAI-MA3, is focused by the Fed Chicago and adopted in previous literature (e.g. Berge and Jordà, 2011; Chava et al., 2020). See also the CFNAI white paper document, available at https://www.chicagofed.org/research/data/cfnai/about. This makes the CFNAI-MA3 the primarily business cycle indicator of interest for the purpose of our paper and the main focus of our empirical analysis.

[31] Oil prices, 10-year and 3-month bond rates, unemployment rate and the S&P Case-Shiller Home price index are collected from the Federal Reserve Bank of St. Louis economic database at https://fred.stlouisfed.org/; the CBOE VIX index, $S\&P500$ price index and the Bloomberg Commodity price index are collected from Bloomberg.

[32] The composite leading indicator is collected from the OECD data base at https://data.oecd.org/leadind/composite-leading-indicator-cli.htm. CLI provides early signals of turning points in business cycles showing fluctuations of the economic activity around its long term potential level.

[33] For more information and data see https://www.businesscycle.com/ecri-reports-indexes/all-indexes.

Table 3
Coincident and leading indicators predictive results.

	Panel A: CFNAI-MA3				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
$C_t \mid X_t$	-0.010	-0.016***	-0.009	-0.016**	-0.014**
	(0.006)	(0.006)	(0.008)	(0.008)	(0.007)
Adj. R^2	37.4	45.3	15.8	18.6	17.8
Benchmark Adj. R^2	37.1	43.5	15.6	17.2	16.5
Obs	250	248	245	242	239
	Panel B: CLI				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
$C_t \mid X_t$	-0.013**	0.003	-0.014*	-0.029***	-0.032***
	(0.006)	(0.007)	(0.008)	(0.010)	(0.011)
Adj. R^2	70.6	60.2	36.8	28.5	23.4
Benchmark Adj. R^2	69.2	60.1	35.7	26.3	20.4
Obs	250	248	245	242	239
	Panel C: U.S.LI				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
$C_t \mid X_t$	-0.103**	-0.166***	-0.263***	-0.221***	-0.084
	(0.048)	(0.058)	(0.062)	(0.064)	(0.067)
Adj. R^2	51.1	30.8	23.2	24.8	17.0
Benchmark Adj. R^2	50.0	28.7	17.0	21.1	16.8
Obs	250	248	245	242	239
	Panel D: CFNAI-3M controlling for CLI				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
$C_t \mid X_t$	-0.019***	-0.022***	-0.015**	-0.016**	-0.010
	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)
CLI	0.458***	0.262***	0.276***	0.002	-0.232***
	(0.063)	(0.064)	(0.081)	(0.082)	(0.082)
Adj. R^2	48.5	48.7	19.4	18.3	20.2
Benchmark Adj. R^2	45.2	45.1	18.3	17.2	20.1
Obs	250	248	245	242	239
	Panel E: CFNAI-3M controlling for U.S.LI				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
$C_t \mid X_t$	-0.016***	-0.017***	-0.011	-0.016**	-0.013**
	(0.006)	(0.006)	(0.008)	(0.008)	(0.006)
U.S.LI	0.110***	0.010	0.020	-0.006	-0.029
	(0.012)	(0.013)	(0.016)	(0.016)	(0.018)
Adj. R^2	54.0	45.2	16.0	18.3	18.4
Benchmark Adj. R^2	51.7	42.8	15.7	17.2	16.9
Obs	250	248	245	242	239

Notes: This table presents the results of the predictive regression in equation (9) between the industry uncertainty network connectedness and the coincident indicator of business cycle, CFNAI-MA3 (Panel A), and the two leading indicators of business cycle, namely CLI and U.S.LI, in Panel B and C, respectively. We also add a set of controls, X. In Panel D and Panel E, the results of the predictive regressions between the industry uncertainty network connectedness and the CFNAI-MA3 coincident indicator of business cycle in which we add a set of controls including also the leading indicators, CLI and U.S.LI are reported, respectively. The five columns of the table represent different predictability horizons with $h \in (1, 3, 6, 9, 12)$. Regressions' coefficients and standard errors (in parentheses), and adjusted-R^2 (in %) are reported. Benchmark adjusted-R^2 (in %) is the adjusted-R^2 of the regression model including only the set of control variables, X. Coefficients are marked with *, **, *** for 10%, 5%, 1% significance levels, respectively. Intercept and controls results are not reported for the sake of space, the only exception being the CLI and U.S.LI controls. Series are considered at a monthly frequency between 01-2000 and 12-2020.

Overall, it appears that the uncertainty network measure that we develop in this paper can usefully anticipate what is commonly viewed as a prominent business cycle leading indicator. This opens up some interesting considerations. Given that the uncertainty network is extracted from options prices contains forward-looking information, it is entirely plausible that our approach can proxy as an ex-ante business cycle monitoring indicator. We know that a business cycle leading indicator should ideally anticipate and predict coincident indicators. We show that our uncertainty network shares such properties and it is also a strong predictor of leading indicators, emphasizing even further the usefulness of its forward-looking information content.

To validate this point, we test whether and to what extent our measure can predict the CFNAI-MA3 coincident indicator after controlling for leading indicators. The results are reported in Table 3, Panel D and Panel E. We find that the uncertainty network predictability still holds up to the 9-month horizon (up to one year excluding 6-month horizon) after controlling for CLI (U.S.LI).[34]

Hence, the uncertainty network clearly shows characteristics of a complementary business cycle leading indicator, even after controlling for leading indicators. The adjusted-R^2s' patterns show that overall, the uncertainty network adds in terms of predictability compared to the information content of other leading indicators. We report the performance of the model with only the control variables (benchmark model) in Table 3. When the uncertainty network is found to be significant in the predictive regressions, across all Panels in Table 3, it contributes to the model performance by increasing the adjusted-R^2 between 1.1% and 6.2%, averaging an increase of 2.3% in addition to the benchmark model.

6.2. Robustness checks

Another possible business cycle coincident indicator is the Aruoba, Diebold, and Scotti (ADS) index of business conditions (see Aruoba et al., 2009).[35] We aggregate the indicator at a monthly frequency. Other possible business cycle coincident proxies are the industrial production (IP) growth rate and the U.S. coincident indicator (U.S.CI) growth rate. They are collected from FRED and the Economic Cycle Research Institute (ECRI), respectively.[36] As a robustness check, we repeat the same predictive regression exercise by replacing the CFNAI-MA3 with one of these alternative coincident indicators. We add the full set of control variables to the regressions as well as the leading indicator, CLI. The results are reported in Table F1 in the online appendix. We find an overall weaker predictive power for the uncertainty network, however still confirming the anticipatory property especially up to 6-month horizons for both models. In addition, we also repeat the empirical analysis replacing the CFNAI-MA3 with the raw monthly CFNAI index and find the adjusted R^2 to decrease sharply after the first month. We attribute this finding to the fact that the raw monthly CFNAI is a shorter term indicator of business cycle, making it more difficult to consistently predict it beyond the first month. Interesting to note that CLI shows no predictive power to predict the future raw monthly CFNAI, while our uncertainty network still shows predictability, hence confirming our network to be a powerful leading indicator also for the raw monthly CFNAI indicator. These results are reported in Table F2 in the online appendix. In sum, we validate the predictive ability of uncertainty network connectedness by confirming that it carries similar predictive power for different business cycle coincident indicators.

As an additional robustness check, we also replace the uncertainty network connectedness measure constructed with time-varying networks with a network measure constructed by using a moving window (e.g. Diebold and Yilmaz, 2009, 2012). We find that the latter is unable to consistently predict future business cycles indicators, showing a weaker predictive ability, and highlighting even further the importance of precisely characterizing the network at any point in time without relying on moving windows when it comes to predicting future levels of the business cycle or the real economy. We show these results in Table F3 in the online appendix.[37]

We also check whether the single industry uncertainty indices $\text{IVIX}^{(\text{Ind})}$ can predict business cycle indicators in a simple univariate predictive regression. We find that $\text{IVIX}^{(\text{Ind})}$ usually classified as hubs (e.g. financials, communications) show good predictive ability. Interestingly, when we add the same set of controls X, the predictive ability of the single $\text{IVIX}^{(\text{Ind})}$ weakens, and even more so, when we also add the leading indicators as controls. When we include the industry uncertainty indices in the same model together with the uncertainty network, they lose or weaken their predictive ability even further, while the network holds its significance. This shows how the network subsumes additional information not enclosed in the single industry uncertainty measures. This analysis underscores the merit of looking at the whole network of industry uncertainties rather than at the single $\text{IVIX}^{(\text{Ind})}$ is more informative. Every industry can trigger a very specific economic and financial crisis or event which may drift into a recession or an economic boom in very different circumstances. However, the information captured by the uncertainty network condenses the idiosyncratic information from each single industry uncertainty together and behaves like a more exhaustive and time-invariant predicting and monitoring tool.

As noted earlier, to further understand the information content of uncertainty networks, we control it by networks created on shocks to the returns itself. We show these results in Table F4 in the online appendix. We document much weaker predictive power of the first moment-based network in contrast to our uncertainty network. These findings are consistent with the empirical evidence in Bloom (2009) who documents how second-moment effects generate a rapid slowdown and bounce-back in economic activity. It is also striking to observe that when we test the predictive ability of the realized returns network for CFNAI-MA3 controlling for the main uncertainty network (Panel D), the predictive power of the former basically disappears, whereas we still uncover a significant forecasting power associated with the uncertainty (second-moment) network. In sum, while, in the previous section, we detect a similar network structure identifying similar industries classified as hubs and non-hubs across first and second moments,

[34] Interestingly, the CLI is found to be negatively related to one-year ahead economic activity. This may be because the CLI captures economic activity within the 3–9 months ahead range (see https://data.oecd.org/leadind/composite-leading-indicator-cli.htm for more information on the index), resulting in a possible inversion after such predictive horizon, as the opposite sign would suggest. For discussions about the CLI's performance and reliability especially for predicting business-cycle turning points see, e.g. Diebold and Rudebusch (1991) and Estrella and Mishkin (1998). This finding highlights even more the importance of our proposed business cycle indicator for longer term (one-year) business cycle predictability.

[35] The Aruoba-Diebold-Scotti (ADS) Business Condition Index tracks real business conditions at a high frequency and it is based on economic indicators. The average value of the ADS index is zero. Progressively positive values indicate progressively better-than-average conditions, whereas progressively more negative values indicate progressively worse-than-average conditions. It is collected from: https://www.philadelphiafed.org/research-and-data/real-time-center.

[36] For more information and data see https://www.businesscycle.com/ecri-reports-indexes/all-indexes.

[37] The results are robust to the choice of the rolling estimation window and the predictive horizon for the underlying variance decomposition.

when it comes to predictability, we show that industry network constructed from options-based uncertainty measures carry forward-looking information useful to predict business cycles indicators which is not embedded in the network structure constructed from first moments. These findings echo previous studies on the importance of second moment shocks and networks (e.g. Bloom, 2009; Bloom et al., 2018; Herskovic et al., 2020; Ludvigson et al., 2020; Fernández-Villaverde and Guerrón-Quintana, 2020).

Finally, we also replace our networks with volume-weighted industry uncertainty measures instead of market-capitalization weights. One can claim that our measures are dependent on time-varying market capitalization, while the alternative of a trading volume weighting might reflect more the actual market sentiment about that stock. Especially, in volatile and turbulent periods, market sentiment and the actual trading of a stock may affect the stock uncertainty as well. In this case, the stock uncertainty will increase, generating uncertainty within its industry which will therefore contribute more actively to shock uncertainty in the network. In line with the preceding argument, in Table F5 in the online appendix, we report the empirical results for the predictive ability of the networks constructed from a volume-weighted industry uncertainty measure. We observe that the network still predicts well the CFNAI-MA3 business cycle indicator from 3-months up to one-year in advance. The network extracted from volume-weighted industry uncertainties is also found to strongly predict leading indicators of business cycle, CLI and U.S.LI, from 3 months up to one year, and up to 9-month horizon, respectively. The network is found to hold its strong predictive ability for the coincident indicator, CFNAI-MA3, also when controlling for CLI. Hence, we can conclude that the predictive results of our uncertainty network are robust to this alternative choice of weights assigned to the single stock uncertainty measure when constructing the industry uncertainty indices.

6.3. Hub and non-hub industry connectedness networks

In this subsection, we study the predictive power of the uncertainty hub-based networks in comparison with the non-hub networks. We repeat the empirical analysis of the previous section, considering now only hub and non-hub based networks, C_t^{hub} and $C_t^{\text{non-hub}}$, respectively. We conjecture that the former leads to greater predictability since it reflects information from the industries detected to be the main uncertainty contributors within the system as discussed in the previous section. Drawing on our earlier analysis, the uncertainty hubs network is constructed from the information enclosed in the communications, financials, IT, and real estate industries, while the non-hubs network derives from the industrials, materials and utilities industries (see also section 5 and Fig. 3). Similar to equation (9), we estimate the following:

$$\mathcal{Y}_{t+h}^{(\ell)} = \beta_0 + \beta_{\text{hub}}\, C_t^{\text{hub}} + \beta_{\text{non-hub}}\, C_t^{\text{non-hub}} + \sum_{i=1}^{N} \beta_{X,i}\, X_{t,i} + \epsilon_t \tag{10}$$

where we add the independent variables that characterize uncertainty hubs and non-hubs based on network connectedness taken jointly and aggregated at a monthly frequency to match the frequency of the indicators we adopt. We include the same set of controls X.

In Table 4, Panel A, we observe that the hubs network predicts well the aggregate indicator of business cycles up to one-year in advance (excluding the 9-month horizon). The hubs network predictive ability shows an even stronger performance than the results obtained for the aggregate network. Moreover, the hubs-based network performance is clearly superior compared to the non-hubs based network for the aggregate CFNAI-MA3.

In Table 4, we also show the predictive results of hubs versus non-hubs networks for the leading indicators CLI and U.S.LI. We find that the hub network connectedness predicts them well up to one year (exception for CLI for the 6-month horizon), whereas the predictive power of the non-hubs network is found to be overall weaker. We also adopt the hubs-based uncertainty network to predict CFNAI-MA3 when including the leading indicators as controls. The hubs network shows a strong predictive ability up to one-year, excluding the 9-month horizon (6- and 9-month horizons) for CLI (for U.S.LI), complementing very well the predictive ability of the leading indicators. Notably, the non-hubs network predictive ability is found to be absent when we also control for the leading indicators. Thus, the uncertainty hubs network shows a stronger predictive power compared to the aggregate network also when interacted for business cycle leading indicators. The hubs-based network can be considered as the main driver of the aggregate network given that it also show a clear predictive superiority when compared to non-hubs.[38]

One may argue that the data from the Covid crisis in 2020 are too extreme to be included. Specifically, the average of CFNAI-MA3 is about -0.16 from 2000 to 2020. The reading in April 2020 is -7.36, which is almost three times the reading in January 2009, -2.6. Therefore, we repeat the empirical analysis by removing the Covid crisis. We show the predictive results for the CFNAI-MA3 in Table F6 in the online appendix. We observe that our findings hold and the role of the uncertainty hubs network is found to be even stronger, especially when controlling for other business cycle leading indicators. This finding is reasonable if we think that during the Covid crisis a larger set of industries has become uncertainty transmitters. These industries were mainly different from the ones we

[38] The performance of the model when adding the hubs and non-hubs networks, when the hubs-network is found to be significant in one of the Panels in Table 4, increases the adjusted-R^2 of about a minimum of 1% to a maximum of 7.4%, averaging an increase of 2.9%. For example, when we run the model without hubs and non-hubs to predict CFNAI-MA3 at the one-year horizon, we get an adjusted-R^2 equal to 16.8% instead of 20.4%, with an increase of 3.6%. To give an idea about the performance of the models considering only the non-hubs network, for instance, in Panel 1 adding only the non-hubs network would lead to adjusted-R^2 equal to 36.2, 44.7, 15.1, 17.8, and 17.2 for h from 1 to 12 months, respectively. This implies a much lower improvement compared to the benchmark model, being equal to 0.7 when the non-hubs network is found significant (at the 10% level). We also run the model without the non-hubs network finding that the majority of the model performance increase is indeed driven by hubs. In fact, about 74% to 100% of the adjusted-R^2 increase is hubs driven.

Table 4
Hubs vs. non-hubs network predictive results.

	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
Panel A: CFNAI-MA3					
$C_t^{\text{hub}} \mid X_t$	-0.009**	-0.008**	-0.009**	-0.006	-0.019***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)
$C_t^{\text{non-hub}} \mid X_t$	-0.004	-0.010*	0.004	-0.008	0.011
	(0.006)	(0.005)	(0.007)	(0.007)	(0.007)
Adj. R^2	37.8	45.2	15.9	17.9	20.4
Benchmark Adj. R^2	36.1	44.0	14.6	17.5	16.8
Panel B: CLI					
$C_t^{\text{hub}} \mid X_t$	0.016***	0.010**	-0.003	-0.013**	-0.023***
	(0.004)	(0.005)	(0.007)	(0.006)	(0.008)
$C_t^{\text{non-hub}} \mid X_t$	-0.016***	-0.023***	-0.019*	-0.018	-0.006
	(0.005)	(0.006)	(0.010)	(0.012)	(0.009)
Adj. R^2	72.2	62.5	37.6	28.4	23.5
Benchmark Adj. R^2	69.2	60.4	36.5	26.3	20.1
Panel C: U.S.LI					
$C_t^{\text{hub}} \mid X_t$	-0.125***	-0.094**	-0.174***	-0.141***	-0.110**
	(0.034)	(0.042)	(0.045)	(0.047)	(0.048)
$C_t^{\text{non-hub}} \mid X_t$	0.001	-0.034	-0.064	-0.010	0.153***
	(0.042)	(0.051)	(0.054)	(0.054)	(0.058)
Adj. R^2	52.7	29.9	23.0	23.8	19.8
Benchmark Adj. R^2	50.4	27.7	15.6	21.3	16.8
Panel D: CFNAI-MA3 controlling for CLI					
$C_t^{\text{hub}} \mid X_t$	-0.020***	-0.014***	-0.017***	-0.006	-0.015**
	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)
$C_t^{\text{non-hub}} \mid X_t$	0.002	-0.006	0.009	-0.008	0.008
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
CLI	0.502***	0.266***	0.332***	-0.017	-0.177**
	(0.064)	(0.066)	(0.084)	(0.086)	(0.085)
Adj. R^2	50.3	48.5	20.9	17.5	21.6
Benchmark Adj. R^2	46.7	46.3	18.5	17.2	20.1
Panel E: CFNAI-MA3 controlling for U.S.LI					
$C_t^{\text{hub}} \mid X_t$	-0.007**	-0.008**	-0.007	-0.004	-0.019***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)
$C_t^{\text{non-hub}} \mid X_t$	-0.006	-0.009*	0.003	-0.009	0.011
	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)
U.S.LI	0.050***	-0.003	0.029***	0.022**	0.003
	(0.008)	(0.008)	(0.010)	(0.011)	(0.011)
Adj. R^2	46.7	45.0	18.4	19.0	20.1
Benchmark Adj. R^2	44.6	43.8	18.2	18.9	15.9
Obs	250	248	245	242	239

Notes: This table presents the results of the predictive regression (10) comparing the predictive ability of the uncertainty hubs vs non-hubs sub-networks with respect to the coincident indicator CFNAI-MA3 (Panel A), leading indicators, CLI (Panel B) and U.S.LI (Panel C). In Panel D and Panel E, the results with respect to the CFNAI-MA3 coincident indicator controlling also for the leading indicators CLI and U.S.LI, respectively, are reported. The five columns of the table represent different predictability horizons with $h \in (1, 3, 6, 9, 12)$. Regressions' coefficients and standard errors (in parentheses), and adjusted-R^2 (in %) are reported. Benchmark adjusted-R^2 (in %) is the adjusted-R^2 of the regression model including only the set of control variables, X. Coefficients are marked with *, **, *** for 10%, 5%, 1% significance levels, respectively. Intercept and controls results are not reported for the sake of space, the only exception being the leading indicator controls. Series are considered at a monthly frequency between 01-2000 and 12-2020.

classify as uncertainty hubs throughout the sample (see Table E1 in the Appendix). This may be the reason why removing the Covid crisis from our sample, not only confirms our findings but even strengthens the predictive power of the uncertainty hubs network.

We know that the CFNAI-MA3 is likely persistent. For alleviating this concern in our analysis, as an additional robustness check, we also include the previous lags of the CFNAI-MA3 indicator as an additional control in our model. The results are reported in

Table F7 in the online appendix. We observe that the predictive power of the uncertainty hubs network holds significant and, again, is superior to the one based on non-hubs.[39] In order to control for previous economic and financial fluctuations which could impact our findings, we also include the credit spread as control variable in the empirical analysis. The credit spread is computed as the difference between Moody's BAA- and AAA-rated corporate bond yields. When we do so, we find that the results hold both qualitatively and quantitatively and, actually, when controlling for the credit spread the predictive ability of the uncertainty network even strengthens as well as the one of the hubs-based network. The results are available from the authors upon request.[40]

We also check whether some industries might capture longer run uncertainty than others, and whether this is reflected in the predictive power of our networks for business cycle fluctuations. We extend our predictive horizons up to 2 years. We report the results in the online appendix of the paper in Tables F7 and F8. We uncover predictive ability for future business cycle indicators up to 18 months when looking at the aggregate network measure (see Table F8). Interestingly, this predictive power is found to be stronger when tested for hubs-based networks compared to non-hubs networks, confirming the previous findings of the paper (see Table F9). In addition, this result implies that certain sectors such as IT or communications (included in our hubs network) may subsume information about longer term uncertainty which may be stimulating the economy and predict business cycle fluctuation in the longer run.

To further validate the greater information content of the hubs-based network for future economic activity and business cycles, we also study the role of the uncertainty networks with respect to the CFNAI-MA3 indicator components. The first set of sub-components includes the four categories of data from which the indicator is built, namely 1) production and income (PI), 2) employment, unemployment, and hours (EUH), 3) personal consumption and housing (CH), and 4) sales, orders, and inventories (SOI). The second set of sub-components includes proxies of expansions and recessions following the approach by Berge and Jordà (2011). More details on the CFNAI-MA3 decomposition as well as the whole set of the empirical results are reported in the online appendix, Section G, from Table G1 to G3. Overall, we confirm the superior predictive power of the hubs-based network compared to the non-hubs based network also for the CFNAI-MA3 sub-indicators.

We conduct two additional robustness checks. First, in Table G4 in the online appendix, we test the predictive ability of C_t^{hub} alone, controlling for X. The predictability of the hubs network is found to be similar and, in a few cases, even stronger than the one achieved by the aggregate network C. This is especially true at the longer horizons and for expansions, as also reflected by a greater adjusted-R^2. These results further suggest a more informative content of the hubs network for business cycle indicators compared to the aggregate network. Second, we conduct the predictive analysis by adopting a stricter construction of the hubs network, including only the main uncertainty hubs, namely communications, financials and IT (showing a time-invariant role as key industries over the entire sample). This will alleviate concerns about i) look-ahead bias for the real estate industry in relation to the data after the GFC, and ii) extra-information bias due to the fact that the hubs network is constructed from four industries against the non-hubs network constructed from three. We report the results in Table G5 in the online appendix for all the coincident indicator CFNAI-MA3, expansions and recessions, and also for the leading indicator CLI. Our previous findings remain robust and we confirm that information enclosed in the hubs-based network is more informative for future business cycle indicators compared to the non-hubs-based network.

6.4. Predicting the U.S. GDP

Inspired by studies on the importance of sectoral sources and changes in volatility to explain GDP changes (e.g. Carvalho and Gabaix, 2013), we check whether or not our uncertainty networks are also able to predict the future U.S. GDP growth rate and volatility. We calculate the growth rate of GDP_t, the U.S. GDP at time t as $g_t = log(GDP_{t+1}/GDP_t)$ where t is expressed in quarterly frequency, end of the quarter. The volatility of GDP growth is measured as the annualized GDP standard deviation over 4 quarters. We check whether or not the aggregate network can predict U.S. GDP indicators in the next h quarters ahead, with $h \in (1, 2, 3, 4)$ by running the predictive equation (9) at a quarterly frequency. We report the whole set of empirical results in Tables H1 and H2 in the online appendix. The aggregate uncertainty network predicts the future GDP growth rate mainly for the second and third quarters ahead with a negative sign, that is an intensification of the network leads to a decreasing GDP growth rate in the following quarters. It also predicts future GDP volatility in the first two quarters ahead. This time, an increase in the uncertainty network leads to an increase in GDP volatility. We confirm, once again, that the hubs network shows useful information to predict the GDP growth rate and its volatility, whereas a weak and almost absent predictive power is found for the non-hubs network (see Table H2 in the online appendix). This exercise emphasizes even further the superior predictive role of the network extracted solely from uncertainty hubs not only for the business cycle indicators but also for the GDP growth rate and its volatility.

6.5. Out-of-sample predictability

In this subsection, we assess the out-of-sample business cycle predictive power of our industry uncertainty networks. To do this, we compare the full model in equation (9), including the aggregate network and the set of control variables X_t, with a restricted

[39] We also replace the CFNAI-MA3 with the raw monthly CFNAI index, still confirming the superior role of the hubs-based networks.

[40] Additionally, to attenuate concerns about the lower bound associated to short-term risk-free in part of our sample, we control for longer term interest rate proxies. We replace the difference between 10-year and 3-month government bond with both i) only the longer-term 10 years bond yield and ii) the difference between the 10-year and 2-year spread. The result hold qualitatively and quantitatively the same and are available from the authors upon request.

model in which the network coefficients are set equal to 0. If the network measure is predictive, we should observe an improvement in the out-of-sample errors of the full model relative to the restricted model. To test the superiority of the hub network over the non-hub network, we compare the full model in equation (10), including the hub network and the set of control variables X_t, with a model including the non-hub network and the same set of control variables. Again, if the hub network measure is more predictive, we should see an improvement in the out-of-sample errors compared to the model including the non-hub network.

We choose 2000–2007 as the in-sample period for our main analysis. We use the mean square forecast error (MSFE) adjusted statistics of Clark and West (2007) to compare our nested model forecasts. The MSFE-adjusted statistic tests the null hypothesis that the average MSFE of the nested models is less than or equal to the MSFE of the full model against the one-sided (upper-tail) alternative hypothesis that the benchmark error of the nested model is greater than the error of the full model. This is equivalent to the null hypothesis that the information contained in the networks does not improve forecasts in terms of error. We generate forecasts using a recursive (i.e. expanding) parameter estimation window.[41] The MSFE-adjusted statistics are reported in Table 5 with respect to the prediction of CFNAI-MA3 and CLI with the aggregate network (panels A and B) and the prediction of the same indicators with hub and non-hub networks (panels C and D).

In addition, we use the Harvey et al. (1998) statistic to test the null hypothesis that our restricted benchmark model forecast i encompasses network forecast j $\left(H_0 : \lambda = 0\right)$ against the (one-sided) alternative hypothesis that the forecast from model i does not encompass the forecast from model j $\left(H_1 : \lambda > 0\right)$.[42] Model j in our setup is the model inclusive of our network measure. In essence, if we reject the null hypothesis of encompassing, then it is useful to combine the forecasts from models i and j rather than relying solely on the forecast from model i (see Rapach et al., 2010). In particular, Harvey et al. (1998) recommends using the $MHLN$ statistic to assess statistical significance.[43] In Table 5, we report the (trimmed $0 \leq \lambda \leq 1$) values of λ with the corresponding significance of the $MHLN$ statistic applied to the out-of-sample forecasts. The statistic corresponds to a one-tailed test of the null hypothesis that the forecast of the benchmark model encompasses the forecast of the full model including the networks of interest (either C or C_{hubs}), against the alternative hypothesis that the forecast of the benchmark model does not encompass the forecast of the full model.

First, from Table 5 we see that the full model including the aggregate network significantly outperforms the restricted model at $h = 9$ and $h = 12$ (from $h = 3$ to $h = 12$) for the CFNAI-MA3 (for CLI). This shows the important role of our aggregate network measure in predicting the leading indicator of the business cycle in particular, and at longer horizons, over and above the set of control variables adopted X_t. The values of λ and the p values for the $MHLN$ statistic of the encompassing test reported in Panel A and Panel B reflect the results of the MSFE-adjusted statistic. We reject the null hypothesis of the test in the corresponding horizons that show a significant MSFE-adjusted statistic.

Next, we consider the model with the hubs-based networks and X_t and compare it with the model with the non-hubs-based network and X_t. We observe a significant MSFE-adjusted statistic mainly at longer horizons for CFNAI-MA3, while at every horizon except $h = 3$ for CLI. This confirms the superior role of the hubs-based network over the non-hub network in predicting business cycle indicators, even out of sample. The values of λ and the p values for the $MHLN$ statistic reflect these findings, as we mainly reject the null hypothesis and detect a frequent inability of the benchmark regression model forecasts to encompass forecasts of the models including the aggregate network or the hubs-based network.[44]

We also perform several additional checks. We repeat the same out-of-sample analysis by changing the in-sample estimation window to 2000–2011.[45] We also check the performance of our models by replacing the benchmark with the control variables X_t with an AR structural benchmark, a random walk process and a simple historical average over the past year, rolled monthly. We check whether the inclusion of the aggregate, hub and non-hub networks in these benchmarks increases the predictability of the business cycle. The Clark and West (2007) mean square forecast error (MSFE) adjusted statistics results are reported in tables I1, I2 to I3 in the online appendix and our conclusions still hold.

Overall, both the in-sample and the out-of-sample results lead us to conclude that the information contained in the industrial uncertainty network, especially when it is based on uncertainty hubs, contains predictive information about future indicators of the business cycle, both coincident and leading indicators. Uncertainty hubs are found to be the main contributors to uncertainty shocks within the system, showing a closer link with the real economy. This exercise validates some policy actions that can be drawn from

[41] We obtain similar results using rolling estimation windows of different sizes.

[42] Consider the formation of an optimal composite forecast of any business cycle indicator of interest, Y, as a convex combination of the forecasts from models i and j:

$$\hat{Y}^*_{t+h} = (1 - \lambda)\hat{Y}_{i,t+h} + \lambda\hat{Y}_{j,t+h},$$

where $0 \leq \lambda \leq 1$. If $\lambda = 0$, then the forecast of model i encompasses the forecast of model j, since model j does not contain any useful information – beyond that already contained in model i – for the formation of an optimal composite forecast. Conversely, if $\lambda > 0$, then the forecast from model i does not encompass the forecast from model j, so model j does contain useful information for forming the optimal composite forecast (again, over and above the information already contained in model i).

[43] For more details on the $MHLN$ statistic, see the definition in Harvey et al. (1998).

[44] Interestingly, when we use the restricted model including the total network as a benchmark to test the performance of the models with hubs and non-hubs networks, we find that only the model including the hub network appears to outperform the benchmark in several cases. These results are also reflected in the predominantly higher MSFE-adjusted statistics associated with the hubs network in Table 5.

[45] The results appear to be independent of the choice of window and our conclusions are qualitatively unchanged.

Table 5
Out-of-sample business cycle prediction and encompassing test.

	Panel A: CFNAI-MA3				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
$C_t \mid X_t$	0.192	0.196	0.219	1.673**	1.692**
Encompassing Test (λ)	0.000	0.000	0.316	1.000**	1.000**
	Panel B: CLI				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
$C_t \mid X_t$	0.295	1.308*	1.921**	1.929**	2.302**
Encompassing Test (λ)	0.280	1.000*	1.000**	1.000**	1.000**
	Panel C: CFNAI-MA3 with Hubs vs non-Hubs				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
$C_t^{\text{hub}} \mid X_t, C_t^{\text{non-hub}}$	0.293	1.231*	0.250	1.886**	3.138***
Encompassing Test (λ)	0.000	0.814*	0.582	1.000**	1.000***
	Panel D: CLI with Hubs vs non-Hubs				
	$h=1$	$h=3$	$h=6$	$h=9$	$h=12$
$C_t^{\text{hub}} \mid X_t, C_t^{\text{non-hub}}$	1.421*	0.875	2.482***	1.478**	2.781***
Encompassing Test (λ)	0.908*	0.549	1.000***	1.000**	1.000***

Notes: The table presents the Clark and West (2007) mean square forecast error (MSFE)-adjusted statistic comparing the out-of-sample predictions from the full models with our industry uncertainty networks and the set of controls, and the restricted benchmark model with only the controls X_t, with $\beta_C = 0$ (Panel A and B), and from the full models with the hubs-based network and X_t, and the model with the non-hubs network and X_t, with $\beta_{hubs} = 0$ as benchmark. Rejections of the null hypothesis, that the full model does not improve the predictions, are reported as $*$, $**$, and $***$, for the 10%, 5%, and 1% significance levels, respectively. In the encompassing test rows, we report the (trimmed $0 \leq \lambda \leq 1$) values of λ with the corresponding significance of the Harvey et al. (1998) $MHLN$ statistic applied to the out-of-sample forecasts. The statistic corresponds to a one-sided (upper-tail) test of the null hypothesis that the forecast of the benchmark model encompasses the forecast of the full model, against the alternative hypothesis that the forecast of the benchmark model does not encompass the forecast of the full model. Rejections of the null hypothesis are reported as $*$, $**$, and $***$, for the 10%, 5%, and 1% significance levels, respectively. The in-sample period is between 2000–2007, while the rest is considered as the out-of-sample evaluation forecast period. The results are reported for the forecast horizons $\in \{1, 3, 6, 9, 12\}$.

our study. Policymakers and regulators could use the proposed network to monitor industry uncertainty for any stage of the business cycle and any time period, given its forward-looking nature combined with accurate estimation of dynamics.

7. Conclusion

We studied the ex-ante uncertainty network of US industries, which is constructed from options-based investors' future expectations about the next month's uncertainty. We relied on a data set of forward-looking industry uncertainties and employed a time-varying parameter VAR (TVP-VAR) to model the ex-ante uncertainty network of industries.

We were able to obtain a precise point-in-time estimate of the uncertainty network to accurately characterise the specific role of industries in uncertainty shocks, dynamically over business cycles. We uncovered a major role for booming industries such as communications and information technology and classified them as uncertainty hubs. Industries such as financials and real estate are also classified as hubs, while industrials, materials and utilities show a more neutral role and are classified as non-hubs.

We used the forward-looking characteristics of the industry connectedness networks in predictability. We found the industry uncertainty network to be a useful tool for predicting future business cycles. Such uncertainty networks can serve as a new tool for regulators and policy makers to monitor the relationship between industry networks, the business cycle and the real economy in an accurate, timely and forward-looking manner.

In particular, we found that the network extracted from the uncertainty hubs is a novel leading indicator of the business cycle. Fluctuations and shocks to uncertainty in the hubs have the potential to shape industry networks and affect the real economy. Our findings suggest a possible direction for policy and government intervention, as uncertainty hubs show a closer link to the real economy. In particular, a reduction in their uncertainty shocks may provide a narrow and direct channel for business cycle amplification. Hence, policy interventions aimed at dampening their shocks to uncertainty can potentially provide a direct channel for business cycle boosts. Finally, while the financial sector has been at the forefront of policy interventions, particularly in the aftermath of the GFC, we argue that careful attention should now also be paid to the communications and IT sectors to mitigate excessive propagation of their uncertainty, which can potentially lead to business cycle contractions.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jedc.2023.104793.

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