MELBOURNE INSTITUTE
Applied Economic & Social Research

Working Paper Series

Domestic and Global Uncertainty: A Survey and Some New Results

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Working Paper No. 13/19
November 2019

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* We thank Mario Alloza, Giovanni Angelini, Giovanni Caggiano, Andrea Carriero, Luca Fanelli, Davide Furceri, Klodiana Istrefi, Stéphane Lhuissier, Sarah Mouabbi, Giovanni Pellegrino, Michele Piffer, Natalia Ponomareva, Chris Redl, Ben Wang, Francesco Zanetti, and seminar participants at Macquarie University for valuable comments. Financial support by the Australian Research Council via the Discovery Grant DP160102281 is gratefully acknowledged. Authors's contacts: efrem.castelnuovo@gmail.com .

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Abstract

This survey features three parts. The first one covers the recent literature on domestic (i.e., country-specific) uncertainty and offers ten main takeaways. The second part reviews contributions on the fast-growing strand of the literature focusing on the macroeconomic effects of uncertainty spillovers and global uncertainty. The last part proposes a novel measure of global financial uncertainty and shows that its unexpected variations are associated to statistically and economically fluctuations of the world business cycle.

JEL classification: C22, E32, E52, E62

Keywords: Uncertainty, uncertainty shocks, spillovers, global financial uncertainty, world business cycle.

1 Introduction

The macroeconomic effects of uncertainty have been hotly debated since the global financial crisis. In fact, uncertainty as an element behind consumption and investment decisions has been investigated for a long time. Papers in the 1980s and 1990s unveiled the role of precautionary savings for consumption (Caballero (1990)) and the optimality of a "wait-and-see" behavior in presence of choices that are costly to reverse, or irreversible (see Eberly (1994) for an application of the real option-theory to durable consumption, Bernanke (1983), Pindyck (1991), and Bertola and Caballero (1994) to investment decisions). More recently, Bloom (2009) has moved the attention from the role of uncertainty in steady state to that of driver of the business cycle. Bloom (2014, 2017) and Castelnuovo, Lim, and Pellegrino (2017) offer surveys of the recent literature.

This paper contributes to the discussion on the relationship between uncertainty and the business cycle along three dimensions:

i) it offers updates on the main empirical findings on the role of uncertainty shocks on the one hand, and endogenous uncertainty on the other. It does so by categorizing the extant contributions into ten different classes, which are related to research questions. Correspondingly, ten main takeaways emerging from the literature are proposed. These takeaways can be seen as basis for further research questions;

ii) it reviews the fast-growing strand of the literature on uncertainty spillovers and global uncertainty, and highlights questions that remain to be addressed;

iii) it documents a novel measure of global financial uncertainty (GFU). This measure is based on proxies for financial volatility of 39 countries. Vector autoregressions (VAR) jointly modeling our measure of global financial uncertainty and a global business cycle indicator point to a statistically and economically significant negative response of world output to unexpected hikes in uncertainty.

Before moving to the rest of the paper, three notes are in order. First, when referring to theoretical models dealing with "uncertainty", this survey will in most occasions conceptually refer to a mean-preserving change in the second moment of a distribution. For instance, we will think of the economy's response to a change in the *volatility* of the technology process conditional on an unchanged *level* of technology. Technically, this concept is actually that of "risk", because it assumes that agents know the probability distribution of the possible outcomes (say, the probability of a better/worse technology materializing in the future). In other words, risk refers to "known unknowns". Differently, "Knightian" uncertainty (from Knight (1921)) refers to "unknown unknowns", i.e., to uncertainty about the probability distribution generating the data. Recent attempts to empirically distinguish these two concepts are Bekaert, Hoerova, and Lo Duca (2013), Bekaert, Engstrom, and Xu (2019), and Rossi, Sekhposyan, and Soupre (2019).

A second note regards the use of ex-post data realizations (as opposed to ex-ante data, i.e., expectations) in some of the empirical analysis reviewed in this paper. While uncertainty obviously refers to future events, many empirical contributions have employed measures of realized volatility (e.g., realized stock market volatility) to approximate uncertainty. In the data, the correlation between these two concepts is often high. However, at times empirical conclusions drawn by using one or the other may be dramatically different. For instance, Berger, Dew-Becker, and Giglio (2019) find that innovations in realized stock market volatility are robustly followed by contractions, while shocks to forward-looking uncertainty have no significant effect on the economy.

Third, the survey will mainly refer to macroeconomic uncertainty. Part of the literature has actually focused on the evidence and effects of microeconomic uncertainty, typically finding a negative correlation with the business cycle. For a review of contributions related to microeconomic uncertainty, see Bloom (2014).

The structure of this survey is the following. Section 2 reviews the main takeaways of the empirical literature on the business cycle effects of uncertainty shocks, with a focus on domestic uncertainty. Section 3 switches to global uncertainty and spillovers across countries. Section 4 describes the construction of our global financial uncertainty measure and documents the outcome of our VAR exercise. Section 5 concludes.

2 Domestic uncertainty: Ten takeaways

1) Uncertainty is countercyclical. The negative correlation between indicators of the business cycle and proxies of uncertainty is a solid empirical fact. Examples in the literature include financial market volatility (Bloom (2009)), disagreement amongst professional forecasters (Bachmann, Elstner, and Sims (2013), Sheen and Wang (2019)), frequency of newspaper articles that refer to economic uncertainty (Alexopoulos and Cohen (2015), Baker, Bloom, and Davis (2016)), frequency of uncertainty-related keywords searched on the internet (Castelnuovo and Tran (2017)) or in the Federal Reserve Beige Books (Saltzman and Yung (2018)), forecast errors about macroeconomic data (Jurado, Ludvigson, and Ng (2015), Scotti (2016), and Rossi and Sekhposyan (2015) for the US economy, and Rossi and Sekhposyan (2017), Moore (2017), Redl (2017), Grimme and Stöckli (2018), Meinen and Röhe (2017), Garratt, Lee, and Shields (2018), Ismailov and Rossi (2018), and Tran, Vehbi, and Wong (2019) for other industrialized countries). Using 100 years of consumption data from 16 OECD countries, Nakamura, Sergeyev, and Steinsson (2017) confirm that macroeconomic volatility strikingly increases in periods of lower growth. The countercyclicality of uncertainty is not just confined to the macro-level territory. In fact, it is robust to using micro-based measures of uncertainty such as cross-firm stock-return variation (Campbell, Lettau, Malkiel, and Xu (2001)), the dispersion of plant-level shocks to total factor productivity (Kehrig (2015), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018)), and cross-firm price changes (Vavra (2014a), Baley and Blanco (2019)).

A natural question is why uncertainty is countercyclical. As discussed by Bloom (2014), several interpretations have recently been advanced, but their empirical relevance is still debated. Take the case of financial volatility. One interpretation for its countercyclicality is that firms take on more debt during recessions, which accentuates their stock-returns volatility. While this leverage-focused story is appealing, Schwert (1989) finds the contribution of leverage to the rise of uncertainty in recessions to be no more than 10 percent. Countercyclical risk aversion could also be behind the increase in financial uncertainty during busts. However, Bekaert, Hoerova, and Lo Duca (2013) show that the movements in the VIX (a measure of expected volatility of the S&P 500 index) are too large to be explained by plausible fluctuations in risk aversion. Baker, Bloom, Davis, and Kost (2019) construct a newspaper-based equity market volatility (EMV) tracker that correlates with the US implied/realized stock market volatilities. They find that 72% of the articles behind their EMV measure refer to the macroeconomic outlook, and 35% to macroeconomic policy (mostly fiscal policy). Pastor and Veronesi (2017) point out that the precision of political signals may affect the relationship between economic policy uncertainty and stock market volatility. For instance, the Trump administration has been characterized by many imprecise signals. If financial market volatility is the result of economic policy uncertainty times the precision of political signals, financial market volatility could fall when signals are imprecise even if economic policy uncertainty remains high. The reason is that investors who are skeptical about politicians' pronouncements and their link to future policy actions downweight such signals. This might explain some phases of the Trump administration characterized by high economic policy uncertainty but low financial market volatility.

Macroeconomic uncertainty has also been found to be countercyclical. Orlik and Veldkamp (2014) stress that forecasters could be more confident in predicting future events in normal times than during recessions, above all extreme event-type of recessions as the 2007-09 one. Forecasters can have troubles predicting how the economy will fare in the future during economic downturns also because of badly communicated, hyperactive (or both) macroeconomic policies (Pastor and Veronesi (2012)). Indeed, the economic policy uncertainty index developed by Baker, Bloom, and Davis (2016) scores record-high levels during the Great Recession.

Berger and Vavra (2019) study two possible sources of the greater dispersion that many economic variables feature in recessions, i.e., bigger shocks and stronger responses by agents to acyclically-sized shocks. Using a novel identification strategy related to price data in an open economy framework, they document a robust and positive relationship between exchange rate pass-through and the dispersion of item-level price changes. They interpret this relationship in favor of a stronger response during recessions. Kozeniauskas, Orlik, and Veldkamp (2018) deal with three different types of uncertainty, i.e., macro uncertainty (about aggregate shocks), micro uncertainty (about firm-level shocks), and higher-order uncertainty (about other agents' beliefs when forecasts differ). They set up a model in which firms estimate the risk of disasters each period before optimally determining their demand for inputs and level of production. This model is able to generate macro, micro and higher-order uncertainty which covary in a realistic way. This is due to the fact that disasters arise infrequently, hence their probability is difficult to quantify and disagreement over it may arise. An increase in disaster risk amplifies forecast errors (macro uncertainty) and disagreements (belief uncertainty), and lead firms having divergent forecasts to choose different inputs and obtain different outputs (micro uncertainty). Hence, time-varying disaster risk may be behind the fluctuations in different types of uncertainty. Bianchi, Kung, and Tirskikh (2019) employ a model featuring more than one type of uncertainty shocks (a "demand" uncertainty shock, i.e., a shock to the volatility of household's preferences, and a "supply" uncertainty shock, which is a second moment shock to technology). They find that both type of shocks imply large real contractions and generate increases in term premia, while supply shocks are relatively more powerful when it comes to explaining inflation and investment.

It is worth noting that the literature has so far largely pointed toward contractionary effects of uncertainty shocks. This fact is informative, among other things, from a model-selection standpoint. In fact, DSGE models can predict short-run expansions in response to jumps in uncertainty. This is the so-called "Oi–Hartman–Abel" effect discussed by, among others, Bloom (2014). An example of this effect is the response of output to an uncertainty shock in a large class of real business cycle models. Suppose aggregate uncertainty (say, demand uncertainty) increases. If households are risk-averse, precautionary savings kick in and a reduction in consumption occurs. This generates an increase in households' marginal utility, which stimulates labor supply. If labor demand does not adjust, employment rises and, consequently, so does output. Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015) and Basu and Bundick (2017) point out that this does not occur when nominal rigidities (say, price rigidities) are present. In that case, demand-driven output contracts due to the fall in consumption, which also implies (under reasonable parametrizations) a fall in hours and investment. While the business cycle impact of the "Oi-Hartman-Abel" effect is likely to be small, a stronger impact of this effect in the long-run could be in place due to the effects of uncertainty shocks on R&D decisions (Bloom (2014)).

Obviously, uncertainty shocks having recessionary effects can generate the countercyclicality observed in the data. On the other hand, first-moment shocks affecting the business cycle can affect uncertainty. The endogeneity of uncertainty and the business cycle is a challenging issue to tackle when it comes to identifying the causes and consequences of exogenous variations in uncertainty and output. Recently, some researchers have tried to solve this identification issue by focusing on different types of macroeconomic uncertainty. In particular, researchers have tried to understand the different information contents of macroeconomic and financial uncertainty. This is what we turn next.

2) Financial and macroeconomic uncertainty have different macroeconomic effects. Ludvigson, Ma, and Ng (2019) use a set of narrative restrictions to separately identify financial and macroeconomic uncertainty shocks in a VAR context. They document a negative response of real activity indicators to a jump in financial volatility. Importantly, they show that the reverse is not true, i.e., first-moment shocks are not found to cause a response in financial volatility (a similar result can be found in Lütkepohl and Milunovich (2016)). Related results are those by Casarin, Foroni, Marcellino, and Ravazzolo (2018), who find stronger business cycle effects when focusing on financial uncertainty as opposed to macroeconomic uncertainty, and by Ma and Samaniego (2019), who work with industry-level data and find that financial uncertainty precedes uncertainty in the rest of the economy. The recessionary effects of financial shocks have also been documented by, among others, Bloom (2009), Caggiano, Castelnuovo, and Groshenny (2014), Carriero, Mumtaz, Theodoridis, and Theophilopoulou (2015), Leduc and Liu (2016), and Basu and Bundick (2017). Interestingly, Ludvigson, Ma, and Ng (2019) find that shocks identified with measures of macroeconomic uncertainty do not trigger a drop in real activity. If anything, an unexpected hike in macroeconomic uncertainty is found to be followed by a short-lived expansion. This result could be due to an endogeneity issue, i.e., it is the business cycle that causes movements in macroeconomic uncertainty, whose fluctuations are then endogenous responses to first-moment shocks. Ludvigson, Ma, and Ng (2019) stress the role that macroeconomic uncertainty plays in amplifying the effects of first-moment shocks and second-moment financial disturbances. One possible story for a reverse causal link relating the business cycle and uncertainty is price experimentation by firms that search for information regarding their optimal mark-up (Bachmann and Moscarini (2012)). A related paper is Bachmann and Bayer (2013). They show that a model with correlated risk and productivity shocks matches the data - i.e., the output response to an uncertainty shock - better than a model with risk shocks only.

Other recent empirical findings suggest that the Ludvigson et al. (2019) result is not written in stone. Building on Bacchiocchi and Fanelli (2015) and Bacchiocchi, Castelnuovo, and Fanelli (2018), Angelini, Bacchiocchi, Caggiano, and Fanelli (2019) exploit the heteroskedasticity in Ludvigson et al.'s (2019) measures of financial and macroeconomic uncertainty and that of indicators of the US business cycle to identify uncertainty and first-moment shocks. They find both financial and macroeconomic uncertainty to be drivers of the business cycle. Using instruments to identify exogenous variations of the business cycle, Angelini and Fanelli (2019) model the same dataset and find similar results. Carriero, Clark, and Marcellino (2019) develop a structural VAR with stochastic volatility in which past and contemporaneous uncertainty can affect the business cycle, and contemporaneous realizations of the business cycle are allowed to have a feedback effect on uncertainty. Shocks to macroeconomic and financial uncertainty are found to be recessionary. However, while macroeconomic uncertainty is found to be exogenous, financial uncertainty is found to be affected by the levels of contemporaneous business cycle indicators. Digging deeper, Carriero, Clark, and Marcellino (2019) find that Ludvigson et al.'s (2019) results are not robust to using alternative, still plausible, sets of identifying restrictions to isolate financial and uncertainty shocks. A response to Angelini, Bacchiocchi, Caggiano, and Fanelli (2019) and Carriero, Clark, and Marcellino (2019) is contained in Ludvigson, Ma, and Ng (2019).

One way to achieve identification is to work with instruments for exogenous movements in uncertainty. A recent example is Piffer and Podstawski (2018). They exploit variations in the price of gold around uncertainty-related events to construct a proxy for uncertainty shocks. Then, they identify uncertainty and news shocks in a proxy SVAR and compare results to the recursive identification. They find the so-instrumented uncertainty shocks to be drivers of the US business cycle. Moreover, they find that uncertainty shocks identified recursively look more like news shocks. This result suggests that VAR identification schemes alternative to the often used triangular zero restrictions are likely needed for a correct quantification of the macroeconomic effects of uncertainty shocks. Identification of uncertainty shocks represents a florid research territory for the years to come.

3) Financial frictions amplify the real effects of uncertainty shocks. The interaction between financial frictions and volatility shocks has been investigated both theoretically and empirically. Christiano, Motto, and Rostagno (2014), Gilchrist, Sim, and Zakrajšek (2014), Bonciani and van Roye (2016), Alfaro, Bloom, and Lin (2018), Arellano, Bai, and Kehoe (2019), and Chatterjee (2019) build up models in which risk shocks interact with financial frictions of different sorts. While the details of the models differ, the robust message across them is that financial frictions magnify the effects of bursts in uncertainty. However, no agreement has been reached yet on the size of the "finance-uncertainty multiplier", which - as defined in Alfaro, Bloom, and Lin (2018) - captures the additional output effects due to financial frictions that materialize after a exogenous increase in uncertainty. Alfaro, Bloom, and Lin (2018) find that adding financial frictions to an otherwise standard real business cycle model featuring real option effects roughly doubles the negative impact of uncertainty shocks on investment and hiring. Gilchrist, Sim, and Zakrajšek (2014) work with a dynamic stochastic general equilibrium (DSGE) framework featuring heterogeneous firms that face time-varying idiosyncratic uncertainty, irreversibility, nonconvex capital adjustment costs, and financial frictions. They find that, without financial frictions, uncertainty shocks would have little effects on the business cycle. Arellano, Bai, and Kehoe (2019) build up a model in which hiring inputs is risky because financial frictions limit firms' ability to insure against shocks. Consequently, a jump in idiosyncratic volatility induces firms to reduce their inputs to reduce such risk. They find that, if firms had access to complete financial markets, an increase in the volatility of persistent productivity shocks would actually lead to an increase in aggregate employment due to the reallocation of resources to the most productive firms, a reallocation which would generate an economic boom.

The contributions cited above justify the need of jointly modeling uncertainty and financial frictions in empirical frameworks. Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016) employs a penalty function approach to identify financial conditions and uncertainty shocks in a VAR context. They find that, even after controlling for financial conditions and identifying financial shocks, uncertainty shocks are an important source of macroeconomic disturbances, in particular when financial conditions are tight. Furlanetto, Ravazzolo, and Sarferaz (2019) works with a sign-restriction identification strategy which crucially relies on the information contained in the response of the ratios of variables (e.g., financial conditions over uncertainty) for separately identify first and second-moment shocks. Their VAR produces a response of investment to an uncertainty shock which features the drop-rebound-overshoot dynamics as in Bloom (2009). Choi, Furceri, Huang, and Loungani (2018) use a difference-in-difference approach to study the impact of changes in aggregate uncertainty on productivity growth in 25 industries based in 18 advanced economies. They find that productivity growth falls more in industries that depend heavily on external finance. Choi and Yoon (2019) model a century of US data and show that, when the response of the BAA-AAA financial spread to an EPU shock is shut down, the negative output effects triggered by such shocks are milder. A similar result is found by Bordo, Duca, and Koch (2016), who focus on the role of banking frictions and find them to be relevant for the transmission of EPU shocks. Alessandri and Mumtaz (2019) employ a regime-switching VAR framework to understand if a finance-uncertainty multiplier is present in the data. They find the real effects of uncertainty shocks to be six times larger when a financial crisis is in place with respect to when financial markets function normally. Lhuissier and Tripier (2019) show that the differences in dynamics across stressed vs. normal financial regimes may be due to agents' expectations around regimes switches, with pessimistic expectations about future financial acting as amplifier of the contractionary effects of uncertainty shocks. Popp and Zhang (2016) use a smooth-transition factor-augmented vector autoregression and a large monthly panel of US macroeconomic and financial indicators to model possibly nonlinear effects of uncertainty shocks. They find such a shock to exert adverse effects on the real economy and financial markets, in particular in recessions, due to financial frictions. Mapping these findings back to theoretical models singling out why financial frictions affect the real effects of uncertainty shocks is a promising avenue for future research. Also, understanding the relative importance of uncertainty shocks vs. other shocks in presence of financial frictions (e.g., news shocks as in Görtz, Tsoukalas, and Zanetti (2016)) appears to be relevant from a modeling as well as policy standpoint.

4) The effects of uncertainty shocks are state-dependent. Caggiano, Castelnuovo, and Groshenny (2014), Nodari (2014), Caggiano, Castelnuovo, and Figueres (2017), and Chatterjee (2018) find that the effects of uncertainty shocks are stronger when an economy is already in a low-growth state. Cacciatore and Ravenna (2018) employ a theoretical model featuring matching frictions in the labor market and an occasionally binding constraint on downward wage adjustment. They show that the effects of uncertainty shocks are in line with those documented by the empirical papers cited above. Pellegrino, Caggiano, and Castelnuovo (2019) work with a nonlinear Interacted VAR à la Pellegrino (2018, 2019), and find the effects of uncertainty shocks to be larger during the Great Recession than in normal times. They interpret this fact via an estimated nonlinear DSGE model in which risk aversion is allowed to be state-dependent and, crucially, higher during the 2007-09 recession (for a related paper, see Bretscher, Hsu, and Tamoni (2018)). Further explorations on the drivers of the different macroeconomic effects of uncertainty shocks in booms and busts are proposed in Andreasen, Caggiano, Castelnuovo, and Pellegrino (2019).

In a "new normal" characterized by historically low interest rates, what is the role played by the zero lower bound for the real effects of uncertainty shocks? Johannsen (2014), Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Nakata (2017), Basu and Bundick (2017), and Seneca (2018) propose new-Keynesian frameworks in which the zero lower bound acts as a magnifier of the real effects of uncertainty shocks due to the inability by the central bank to set the real interest rate as low as desired. Caggiano, Castelnuovo, and Pellegrino (2017) employ a nonlinear VAR to study normal times vs. the zero lower bound phase in the US. They confirm that uncertainty shocks have larger effects on output, consumption, and above all investment when the federal funds rate is constrained below. This evidence is in line with the one proposed by recent research studying the effects of first-moment macroeconomic shocks in presence of the zero lower bound (Liu, Theodoridis, Mumtaz, and Zanetti (2018)). (For contrasting evidence, Debortoli, Galí, and Gambetti (2019) and Swanson (2019).) Going back to uncertainty shocks, Castelnuovo and Tran (2017) compare the real activity effects of uncertainty shocks constructed by appealing to information related to google searches. They find that such shocks are much more damaging in the US than in Australia. Castelnuovo and Tran (2017) propose the absence of recessions and zero lower bound-type of events in Australia as possible interpretations for the different real effects of uncertainty shocks in these two countries. A natural question is how to conduct monetary policy when it comes to tackling the effects of uncertainty shocks in presence of the zero lower bound. This question is tackled by Basu and Bundick (2015), who stress the importance of tracking the fluctuations in the real natural interest rate with the policy rate in response to an uncertainty shock.

5) The response of inflation to uncertainty shocks is uncertain. Leduc and Liu (2016) conduct a VAR analysis and find that jumps in uncertainty exert demand shock-type of effects, i.e., they increase unemployment and decrease inflation. They interpret this result with a new Keynesian model featuring sticky prices and frictions on the labor market. However, Fasani and Rossi (2018) show that Leduc and Liu's model predictions on inflation can be overturned by modeling interest rate inertia. In particular, degrees of interest rate smoothing in line with the Taylor rule-related empirical evidence (see Clarida, Galí, and Gertler (2000), Castelnuovo (2003, 2007), Coibion and Gorodnichenko (2011, 2012), and Ascari, Castelnuovo, and Rossi (2011), among others) lead to an increase in both unemployment and inflation, a response typically associated to a supply shock.

Theoretically, in models featuring price rigidities the sign of the response of inflation to an uncertainty shock is a-priori unclear due to the joint presence of two channels. On the one hand, the standard demand channel would imply a deflationary response to an uncertainty shock given its negative effects on real activity in most models of the business cycle (for an example of this mechanism driven by precautionary savings, see Basu and Bundick (2017)). On the other hand, firms subject to price stickiness have the incentive to set prices above the level they would target in absence of uncertainty to avoid losing profits in case favorable economic conditions realize in the future (Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015), Mumtaz and Theodoridis (2015b), Basu and Bundick (2017)). An analysis on the relative role of price vs. wage stickiness is proposed by Born and Pfeifer (2019).

Given that these models' predictions on the response of inflation to an uncertainty shock can change depending on their calibrations, guidance from empirical analysis is needed. As noted earlier, Leduc and Liu (2016) find uncertainty shocks to be deflationary. However, working with a nonlinear VAR framework, Alessandri and Mumtaz (2019) find them to be inflationary in normal times, although deflationary during financial crisis. Meinen and Röhe (2018) estimate SVAR models with sign restrictions and focus on the response of inflation to financial and uncertainty shocks in the US and Euro area. They find such response to be ambiguous. More work is needed to understand the response of inflation to uncertainty shocks.

6) Macroeconomic policies are weaker in presence of uncertainty. Pellegrino (2018, 2019) works with nonlinear Interacted VAR models to show that monetary policy shocks affect the US and Euro area business cycle more weakly in periods of high uncertainty. In his empirical framework, which treats uncertainty as an endogenous variable, the response of uncertainty to a monetary policy shock is found to be significant. A similar finding is proposed by Aastveit, Natvik, and Sola (2017), and with similar frameworks by Eickmeier, Metiu, and Prieto (2016), and Castelnuovo and Pellegrino (2018). This last paper interprets the lower effectiveness of monetary policy shocks in presence of high uncertainty by estimating a (linearized) medium-scale DSGE model in a state-dependent fashion. The authors finds that, in presence of uncertainty, the slope of the Phillips curve is steeper. Hence, all else being equal, a shift in aggregate demand triggered by a monetary policy shock has a lower impact on output (for a related paper, see Vavra (2014b)). Caggiano, Castelnuovo, and Nodari (2019) focus instead on systematic monetary policy. They find it to be less effective in stabilizing the business cycle when an uncertainty shock materializes during recessions, which - as pointed out above - are typically characterized by high levels of uncertainty. A possible interpretation of this result is the difficulty of influencing agents' decisions by policymakers (the central bank in this case) when uncertainty is high and, therefore, the real option value of waiting until the "smoke clears" is high too (Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018)).

The literature has also investigated the connection between uncertainty and fiscal policy. Ricco, Callegari, and Cimadomo (2016) find that the effectiveness of unsystematic fiscal policy interventions is lower when fiscal policy uncertainty is high. This is an interesting finding, because recent research finds that fiscal spending shocks are actually associated to larger fiscal multipliers in recessions (Auerbach and Gorodnichenko (2012), Auerbach and Gorodnichenko (2013), Caggiano, Castelnuovo, Colombo, and Nodari (2015)), perhaps thanks to a confidence channel (Bachmann and Sims (2012), Figueres (2015)), although not all contributions in the extant literature confirm this result (Ramey and Zubairy (2018).) This begs the question: Is the state of the business cycle or that of uncertainty one should look at to correctly quantify the role of fiscal spending shocks? Alloza (2018) estimates the impact of government spending shocks on economic activity during periods of high and low uncertainty and during periods of boom and recession. He finds that government spending shocks have larger impacts on output in booms than in recessions and during tranquil times than uncertain times. He attributes the differences between his findings and those in the literature to details about the definitions of recessions and the way in which the transition from a state of the business cycle to another is modeled. Turning to open economies, Ismailov and Rossi (2018) use Consensus survey forecasts to construct an index of exchange rate uncertainty for five economic areas, i.e., Canada, Switzerland, England, Japan, and the

Euro area. Then, they estimate uncovered interest parity (UIRP) equations admitting for state-dependent parameters, i.e., parameters that may change when the economy switches from a high uncertainty regime to a low uncertainty state. They find that, while UIRP does not hold when uncertainty is high, it is actually supported by the data when uncertainty is low. Given the contribution of monetary policy shocks and systematic monetary policy to the exchange rate dynamics, we see this evidence as linking monetary policy to the UIRP, also in light of the effects that monetary policy shocks may have on uncertainty (Pellegrino (2019)). The impact of uncertainty on the effectiveness of macroeconomic policies seems to represent an important research avenue.

7) Macroeconomic policies generate uncertainty. Monetary policy can generate uncertainty because of issues related to communication and credibility. The same issues affect fiscal policy, which is also characterized by delays related to decisions (often difficult in countries where the leading parties do not enjoy a large majority in Parliament) and implementation (fiscal policy is typically associated to multi-year plans). Hence, it is perhaps not surprising that both policies are associated to uncertainty. Mumtaz and Zanetti (2013) study the impact of monetary policy uncertainty using a VAR framework featuring time-varying variance of monetary policy shocks via a stochastic volatility specification and a volatility-in-mean effect which allows volatility shocks to affect the endogenous variables of the VAR. They find a negative response of the nominal interest rate, output growth, and inflation to a jump in monetary policy volatility. They then propose a DSGE model with stochastic volatility to monetary policy that generates similar responses. Istrefi and Mouabbi (2018) quantify monetary policy uncertainty by accounting for both disagreement among forecasters over predictions related to future interest rates and the perceived variability of future aggregate shocks. They use this proxy, which they construct for the US, Japan, the UK, Canada, Sweden, Germany, France, Italy, and Spain, to quantify the effects of uncertainty shocks on these countries' business cycle. They find such effects to be large, negative and persistent, with a distinct cross-country heterogeneity when it comes to peak effects. Bundick, Herriford, and Smith (2017) identify monetary policy uncertainty shocks using unexpected changes in the term structure of implied volatility around monetary policy announcements, which they construct following the methodology used to construct the VIX. They find that an unexpected decline in the slope of implied volatility lowers term premia in longer-term bond yields and leads to higher economic activity and inflation. Their results suggest that forward guidance about future monetary policy can materially affect bond market term premia. Mumtaz and Theodoridis (2019) employ a VAR model that allows shocks to affect second moments, and show that contractionary monetary policy shocks are associated with higher macroeconomic volatility. They interpret this fact with a nonlinear DSGE framework featuring Epstein-Zin preferences and labor market frictions, and show that such frictions, joint with policy rate gradualism, are important for describing their stylized facts. Following the keywords approach proposed by Baker, Bloom, and Davis (2016), Husted, Rogers, and Sun (2018) construct a news-based index of monetary policy uncertainty to capture the degree of uncertainty that the public perceives about central bank policy actions and their consequences. Working with a variety of different VARs, they find that positive shocks to monetary policy uncertainty raise credit spreads and reduce output, with effects that are comparable in magnitude to those of conventional monetary policy shocks.

As anticipated above, fiscal policy uncertainty is also present in a number of countries. Baker, Bloom, and Davis (2016) rank fiscal policy as the first driver of the elevated level of economic policy uncertainty during and after the Great Recession. Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2015) estimate stochastic volatility processes for US capital taxes, labor taxes, and government expenditures. When coupling these estimated processes with a nonlinear DSGE framework, they find that a jump in fiscal policy uncertainty is clearly detrimental for the US business cycle. Ricco, Callegari, and Cimadomo (2016) propose a novel index which measures the coordination effects of policy communication on private agents' expectations. Such index is based on the disagreement amongst US professional forecasters about future government spending. When modeling this index with selected macroeconomic aggregates in a nonlinear VAR framework, they find that, in times of low disagreement, the output response to fiscal spending innovations is positive and large, mainly due to private investment response. Conversely, periods of elevated disagreement are characterized by muted output response. Mumtaz and Surico (2018) estimate a volatility-in-mean VAR framework to study the effects of fiscal spending, tax, and public debt volatility on the US economy. They find debt uncertainty to have the largest impact on real activity. Finally, a contribution on the role of political uncertainty in the US in the aftermath of the global financial crisis is Born and Pfeifer (2014a).

"Natural experiments" as the Brexit referendum are also informative on the cost of uncertainty. The Brexit event is unusual because it is a rare example of very persistent uncertainty shock - three years after the "leave" decision, the UK had not left the European Union yet, and uncertainty on the implementation of the exit strategy was still substantial. Bloom, Bunn, Chen, Mizen, Smietanka, and Thwaites (2019) exploit data from the Decision Maker Panel (DMP), which is a large survey of UK firms currently featuring about 3,000 respondents per month, to gauge the costs of Brexit for the UK economy. Using a difference-in-difference approach, they find the high and persistent uncertainty related to Brexit to have negatively impacted investment (about 11% over the three years following the June2016 vote) and productivity (2% to 5% over the same time span). They associate the drop in productivity to the time managers need to spend to sort out the consequences of Brexit and re-plan. Also, more productive, internationally-exposed, firms are found to be more negatively impacted than less productive ones. Born, Müller, Schularick, and Sedlacek (2019) employ synthetic control methods and find the output loss for the UK due to Brexit to be about 2.4 percent by year-end 2018. Using an expectations-augmented VAR, they find that this loss is to a large extent associated to a drop in growth expectations in response to the vote. While these studies point to large costs associated to the uncertainty generated by the "leave" decision by the UK, other investigations point to a more moderate contribution. Steinberg (2019) works with a DSGE model with heterogeneous firms, endogenous export participation, and stochastic trade costs to quantify the impact of uncertainty about post-Brexit trade policies. He calibrates the model on 2011 data (when Brexit was not predictable), then assumes that either a "soft Brexit" or a "hard Brexit" could realize in the future, the latter scenario being characterized by higher trading costs after leaving the EU. According to his simulations, the total consumption-equivalent welfare cost of Brexit for UK households is between 0.4 and 1.2 percent. However, less than a quarter of a percent of this cost is due to uncertainty.

Other events that might generate uncertainty are elections. Following Jurado et al.'s (2015) econometric strategy, Redl (2019) employs a data-rich approach to construct proxies for financial and macroeconomic uncertainty for eleven developed countries. He combines this information with the one regarding close elections, which he interprets as macro uncertainty-generators, and periods of financial stress, which he associates to exogenous changes in financial uncertainty. He finds evidence in favor of the contractionary effects of macroeconomic uncertainty shocks, which emerge as more powerful drivers of the business cycle than financial uncertainty disturbances.

These empirical findings point to the need of understanding how to conduct macroeconomic policies in presence of uncertainty. Bloom (2009) points to a trade-off between policy "correctness" and "decisiveness", and conjectures that it may better to act decisively (even if occasionally incorrectly) than to deliberate on policy, which could generate uncertainty. Theoretical and empirical investigations of this conjecture are warranted.

8) Monetary policymakers act as risk managers. Evans, Fisher, Gourio, and Krane (2015) estimate a battery of Taylor rules and show that the Greenspan period can be described by a systematic response of the policy rate to measures of uncertainty even after controlling for inflation and output (which are the typical arguments on the right-hand side of a monetary policy rule). Caggiano, Castelnuovo, and Nodari (2018) elaborate on Evans et al. (2015) and show that the evidence in favor of a risk management approach by the Federal Reserve and conditional on financial volatility is confined to the Greenspan-Bernanke policy regimes. Moreover, they propose a novel object, i.e., the risk management-driven policy rate gap, which measures the impact of the risk management approach by the Fed on the federal funds rate. They find the risk management-driven policy rate gap to be as large as 75 basis points (equivalent to three standard policy moves by the Federal Reserve) in correspondence with financial volatility-triggering events such as the Black Monday and the 2008 credit crunch. Castelnuovo (2019) estimates the response of the US yield curve to a change in US financial uncertainty as proxied by the financial uncertainty measure constructed by Ludvigson et al. (2019). He finds both short and long term rates to temporarily decrease, with the yield curve steepening in the short run before going back to its pre-shock slope. Ponomareva, Sheen, and Wang (2019) construct a novel measure of uncertainty using data on monetary policy recommendations given by members of the shadow board of Reserve Bank of Australia. They find that the Reserve Bank of Australia tends to lower the cash rate when predictions about the future policy decisions by the RBA are very different among experts, a result that is robust to using other measures of uncertainty. This evidence is consistent with the risk management approach mentioned above. However, it has to be kept in mind that other contributions on Taylor rules point to a systematic response by monetary policymakers to indicators such as, for instance, money growth (Ireland (2001), Castelnuovo (2007), Canova and Menz (2011), Castelnuovo (2012)), credit spreads (Castelnuovo (2003), Caldara and Herbst (2018)), stock prices (Castelnuovo and Nisticò (2010), Furlanetto (2011)), or to richer policy rate dynamics (Clarida, Galí, and Gertler (2000), Ascari, Castelnuovo, and Rossi (2011), Coibion and Gorodnichenko (2011, 2012). Then, is the evidence in favor of a systematic response to measures of uncertainty actually speaking in favor of other omitted variables in the Taylor rule? Horse races contrasting different estimated simple rules could provide us with relevant information to answer this question.

9) The real effects of uncertainty shocks are stronger in developing countries. Developing countries experience more volatile business cycles than developed ones. Koren and Tenreyro (2007) point out three reasons to interpret this fact. First, developing countries tend to have less diversified economies. For instance, they produce and export less products, so their economies are more exposed to demand fluctuations for those goods. In other words, they have a less diversified portfolio of products, and such portfolio bears a higher risk. Second, part of the goods they trade are commodities, whose prices are pretty volatile. Third, developing countries are more subject to shocks such as coups, revolutions, wars, natural disasters, and have less effective stabilizing macroeconomic policies. Koren and Tenreyro (2007) perform a volatility-accounting analysis and find that the choice of specializing in more volatile sectors account for roughly fifty percent of the difference in volatility between developing and developed countries, while more frequent and severe aggregate shocks explains the remaining fifty percent.

What do we know about the effects of uncertainty shocks in developing countries? Chatterjee (2018) finds that they trigger sharper declines in consumption, investment, GDP and a stronger countercyclical response in trade-balances in emerging countries compared to advanced economies. In a related paper, Chatterjee (2019) interprets this fact with a higher degree of financial frictions estimated for the set of emerging economies she consider. Bhattarai, Chatterjee, and Park (2019) study the spillover effects of US uncertainty shocks in a panel VAR of fifteen emerging market economies (EMEs). A US uncertainty shock negatively affects EME's output, consumer prices, stock prices, exchange rates, and capital inflows while raising spreads and net exports. The negative effects on output and asset prices are weaker, but the effects on external balance stronger, for Latin American EMEs. Bhattarai, Chatterjee, and Park (2019) attribute such heterogeneity to different monetary policy responses by Latin American countries to US uncertainty shocks. An analysis of central bank minutes confirms that Latin American EMEs pay less attention to smoothing capital flows. Exploiting a large database covering 143 countries, Ahir, Bloom, and Furceri (2018) find that innovations in a novel measure of uncertainty at a world level (explained in the next Section) foreshadow significant declines in output in all countries, but in particular in emerging countries characterized by lower institutional quality. Further investigations on the role of uncertainty in developing countries seem to represent a promising way to go for a more complete understanding of the role of uncertainty shocks.

The use of data from emerging countries should help econometricians overcome the endogeneity issue naturally affecting empirical studies involving uncertainty and business cycle measures. This because emerging countries are typically hit by external shocks coming from the rest of the world, which are likely to be exogenous to emerging countries' business cycles (Bloom (2017)). Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011) document the time-varying volatility in the world real interest rates faced by Argentina, Ecuador, Venezuela, and Brazil. After estimating a process for the real interest rate featuring stochastic volatility, they feed it into a nonlinear open economy framework and show that, for these countries, an increase in real interest rate volatility triggers a fall in output, consumption, investment, and hours worked, and a notable change in the current account of the economy. Born and Pfeifer (2014b) reach the same qualitative (although different quantitative) conclusions.

10) Uncertainty is harmful for trade. Baley, Veldkamp, and Waugh (2019) work with a trade model with information frictions. In equilibrium, hikes in uncertainty increase both the mean and the variance in returns to exporting. This implies that trade can increase or decrease with uncertainty depending on preferences. Higher uncertainty may lead to increases in trade because agents receive improved terms of trade, particularly in states of nature where consumption is most valuable. Trade creates value, in part, by offering a mechanism to share risk and risk sharing is most effective when both parties are uninformed. Different conclusions are reached by Handley and Limão (2017), who examine the impact of policy uncertainty on trade, prices, and real income through firm entry investments in general equilibrium. They estimate and quantify the impact of trade policy on China's export boom to the United States following its 2001 WTO accession. They find the accession reduced the US threat of a trade war, which can account for over one-third of that export growth in the period 2000-2005. Reduced policy uncertainty lowered US prices and increased its consumers' income by the equivalent of a 13-percentage-point permanent tariff decrease. Maggi and Limão (2015) study the conditions under which trade agreements are desirable because they work in favor of reducing trade-policy uncertainty. They find that this is likely to happen when economies are more open, export supply elasticities are lower and economies more specialized. Governments have stronger incentives to sign trade agreements when the trading environment is more uncertain. Ahir, Bloom, and Furceri (2019) constructs a World Trade Uncertainty (WTU) index on the basis of the frequency of keywords related to trade, tariffs, trade agreements and organizations present in the Economist Intelligence Unit (EIU) country reports. Their quarterly index covers 143 countries from 1996 onwards. They note that, after having remained relatively stable for about 20 years, the index has dramatically increased since 2016. According to their estimates, the increase in trade uncertainty observed in the first quarter could be enough to reduce global growth by up to 0.75 percentage points in 2019. While the question on the relationship between uncertainty and trade is still an open one, our understanding is that the empirical evidence cumulated so far tends to speak in favor of a negative relationship. Caldara, Iacoviello, Molligo, Prestipino, and Raffo (2019) construct various measures of trade policy uncertainty (TPU) by exploiting information coming from newspapers, firms' earnings conference calls, and data on tariff rates. Then, they work with local projections and VAR analysis to quantify the effects of TPU shocks on investment and real activity using firm-level as well as macroeconomic data. They find a one-standard deviation increase in TPU uncertainty to imply a reduction in investment of about -2% over one year. They interpret this fact via a two-country general equilibrium model featuring nominal rigidities and firms' export participation decisions. The model predicts, very much like the data, that news and increased uncertainty about higher future tariffs are contractionary. All in all, the literature seems to be converging toward an agreement on the negative role that uncertainty has on trade and the business cycle.

3 Uncertainty spillovers and global uncertainty: What does the literature say?

Most of the empirical analysis on the macroeconomic effects of uncertainty shocks have entertained the assumption of "autarkic" economies, i.e., economies where domestic shocks are the unique drivers of the business cycle. However, a fast growing literature has recently focused on the effects of external shocks. Two strands can be identified. The first one deals with uncertainty spillovers, i.e., the effects on a country i of an hike in uncertainty originating in a country j, with $i \neq j$. The second one focuses on global uncertainty, a concept that regards uncertainty-inducing events occurring all around the globe. We analyze these two interconnected strands of the literature in turn.

Uncertainty spillovers. Colombo (2013) estimates a VAR framework modelling US and Euro area indicators and finds that a jump in economic policy uncertainty in the former area exerts a significant effect on inflation and output in the latter. A similar exercise, which also proposes a novel measure of uncertainty for China, is conducted by Huang, Tong, Qiu, and Shen (2018). They find the spillover effect to be unidirectional and go from the US to China. Klößner and Sekkel (2014) study economic policy uncertainty spillovers for Canada, France, Germany, Italy, United Kingdom and United States. They find sizeable spillovers across countries, with the US and the UK playing the role of big exporters of uncertainty during the Great Recession. Caggiano, Castelnuovo, and Figueres (2019) estimate a non-linear smooth-transition VAR model designed to quantify the effects of US EPU shocks on the Canadian economy when the latter is in an economic boom vs. bust. They find that such shocks exert a substantial effect on the Canadian unemployment rate, with a stronger effect when the Canadian economy's growth rate is below its historical average. Interestingly, evidence of negative spillovers is present also when analyzing the US-UK economies, with EPU shocks in the former affecting unemployment in the latter. Benigno, Benigno, and Nisticò (2012) estimate the macroeconomic effects of a jump in the US monetary policy uncertainty for the G7 countries. Their VAR analysis finds an increase in monetary policy uncertainty to be followed by an appreciation of the US dollar in the medium run. Differently, an increase in the volatility of productivity leads to a dollar depreciation. They propose a general-equilibrium theory of exchange rate determination based on the interaction between monetary policy and time-varying uncertainty which is able to replicate their stylized facts. Angelini, Costantini, and Easaw (2018) investigate macroeconomic uncertainty shocks spillovers in four Eurozone countries. They work with a VAR model featuring a core economy (Germany) and an Euro area periphery (France, Italy, Spain). Uncertainty shocks are allowed to spread from one country to another, with potential feedback from the periphery economies to the core one. They find evidence in favor of uncertainty spillovers among the Eurozone countries, with some feedback from periphery economies to the core economies during the financial crisis period. Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011) document the time-varying volatility in the world real interest rate faced by four emerging economies, i.e., Argentina, Brazil, Ecuador, and Venezuela. Then, they feed this process in a small-scale open economy model approximated at the third order around the steady state to account for the role of uncertainty and, consequently, precautionary savings. They show that, in equilibrium, a jump in the real interest rate volatility triggers a fall in consumption, investment, hours, and debt. Born and Pfeifer (2014b) confirm that a jump in interest rate volatility implies a negative response of the business cycle in the four Latin American countries indicated above (although their estimates point to a milder response of real activity than the one documented in Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011)). Mumtaz and Theodoridis (2015b) use a volatility-in-mean VAR and find that a one standard deviation increase in the volatility of the shock to US real GDP leads to a decline in UK GDP of 1% relative to trend and a 0.7% increase in UK CPI relative to trend at the two-year horizon. They show that these facts are consistent with the predictions coming from a nonlinear open-economy DSGE model in which foreign "supply" shocks are simulated.

Carrière-Swallow and Céspedes (2013) quantify the effects of uncertainty spillovers by studying large jumps in the US financial volatility. Working with data related to 40 countries (20 developed, 20 emerging), they find heterogenous effects of uncertainty shocks. Developed economies suffer less in relative terms with respect to EMEs, which experience substantially more severe falls in investment and private consumption following an exogenous uncertainty shock, take significantly longer to recover, and do not experience a subsequent overshoot in activity. Carrière-Swallow and Céspedes (2013) show that the credit channel can account for up to one-half of the increased fall in investment generated by uncertainty shocks among EMEs with less-developed financial markets. As already pointed out above, Bhattarai, Chatterjee, and Park (2019) study the spillover effects of US uncertainty shocks in a panel VAR of fifteen emerging market economies (EMEs), and find economically significant effects on a variety of indicators. Miescu (2018) works with a panel proxy SVAR featuring a hierarchical structure to model the effects of uncertainty shocks on fifteen EMEs. After building up a measure of global uncertainty by using a large international dataset and the methodology proposed by Jurado, Ludvigson, and Ng (2015), she employs innovations to global uncertainty as instruments to circumvent the business cycle-uncertainty endogeneity. She finds that uncertainty shocks cause severe falls in GDP and stock price indexes, depreciate the currency, and increase consumer prices. Differently, the response of monetary policy is ambiguous.

Global uncertainty. A related strand of the literature has recently investigated the macroeconomic consequences of shocks to global uncertainty. Building on Baker, Bloom, and Davis (2016), Davis (2016) constructs a monthly index of Global Economic Policy Uncertainty (GEPU) based on 16 countries (covering two-thirds of global output) from January 1997 to August 2016. GEPU rises sharply in correspondence to clearly identified events (e.g., the Asian Financial Crisis, the 9/11 terrorist attacks, the U.S.-led invasion of Iraq in 2003, and the Global Financial Crisis in 2008-09), and it fluctuates around consistently high levels during the 2011-2013 sovereign debt and banking crises in the Eurozone, intense partisan battles over fiscal and healthcare policies in the United States, and a generational leadership transition in China. Davis (2019) updates Davis (2016) and notices an increase of global uncertainty in recent years. He relates such increase to trade uncertainty, driven in particular by the US-China tensions. Appealing to a similar word-reading technique, Ahir, Bloom, and Furceri (2018) construct a World Uncertainty Index (WUI) for 143 individual countries from 1996 onwards. This is defined using the frequency of the word "uncertainty" in the Economist Intelligence Unit country reports. Globally, WUI spikes near the 9/11 attack, SARS outbreak, Gulf War II, Euro debt crisis, El Niño, European border crisis, UK Brexit vote and the 2016 US election. Uncertainty spikes tend to be more synchronized within advanced economies and between economies with tighter trade and financial linkages. The level of uncertainty is significantly higher in developing countries and is positively associated with economic policy uncertainty and stock market volatility, and negatively with GDP growth. Running a panel vector autoregressive analysis, Ahir, Bloom, and Furceri (2018) find a jump in WUI equal to change in the average value of the index from 2014 to 2016 to be associated to a drop in output of about 1.4 percent after 10 quarters. Caldara and Iacoviello (2017) construct a monthly indicator of geopolitical risk based on a tally of newspaper articles covering geopolitical tensions, and examine its evolution and effects since 1985. The geopolitical risk (GPR) index spikes around the Gulf War, after 9/11, during the 2003 Iraq invasion, during the 2014 Russia-Ukraine crisis, and after the Paris terrorist attacks. A VAR analysis based on monthly, post-1985 US data point to a decline in real activity, lower stock returns, and movements in capital flows away from emerging economies and towards advanced economies following an unexpected increase in GPR. Moving from text-based investigations to model-based ones, Redl (2017) employs the methodology proposed by Jurado et al. (2015) to construct a global macroeconomic uncertainty index with a variety of macro and financial aggregates of industrialized countries around the world with the exception of the UK. Such global index correlates with both the UK macro uncertainty index constructed by the same author (0.52), and with the UK financial uncertainty one (0.74).[1] Berger, Grabert, and Kempa (2016) use real GDP quarterly data of 20 OECD countries spanning the period 1970Q1-2013Q4 to identify global and country-specific measures uncertainty for a large OECD country sample via a dynamic factor model with stochastic volatility. Their evidence points to major jumps in global uncertainty in the early 1970s and late 2000s, and a number of periods with elevated levels of either global or national uncertainty, particularly in the early 1980s, 1990s and 2000s. VAR impulse responses of national macroeconomic variables reveal that global uncertainty is a major driver of the business

[1] Our computations, based on the data available at Chris Redl's website: https://sites.google.com/site/redlchris/research .

cycle in most countries, whereas the impact of national uncertainty is small and frequently insignificant. Their evidence points to investment and trade flows (as opposed to consumption) as the main transmitters of global uncertainty shocks to the business cycle. In a related paper, Berger, Grabert, and Kempa (2017) identify global macroeconomic uncertainty using a dynamic factor model with stochastic volatility. Applying this methodology to quarterly output and inflation data for 20 OECD countries over the period 1970Q1-2012Q4, they find the early 1970s and early 1980s recessions as well as the Great Recession to be associated with increases in uncertainty at the global level. Global uncertainty is also found to negatively affect country-level business cycles and raise inflation rates.

Mumtaz and Theodoridis (2015a) employ a factor model with stochastic volatility to model quarterly macroeconomic and financial variables of 11 OECD countries over the period 1960Q1-2013Q3. They decompose the time-varying variance of macroeconomic and financial variables into contributions from country-specific uncertainty and uncertainty common to all countries. They find that global uncertainty plays an important role in driving the time-varying volatility of nominal and financial variables, and that the cross-country co-movement in volatility of real and financial variables has increased over time. They interpret their empirical facts with a two-country DSGE model featuring Epstein-Zin preferences. Such model points to increased globalization and trade openness as the possible forces behind the increased cross-country correlation in volatility. Carriero, Corsello, and Marcellino (2019) study the drivers of country-specific inflation rates using a framework that allows for commonality in both levels and volatilities, in addition to country-specific components. They find that a substantial fraction of country-level inflation volatility can be attributed to a global factor that is also driving inflation levels and their persistence. The evolution of the Chinese PPI and oil inflation is found to be relevant to understand that of global inflation, above all since the 1990s. Kang, Ratti, and Vespignani (2017) construct a global financial uncertainty index by conducting a principal component analysis based on monthly data on stock market volatility for 15 OECD countries. Then they run a VAR analysis that models their global uncertainty proxy jointly with measures of global output growth, global inflation, and global interest rates. Such global indicators are factors extracted from data of 40 OECD countries. They find a significant drop in global output and inflation after a jump in global uncertainty.

Bonciani and Ricci (2018) construct a proxy for global financial uncertainty by extracting a factor from about 1,000 risky asset returns from around the world. They study how shocks to the factor affect economic activity in 36 advanced and emerging small open economies over the 1990-2017 sample by estimating local projections in a panel regression framework. While finding cross-country heterogeneity, the effect of a jump in financial uncertainty is in general recessionary. Such effects are found to be stronger in countries with a higher degree of trade and/or financial openness, higher levels of external debt, less developed financial sectors, and higher risk rating. Mumtaz and Musso (2018) build a dynamic factor model with time-varying parameters and stochastic volatility and use it to decompose the variance of a large set of quarterly financial and macroeconomic variables for 22 OECD countries spanning the sample 1960-2016 into contributions from country and region-specific uncertainty vs. from uncertainty common to all countries. They find that global uncertainty plays a primary role in explaining the volatility of inflation, interest rates and stock prices, although to a varying extent over time. Region-specific uncertainty drives most of the exchange rate volatility for all Euro Area countries and for countries in North-America and Oceania, while uncertainty at all levels contribute to explaining the volatility of real activity, credit, and money for most countries. All uncertainty measures are found to be countercyclical and positive correlated with inflation. Carriero, Clark, and Marcellino (2018) use a large VAR to measure international macroeconomic uncertainty and its effects on major economies with a large VAR in which the error volatilities evolve over time according to a factor structure. The volatility of each variable in the system reflects time-varying common (global) components and idiosyncratic components. In this model, global uncertainty is allowed to contemporaneously affect the economies of the included nations—both the levels and volatilities of the included variables. The analysis focuses alternatively on quarterly GDP growth rates for 19 industrialized countries covering the 1985Q1-2016Q3 period and on a larger set of macroeconomic indicators for the U.S., Euro area, and United Kingdom spanning the 1985Q4-2013Q3 sample. Their estimates yield new measures of international macroeconomic uncertainty, and indicate that uncertainty shocks (surprise increases) lower GDP and many of its components, adversely affect labor market conditions, lower stock prices, and in some economies lead to an easing of monetary policy. Ozturk and Sheng (2018) develop monthly measures of macroeconomic uncertainty covering 45 countries and construct measures of common and country-specific uncertainty using individual survey data from the Consensus Forecasts over the period of 1989-2014. Using a VAR analysis, they show that global uncertainty shocks are followed by a large and persistent negative response in real economic activity, whereas idiosyncratic uncertainty shocks are not found to be relevant drivers of the business cycle. Cesa-Bianchi, Pesaran, and Rebucci (2018) employ a multi-country model to compute two common factors, a "real" and a "financial" one. These factors are identified by assuming different patterns of cross-country correlations of country-specific innovations to real GDP growth and realized stock market volatility. They find that most of the unconditional correlation between volatility and growth can be accounted for by the real common factor. However, shocks to the common financial factor also have a large and persistent impact on growth. In contrast, country-specific volatility shocks account for a moderate amount of the growth forecast error variance.

4 Global Financial Uncertainty: Evolution and effects

We now propose novel results on the global effects of uncertainty shocks. To do so, we construct a new measure of global financial uncertainty (GFU henceforth). This measure is constructed via a principal component analysis that considers three measures of volatility of financial returns constructed at a monthly level by considering stock market returns, exchange rate returns, and 10-year government bond yields for 39 countries from July 1992, to April 2018.[2] According to the International Monetary Fund, these 39 countries account for more than 80% of the 2019 GDP (based on purchased power parity) at a world level.[3]

Figure 1 plots the GFU series. It is immediate to appreciate the truly global nature of this uncertainty measure, which peaks in correspondence of events occurred all around the globe such as, for instance, the EMS collapse, the Asian crisis, the Russian one, 9/11, the second Gulf War, the Madrid attacks, the European financial turmoils, those related to the Chinese credit and financial sector, and - above all - the global financial crisis. This last event identifies the global maximum of the GFU series.

It is of interest to compare the GTU series with two other financial indicators recently proposed by the literature. The first one is the US financial uncertainty index

[2] Missing observations are dealt with by following the approach developed by Banbura and Modugno (2014). A version of GFU constructed via a dynamic hierarchical factor model to control for regional and country-specific uncertainty factors is proposed by Caggiano and Castelnuovo (2019).

[3] See https://www.imf.org/external/datamapper/PPPSH@WEO/OEMDC/ADVEC/WEOWORLD .The countries considered to build up the GFU index are: Canada, Mexico, United States (North America); Belgium, Czech Republic, Denmark, Finland, France, Germany, Great Britain, Greece, Hungary, Ireland, Italy, Holland, Norway, Poland, Russia, Spain, Sweden, Switzerland, Turkey (Europe); Australia and New Zealand (Oceania); Argentina, Brazil, Chile, Colombia, Peru (Latin America); China, India, Indonesia, Japan, Korea, Pakistan, Philippines, Singapore, Taiwan, Thailand (Asia).

constructed by Ludvigson, Ma, and Ng (2019). Such index is the time-varying volatility of the one-step ahead forecast errors related to 148 monthly financial series and computed over the period 1960-2018.[4] They find a jump in the US-related measure of financial uncertainty to be a driver of the US economic cycle. The second financial indicator - related to credit - is the one constructed by Miranda-Agrippino and Rey (2019), who work with a dynamic factor model to model 858 series on risky asset prices traded on all the major global markets, corporate bond indices, and commodities price series over the sample 1990 to 2012.[5] They find that one global factor explains about 20% of the variance in the data.

Figure 2 (upper panel) proposes a comparison between the GFU index, the US financial uncertainty index by Ludvigson, Ma, and Ng (2019), and the global credit cycle produced by Miranda-Agrippino and Rey (2019) (we flipped the sign of this last measure to enhance comparability). The comparison tells us a few things. The GFU index correlates positively with the US financial uncertainty index (the correlation coefficient is 0.78). Given the dominant role played by the US economy in the world financial markets, this is not a surprise. However, the US financial uncertainty features a lower number of spikes and, indeed, appears to interpolate the GFU index. Possibly, this speaks in favor of the information content of the GFU index when it comes to isolating spikes in global financial uncertainty and their effects on the world business cycle (an exercise we will present later). Turning to Miranda-Agrippino and Rey's (2019) (flipped) global credit cycle, the correlation with GFU is 0.56. (The correlation with the original series of the global credit cycle would obviously be -0.56). This correlation is economically meaningful, because it points to higher (lower) global financial stress in presence of higher (lower) financial uncertainty (an observation also made in Miranda-Agrippino and Rey (2019), who correlated their global credit cycle with the VIX).

How does GFU relate to other measures of global uncertainty proposed by the literature? Figure 2 (lower panel) plots the GFU index against five different measures of global uncertainty: Davis' (2016, 2019) measure of global economic policy uncertainty (constructed with a text search-approach), Ahir, Bloom, and Furceri's (2019) World Uncertainty Index (GDP weighted average), and Mumtaz and Theodoridis' (2017), Carriero, Clark, and Marcellino's (2019), and Redl's (2017) estimates of global macroeconomic uncertainty.[6] All series positively comove, with the correlation coefficient

[4] This series is available at https://www.sydneyludvigson.com/data-and-appendixes .

[5] This series is available at http://silviamirandaagrippino.com/code-data .

[6] The GEPU series is available at http://www.policyuncertainty.com/global_monthly.html . The WUI series can be found here: http://www.policyuncertainty.com/wui_quarterly.html . Redl's global

between GFU and GEPU being 0.57, that between GFU and WUI 0.07, that between GFU and the macroeconomic uncertainty series 0.71 (with Carriero et al.'s 2019), 0.76 (with Mumtaz and Theodoridis' 2017), and 0.83 (with Redl's 2017). All series, with the exception of the World Uncertainty Index, peak in correspondence of the global financial crisis. GFU features the largest number of distinct peaks, which is not surprising given that this series is constructed on financial data's volatility. GEPU and WUI feature higher levels at the end of the sample (possibly related to events such as Brexit and the US-China trade tensions), while the other proxies do not.

To what extent fluctuations in global financial uncertainty, proxied by the GFU series, can be relevant to understand the world business cycle? We address this question by running a VAR analysis jointly modeling GFU, the global credit cycle by Miranda-Agrippino and Rey (2019), and the world's real GDP quarterly growth rate, which we proxy with the one of the OECD total area.[7] We compute the impulse responses of the global credit cycle, the world's real GDP quarterly growth rate, and GFU by proceeding as follows. First, we estimate a reduced-form VAR modeling these three series over the period 1992Q3-2012Q4 (the beginning of the sample being that of the GFU measure, and the end being due to the availability of the global credit cycle). The VAR features two lags as suggested by standard information criteria. Given that the output growth measure is available at a quarterly frequency, we construct quarterly series of GFU and the global credit cycle by taking within-quarter averages of the monthly values. Second, we move from the reduced-form representation of the data to a structural one by assuming that the contemporaneous relationships among the three variables we model are captured by a lower triangular matrix whose coefficients we obtain by computing the Cholesky decomposition of the covariance matrix of the reduced-form residuals.

As it is well known, this identification strategy implies that the ordering of the variables in the VAR matters. We order the global credit cycle indicator first, GFU second, and output third. The ordering is justified by the following reasons. First, as pointed out by Stock and Watson (2012), it is extremely challenging to separate first and second-moment financial shocks. Hence, given the relevance of first moment shocks for the global business cycle (a prominent example being the Great Recession), we put

uncertainty measure is available at https://sites.google.com/site/redlchris/research . We thank Andrea Carriero and Haroon Mumtaz for sharing the estimated global uncertainty measures documented in (respectively) Carriero, Clark, and Marcellino (2019) and Mumtaz and Theodoridis (2017).

[7] The series can be downloaded from the Federal Reserve Bank of St. Louis' database available at https://fred.stlouisfed.org/ . The code of the series is NAEXKP01O1Q657S.

the global credit cycle first to be conservative and avoid assigning to financial uncertainty shocks the role possibly played by first moment financial shocks in explaining the contemporaneous responses of financial and real variables to an exogenous jump in uncertainty. Consequently, our findings should be interpreted as a lower bound as far as the real effects of an uncertainty shock are concerned. We order GFU before output because Granger causality tests conducted with a bivariate VAR speak loud: GFU is found to Granger cause output (the p-value is basically zero), while output is found to not Granger cause GFU (p-value: 0.84).

Figure 3 plots the impulse responses of the three variables to a GTU shock (size - one standard deviation). All variables respond significantly and persistently. In the short run, financial stress increases (i.e., the financial markets go bust), uncertainty increases, and output growth registers negative values. Our VAR assigns about 18% of the forecast error variance decomposition of output growth (computed by considering a forecast horizon $h \to \infty$) to a GTU shock against 36% to a global credit cycle shock.[8] When swapping the global credit cycle and GFU in the vector, these figures swap too, i.e., the VAR assigns 37% of the output growth forecast error variance decomposition to a GTU shock and 17% to a global credit cycle shock. This confirms that our estimates are a lower bound, and that separately identify financial (in this case, credit) and uncertainty shocks is challenging. We also note that a shock to GTU negatively affects the global credit cycle, at least in the short run.

The response of global output to a GFU shock produced by our VAR is economically sizeable. To better appreciate this point, we propose the following back-of-the-envelope computation. The standard deviation of the GFU shock in Figure 3 is about 0.70. When checking the series of the estimated GFU shocks, one evident spike is the 2008Q3 one (value: 1.6). Then, we can calibrate the size of the shock hitting the global economy in 2008Q3 to be $1.6/0.70 \approx 2.3$ standard deviations. The peak response of output in Figure 3 is about -0.15 percent. Hence, our linear VAR would suggest a $2.3(-0.15) \approx -0.35$ percent peak response of global output growth to such a shock. The peak response of the actual global output growth series during the Great Recession, which occurs in 2009Q1,

[8]Miranda-Agrippino and Rey (2019) document a significant impact of monetary policy shocks originating in the US on the global financial cycle. We then run a robustness check by adding the shadow rate à la Wu and Xia (2016) (quarterly observations constructed by taking within-quarter averages) to the vector (ordered last). We notice three things. First, a GFU shock significantly affects all variables (shadow rate included). Second, the contribution of GFU shocks to the forecast error variance of global real output is slighly reduced (14%), but still clearly present. Third, the contribution of GFU shocks to the forecast error variance of the shadow rate is 19%, while that of monetary policy shocks to the forecast error variance of GFU is 5%.

is -2.27 percent. Hence, our computation points to a contribution by GFU shocks to the drop in global output occurred during the Great Recession of about 1/6-1/7.

A final note regards the global flavor of the GFU measure used in this paper. As documented above, the correlation between the US financial uncertainty measure constructed by Ludvigson, Ma, and Ng (2019) and GFU is high. However, the two series carry a different type of information. When replacing GFU with the US-specific measure of financial uncertainty in our VAR, we do not get the same dynamic response of global output to a US financial uncertainty shock. Figure 4 depicts such response, which is quantitatively much more modest than the one documented in Figure 3 and not significant from a statistical standpoint. We interpret this result in favor of GFU as a truly global indicator, as opposed to the US financial uncertainty index proposed by Ludvigson, Ma, and Ng (2019) which, by construction, focuses on the US financial market. It is important to note, however, that a shock to the US financial uncertainty measure does trigger a significant response of the global credit cycle.

5 Conclusions

This survey has reviewed the most recent empirical research on the role of domestic uncertainty, uncertainty spillovers, and global uncertainty for country-specific and global business cycles. We have presented and discussed ten main takeaways related to the literature on the macroeconomic effects of domestic uncertainty. Then, we have reviewed recent contributions on uncertainty spillovers, global uncertainty, and their effects at a country and global level. Finally, we have proposed a novel measure of global financial uncertainty, constructed as a weighted-average of measures of financial volatility for 39 countries. A VAR analysis conducted by modeling such a measure, a proxy for the global business cycle, and one for the global credit cycle points to a significant role played by unexpected changes in global financial uncertainty as a driver of the global business cycle. Our estimates suggest that the contribution of global financial uncertainty shocks to the peak response of world output during the Great Recession could be as large as 1/6-1/7.

Since the Great Recession, a lot of research has been undertaken to understand the macroeconomic effects of uncertainty. Much still has to be done to fully understand how to deal with uncertainty at a domestic and, in light of numerous events around the world, global level. As Bloom (2014) puts it, *"[...] there is still much about uncertainty about which we remain uncertain."*

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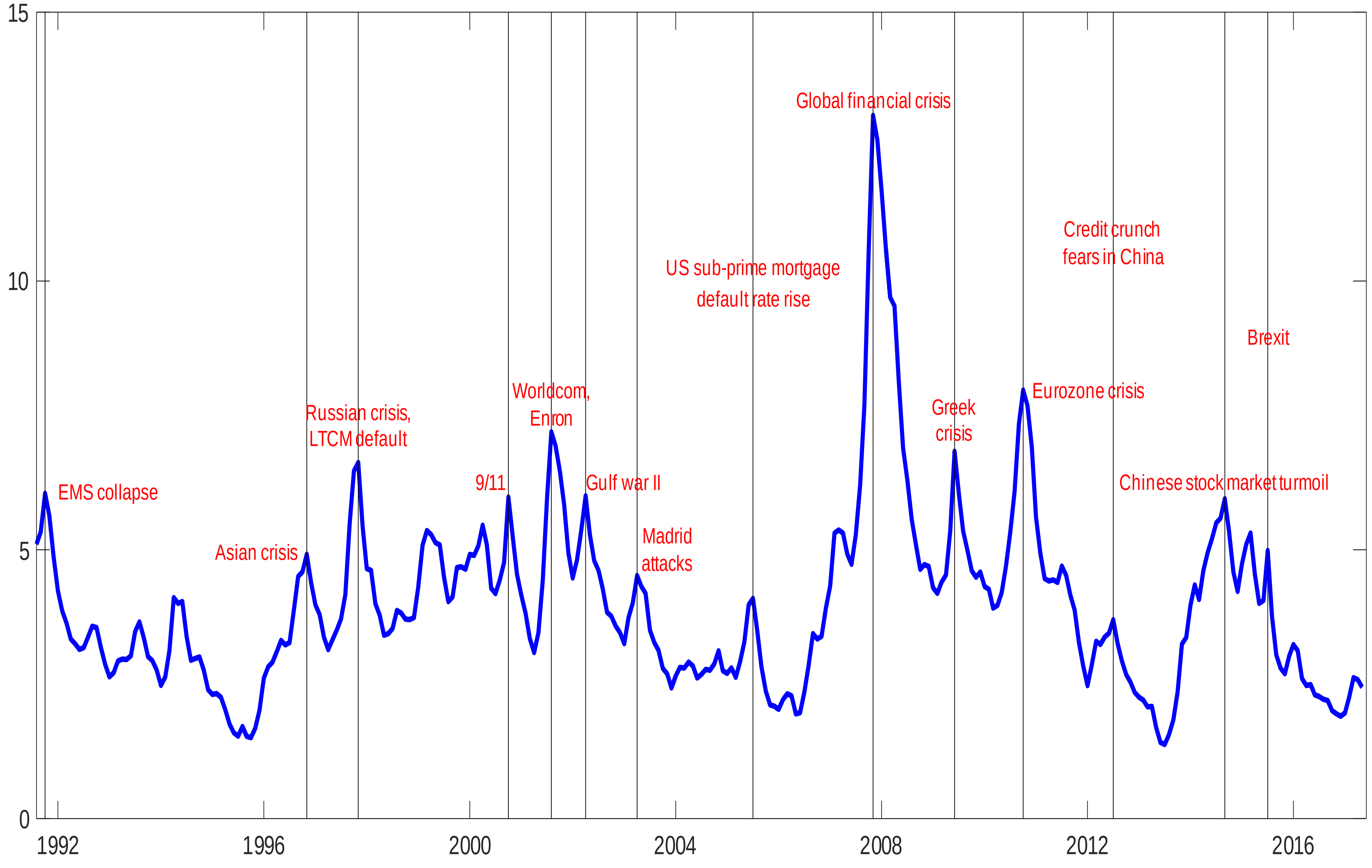

Figure 1: **Caggiano and Castelnuovo's (2019) Global Financial Uncertainty Measure.** Construction of the series explained in the text.

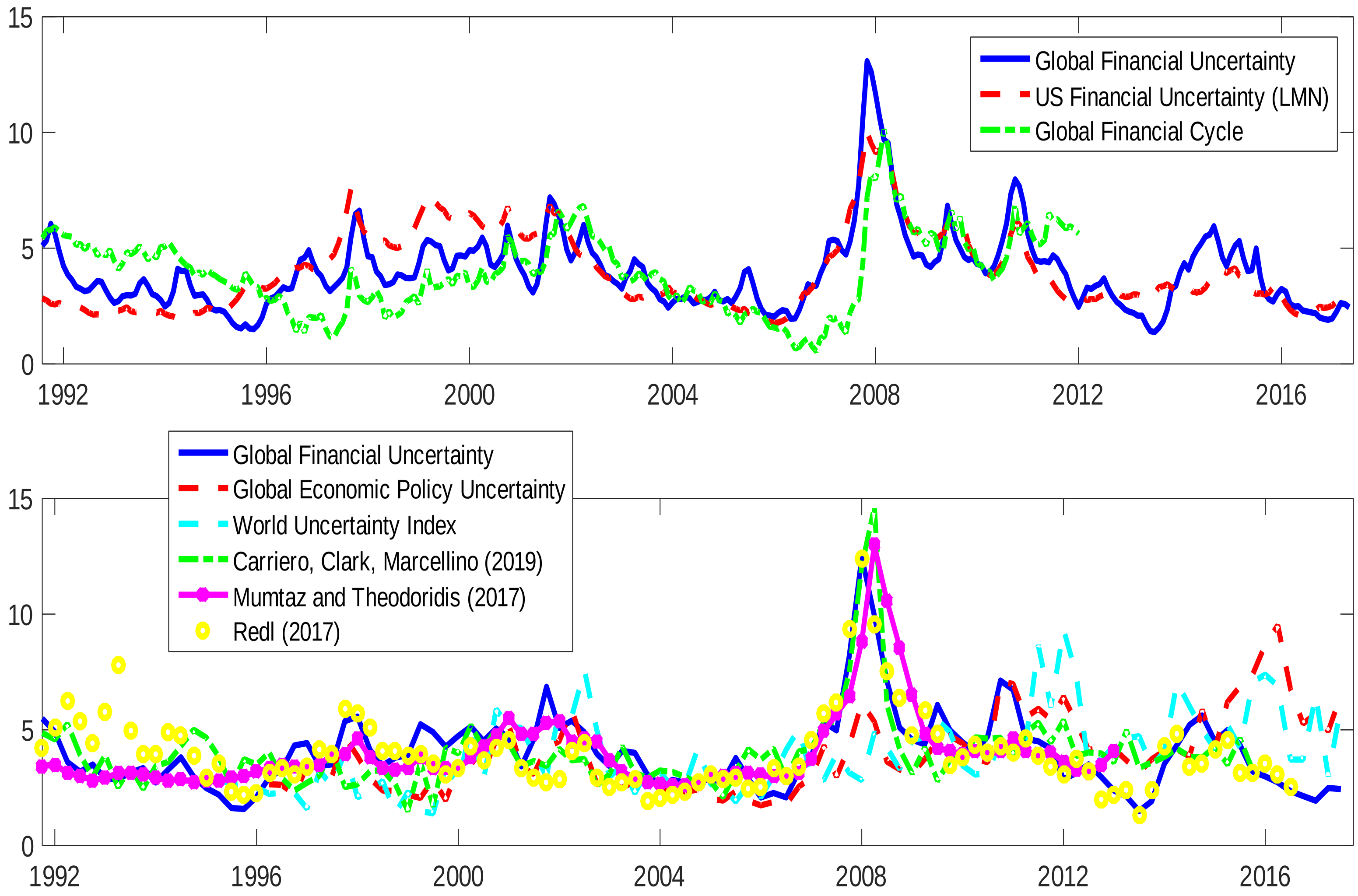

Figure 2: **Global Financial Uncertainty vs. Alternative Financial and Uncertainty Measures.** Upper panel: Global Financial Uncertainty as in Caggiano and Castelnuovo (2019) vs. Ludvigson et al.'s (2019) US financial uncertainty index and Miranda-Agrippino and Rey's (2019) global financial cycle index. Monthly frequencies. Lower panel: Global Financial Uncertainty as in Caggiano and Castelnuovo (2019) vs. Global Economic Policy Uncertainty as in Davis (2016, 2019), World Uncertainty Index as in Ahir, Bloom, and Furceri (2019), Global Macroeconomic Uncertainty as in Carriero, Clark, Marcellino (2019), Global Macroeconomic Uncertainty as in Mumtaz and Theodoridis (2017), and Global Macroeconomic Uncertainty as in Redl (2017). Quarterly frequencies. All series in this Figure are normalized to have the same mean and standard deviation of the GFU series. Global Financial Cycle's sign (upper panel) flipped to ease comparability.

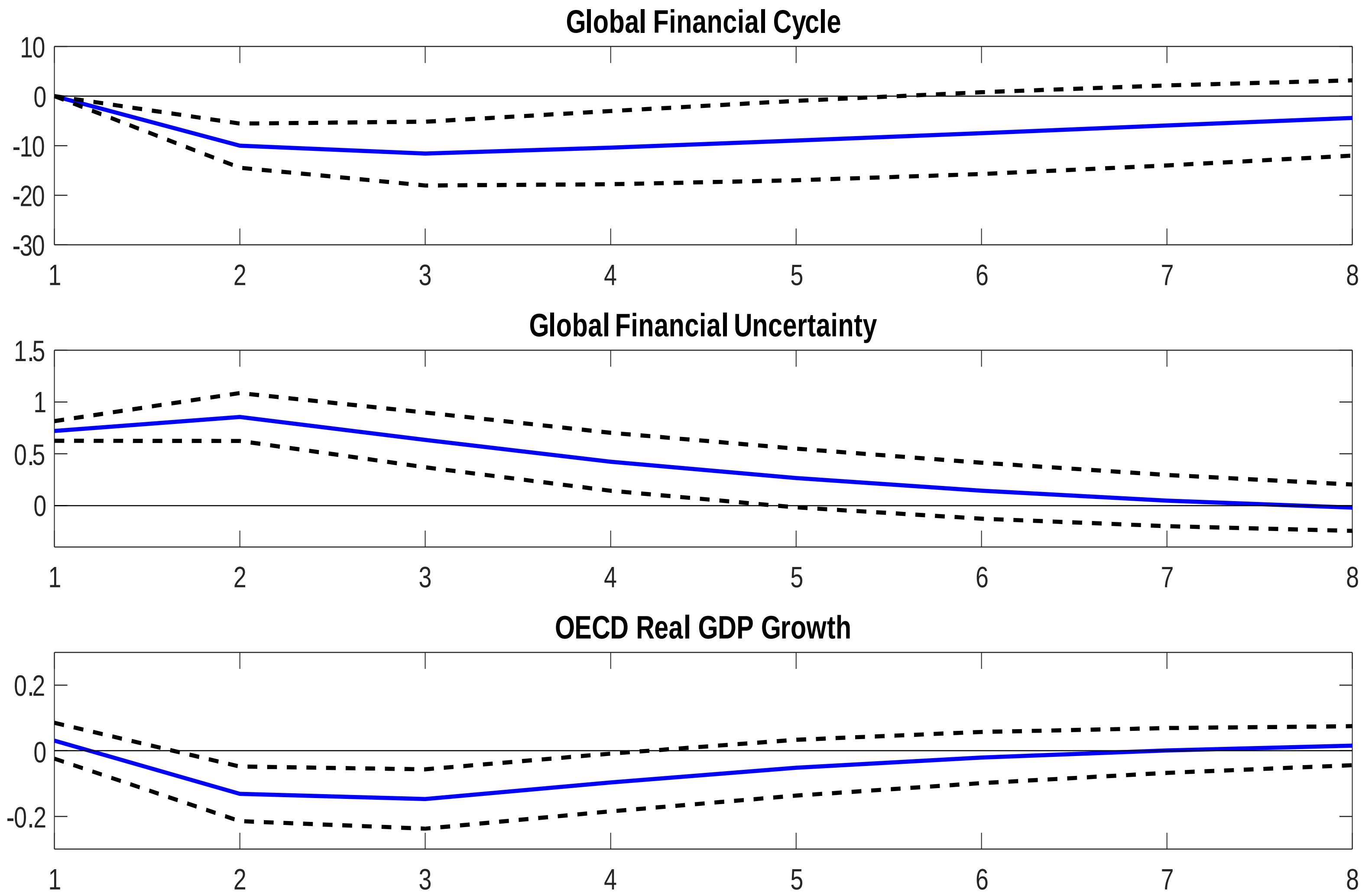

Figure 3: **Global Financial Uncertainty Shock: Impulse Responses.** VAR(2) estimated with a constant. Size of the shock: One standard deviation. 90 percent confidence bands produced via simple bootstrap (500 repetitions).

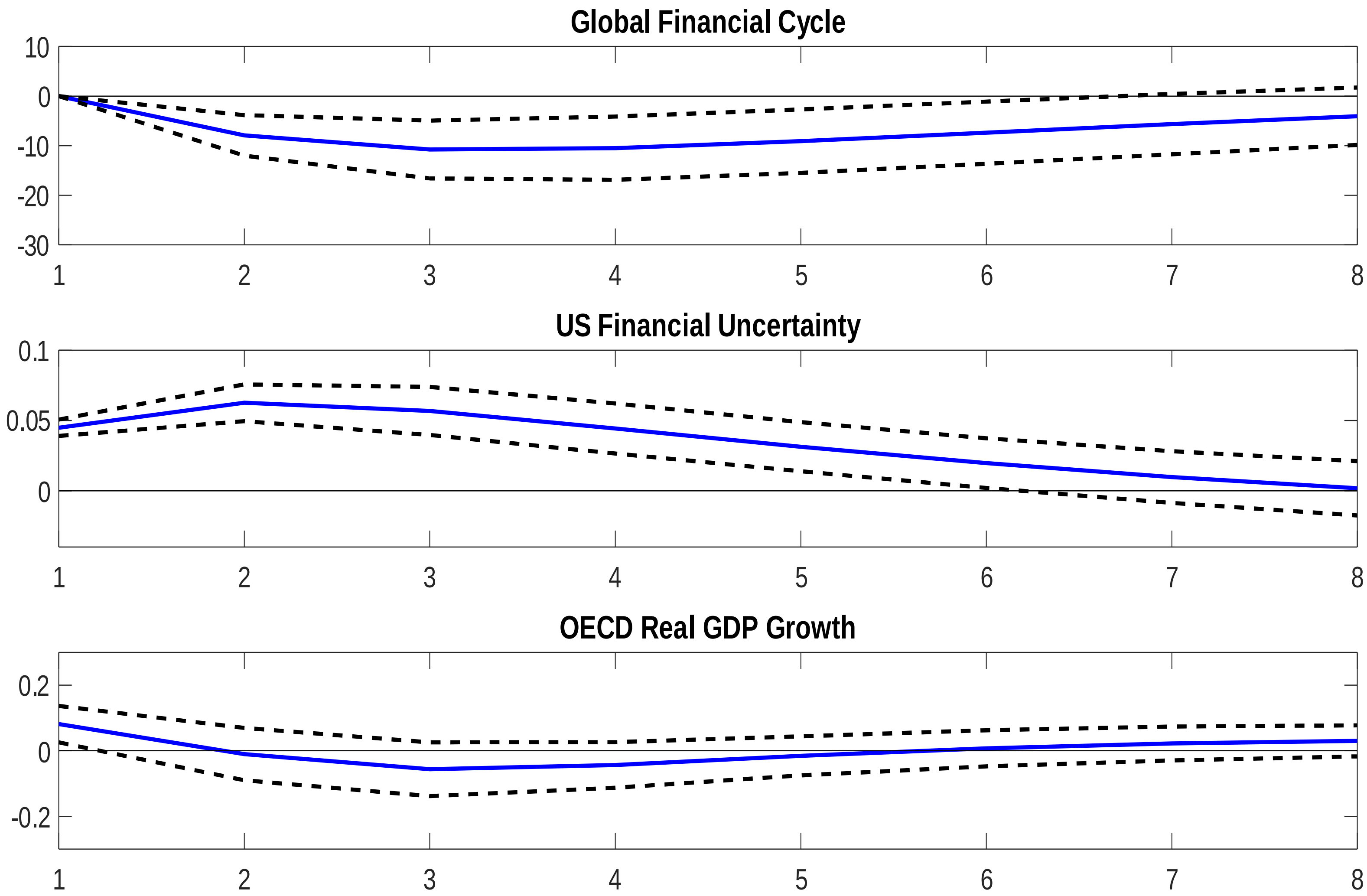

Figure 4: **US Financial Uncertainty Shock: Impulse Responses.** VAR(2) estimated with a constant. Size of the shock: One standard deviation. 90 percent confidence bands produced via simple bootstrap (500 repetitions).

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