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UNCERTAINTY BEFORE AND DURING COVID-19: A SURVEY

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Abstract

This survey features three parts. The first one reviews the most recent literature on the relationship between domestic (i.e., country-specific) uncertainty and the business cycle, and offers ten main takeaways. The second part surveys contributions to the fast-growing strand of the literature that focuses on the macroeconomic effects of uncertainty spillovers and global uncertainty. The last part presents contributions on the role played by uncertainty during the COVID-19 pandemic.

Keywords: Uncertainty, business cycle, spillovers, global uncertainty, global output, COVID-19.

JEL codes: C22, E32, E52, E62.

1 Introduction

The COVID-19 pandemic has reinvigorated the discussion on the connection between uncertainty and the business cycle. Figure 1 displays the evolution of four popular proxies for uncertainty, i.e., the measures of macroeconomic and financial uncertainty estimated by Jurado et al. (2015) and Ludvigson et al. (2021b), the Economic Policy Uncertainty index proposed by Baker et al. (2016), and the VXO, a measure of implied financial volatility produced by the Federal Reserve Bank of Chicago. These measures clearly point to a massive increase in uncertainty during the recession, which is confirmed by survey data on US (Altig et al. (2021b)) and UK firms (Altig et al. (2021a)). This level of uncertainty parallels or exceeds (depending on the proxy one considers) the one recorded during the Great Recession.

Unsurprisingly, since the materialization of the Great Recession the number of studies aimed at understanding from a theoretical and empirical standpoints the role played by uncertainty during extreme events and normal times has (almost) exploded. This survey's goal is to review the most recent findings on the relationship between uncertainty and the business cycle. With a clear focus on empirical contributions, the survey covers three main areas: i) the domestic uncertainty-business cycle nexus; ii) global uncertainty, an area including both studies on spillover effects from hegemon countries to open economies and investigations on the global uncertainty-global business cycle relationship; iii) the role played by uncertainty during the COVID-19 pandemic.

Two considerations are in order. First, when referring to theoretical models dealing with "uncertainty", this survey will in most occasions conceptually refer to a mean-preserving expected change in the second moment of a distribution. For instance, we will think of the economy's response to an expected change in the *volatility* of a process (e.g., technology) conditional on an unchanged *mean* of such a process. Technically, this concept captures the concept 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 the uncertainty about the probability distribution generating the data. Recent attempts to empirically distinguish these two concepts include Bekaert et al. (2013), Rossi et al. (2019), and Bekaert et al. (2021). A second consideration regards the use of ex-post data realizations as opposed to ex-ante data, i.e., expectations. 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 et al. (2020) find that innovations in realized stock market volatility are followed by contractions, while shocks to forward-looking uncertainty have no significant effect on the economy.

This survey joins other surveys on uncertainty and the business cycle that have been offered by various authors in recent times. Our survey's marginal contribution is the following. With respect to previous reviews of the literature (Bloom (2014), Castelnuovo et al. (2017)), ours offers updates on the role of uncertainty as a driver of the business cycle that include nonlinear effects of uncertainty shocks (e.g., due to financial frictions, or the zero lower bound), as well as evidence on the way in which uncertainty affects policy interventions; reviews the voluminous literature that has investigated the role of uncertainty spillovers and global uncertainty; and discusses the recent contributions on the role of uncertainty during the COVID-19 pandemic. Moreover, it covers recent proposals that aim at identifying uncertainty shocks without imposing zero restrictions on the uncertainty-business cycle contemporaneous relationship. Our survey, which is mostly based on empirical contributions, complements Fernández-Villaverde and Guerron-Quintana's (2020), which reviews the theoretical frameworks used to understand the transmission channels of uncertainty shocks in nonlinear DSGE frameworks (for a related paper, see Bianchi et al. (2019)). Finally, this paper complements the one by Cascaldi-Garcia et al. (2021), which offers a thorough review of the different measures of uncertainty the literature has dealt with, and that of Bloom (2014), which we update and expand along the dimensions explained above.

The reminder of the paper is structured as follows. Section 2 reviews the main takeaways of the empirical literature on the business cycle effects of domestic uncertainty shocks. Section 3 switches to global uncertainty and uncertainty spillovers across countries. Section 4 focuses on the role played by uncertainty shocks during the COVID-19 pandemic. Section 5 concludes by offering a few ideas for future research.

2   Domestic uncertainty: Ten takeaways

This Section organizes the various contributions to the literature under ten different takeaways. The classification is somewhat arbitrary, and many papers could easily belong to more than one category. This being said, let us move to the first category.

2.1 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 et al. (2013), Sheen and Wang (2019)),[1] frequency of newspaper articles that refer to economic uncertainty (Alexopoulos and Cohen (2015), Baker et al. (2016)), frequency of uncertainty-related keywords searched on the internet (Castelnuovo and Tran (2017), Shields and Tran (2019), Bontempi et al. (2021)) or in the Federal Reserve Beige Books (Saltzman and Yung (2018)), forecast errors about macroeconomic data (Jurado et al. (2015), Scotti (2016), Rossi and Sekhposyan (2015), and Ludvigson et al. (2021b) for the US economy, Rossi and Sekhposyan (2017), Moore (2017), Redl (2017), Grimme and Stöckli (2018), Meinen and Röhe (2017), Garratt et al. (2018), Ismailov and Rossi (2018), and Tran et al. (2019) for other industrialized countries), survey data (Clark et al. (2020), Altig et al. (2021b)). Using 100 years of consumption data from 16 OECD countries, Nakamura et al. (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 et al. (2001)), the dispersion of plant-level shocks to total factor productivity (Kehrig (2015), Bloom et al. (2018)), cross-firm price changes (Vavra (2014a), Baley and Blanco (2019)), and survey data (Bachmann et al. (2021)).

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) documents a relatively mild contribution of leverage to the rise of uncertainty in recessions (no more than 10 percent). Countercyclical risk aversion could also be behind the increase in financial uncertainty during busts. However, Bekaert et al. (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

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[1]Interestingly, not all measures of disagreement are countercyclical. Falck et al. (2021) show that disagreement about inflation expectations displays no clear correlation with the US NBER recessions. They stress this feature as a distinguishing one with respect to the measures of uncertainty present in the extant literature. For a link between uncertainty and disagreement in a monetary policy model with rationally inattentive price-setters, see Esady (2019).

et al. (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. 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 et al. (2016) scores record-high levels during the Great Recession and the COVID-19 pandemic.

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 et al. (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 co-vary 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 et al. (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 (2009, 2014) and Ludvigson et al. (2021b). 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 the labor demand schedule stays still, employment rises and, consequently, so does output. Fernández-Villaverde et al. (2015) and Basu and Bundick (2017) point out that this does not occur when price rigidities are present. In this case, demand-driven output contracts due to the fall in consumption, which also implies (under reasonable parameterizations) a fall in hours and investment. A complementary paper is Born and Pfeifer (2021), which explains why nominal wage rigidities imply that uncertainty shocks are recessionary.

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, which may indeed get boosted when uncertainty is high (Bloom (2014)). However, from a theoretical standpoint, it is unclear if firms should actually increase R&D spending in presence of uncertainty. For instance, Bonciani and Oh (2020) propose a new Keynesian model of the business cycle that features endogenous growth via R&D investment. In presence of uncertainty shocks, precautionary savings and countercyclical price markup work in favor of weakening aggregate demand (see also Fernández-Villaverde et al. (2015) and Born and Pfeifer (2021)). One implication is that the degree of utilization of the R&D stock declines. Consequently, aggregate productivity declines too, and said decline exerts a negative impact in the

6

long-run, i.e., cyclical and potential output are both affected. Bonciani and Oh (2020) show that the way in which one models households' preferences matters. In particular, if households feature Epstein-Zin preferences, the above-described long-term risk affects households' contemporaneous consumption choices, therefore exacerbating the business cycle negative effects of uncertainty shocks. Another observation relates prolonged periods of low volatility. Danielsson et al. (2018) study the effect of stock market volatility on risk-taking and financial crises. They do so by constructing a cross-country database spanning up to 211 years and across 60 countries. They find that prolonged periods of low volatility anticipate banking crisis. Differently, volatility *per se* is found to not have predictive power over banking crisis. These facts are consistent with models in which low volatility leads to excessive risk taking and balance sheet leverage.

A labor market channel explaining why uncertainty is countercyclical is proposed by Den Haan et al. (2021). Working with a search-and-matching model, they show that search frictions *per se* are not sufficient for unemployment to increase in response to an increase in perceived uncertainty by firms. However, when combined with Nash bargaining-determined wages, they might. Importantly, the authors show that option-value considerations play no role in the standard model with free entry. Differently, with a finite mass of entrepreneurs plus heterogeneity in firm-specific productivity, an increase in perceived uncertainty does affect the option value of waiting, therefore reducing job creation, increasing unemployment, and contributing to generate a recession. The labor market plays a central role also in the analysis proposed by Rogantini Picco and Oh (2020). Working with a model with heterogeneous agents with search and matching frictions and Calvo pricing, they show that uninsured workers are a mechanism that magnifies the more moderate real effects of uncertainty shock that one would find when playing with a standard new Keynesian model. This happens because the initial reduction in real activity caused by the precautionary saving motive and firms' upward pricing bias increases the unemployment risk of imperfectly insured households, therefore strengthening the precautionary saving effect. Then, a feedback loop kicks in, leading in equilibrium to a large drop in real activity, a negative response of inflation, and an unequal reaction of consumption among heterogeneous agents, all predictions consistent with the empirical evidence. Interestingly, Bonciani and Oh (2021) show that this feedback loop is operative even in presence of the zero lower bound if a central bank can follow a Taylor rule calibrated in a standard manner and engineer a negative interest rate, but not necessarily under optimal policy.

2.2 Identifying uncertainty shocks is difficult

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. 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. Ilut and Saijo (2021) propose a framework in which firms face Knightian uncertainty about their profitability and learn it through production. Via the feedback between economic activity and uncertainty, the model generates co-movement driven by demand shocks, with dynamics that are more powerful with respect to those predicted by standard new-Keynesian frameworks. Fajgelbaum et al. (2017) also appeal to a learning mechanism in a model where uncertainty is endogenous. In their framework, higher uncertainty about fundamentals discourages investment. In phases where little action is present (recessions), agents learn less rapidly over technology, and uncertainty can remain high for a long time. Hence, short-lived shocks can generate long-lasting recessions. In this environment, uncertainty traps can occur, i.e., self-reinforcing episodes of high uncertainty and low activity can materialize. Fajgelbaum et al. (2017) show that their learning mechanism is relevant to replicate the evolution of uncertainty and the large drop in real activity during the Great Recession. While Fajgelbaum et al.'s (2017) model does not feature credit frictions, Straub and Ulbricht (2021) show that such frictions may exacerbate the uncertainty-real activity loop and contribute to produce even larger and longer lasting recessionary effects.

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 attempted to understand the different information contents of macroeconomic and financial uncertainty. This is what we turn next.

Ludvigson et al. (2021b) 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 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 re-

sponse in financial volatility (a similar result can be found in Lütkepohl and Milunovich (2016)). Related results are those by Casarin et al. (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 et al. (2014), Carriero et al. (2015), Leduc and Liu (2016), and Basu and Bundick (2017). Interestingly, Ludvigson et al. (2021b) 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 related to the "Oi-Hartman-Abel" described in Section 2.1. Ludvigson et al. (2021b) stress the role that macroeconomic uncertainty plays in amplifying the effects of first-moment shocks and second-moment financial disturbances.

Other recent empirical findings suggest that the Ludvigson et al. (2021b) result is not written in stone. Building on Bacchiocchi and Fanelli (2015) and Bacchiocchi et al. (2018), Angelini et al. (2019) exploit the heteroskedasticity in Ludvigson et al.'s (2021) 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 et al. (2019a) 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 et al. (2019a) 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 et al. (2019) and Carriero et al. (2019a) is contained in Ludvigson et al. (2021b). Finally, Forni et al. (2021b) also find macroeconomic uncertainty shocks to be relatively more powerful drivers of the business cycle than financial uncertainty shocks.

One important implication of the investigations cited above is that the recursive identification strategy often used by the literature is questionable. 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. Alessandri et al. (2020) identify exogenous variations in uncertainty by working with an instrument constructed by isolating changes in expected financial volatility around FOMC dates that are not related to variations in the underlying price. Their VAR analysis attributes 20% of the observed volatility in the US employment and industrial production to uncertainty shocks. These findings suggest 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. Following the identification strategy proposed by Antolín-Díaz and Rubio-Ramírez (2018) for first-moment shocks, Redl (2020) identifies macro uncertainty shocks for 11 advanced nations via the imposition of restrictions on the sign of the shocks around political events, and financial shocks with financial stress during financial crises. He finds that macro uncertainty shocks matter for the majority of countries and that the real effects of macro uncertainty shocks are generally larger conditioning on close elections. A complementary paper is Rivolta and Trecroci (2021), who employ sign restrictions in a model featuring uncertainty proxies and the excess bond premium (EBP) measure proposed by Gilchrist and Zakrajšek (2012) to identify uncertainty shocks in the US and their effects on emerging economies. Brianti (2020) separately identifies financial and uncertainty shocks using a novel identification approach that crucially relies on the qualitatively different responses of corporate cash holdings to an uncertainty shock (that pushes firms to increase their cash holdings for precautionary reasons) vs. a first-moment financial shock (that leads firms to reduce cash reserves as they lose access to external finance). Such predictions are provided by a theoretical model built up by the author himself. He finds uncertainty shocks to explain about 20% of the forecast error variance of real GDP, while financial shocks explain about 40% of it. A related paper is Benati (2019), who is concerned with the role played by shocks to Baker et al.'s (2016) economic policy uncertainty (EPU) in driving the US, Canadian, UK, and Euro area business cycles. He finds that it is crucial to separately identify uncertainty and financial shocks to correctly quantify the real impact of the former ones. He then achieves separate identification of these two shocks

by requiring the uncertainty (financial) shock to i) explain as much (little) as possible of the forecast error variance decomposition of EPU, and as little (much) as possible of that of EBP. He finds EPU shocks to have substantial effects on the US unemployment rate.

Binding and Dibiasi (2017) exploit a discontinuity in the exchange rate management implemented by the Swiss National Bank on January 2015 - said central bank suddenly and unexpectedly removed the lower exchange rate bound vs. the Euro - to gauge the response of a battery of Swiss real activity indicator to the jump in exchange rate uncertainty that followed this policy change. Working with survey data, they show that uncertainty had a negative effect on investment in durable goods, something that they interpret as an optimal response by firms according to the "wait-and-see" theory. However, expenditures in R&D increased after the policy change, an evidence which can be rationalized via growth-option effects. They then conclude that focusing on aggregate capital formation may mask important heterogeneities when it comes to understanding the response of investment to an uncertainty shock. Exploiting again survey data on Switzerland, Abberger et al. (2018) investigate the role played by the uncertainty affecting firms after that a referendum to invalidate the Swiss-EU agreement on freedom of movement was supported by 50.3% of the population in February 2014. Working with firm-level panel data covering the 2009–2015 plus data on two surveys administered shortly after the vote, the authors examine the effects of the inducted policy uncertainty on investment by Swiss firms. They find compelling evidence that uncertainty dampened investment by exposed firms (in particular, those engaging in irreversible investment) by as much as one quarter in the two years following the vote. If anything, exposed firms that are not affected by irreversibilities increased investment in the year after the vote. Aggregation biases may also affect the identification of uncertainty shocks. For instance, Paccagnini and Parla (2021) work with a Bayesian approach which enables to mix high-frequency financial volatility data with low(er) frequency macroeconomic indicators. They find the real activity response estimated with their mixed-frequency approach to be milder than the one estimated with data available at a lower frequency.

A difficult distinction to draw is that between news shocks and uncertainty shocks in VAR investigations, as pointed out by Cascaldi-Garcia and Galvão (2021). They document this difficulty by showing that identifying such shocks one at a time - something often done in the literature - leads to obtaining proxies for these shocks that are correlated. Hence, the so-identified shocks are in fact convolutions of truly structural

shocks. This calls for an identification strategy able to separate news and uncertainty shocks. Cascaldi-Garcia and Galvão (2021) propose to separately identify them by maximizing the respective forecasting error variances of productivity and observed uncertainty using the same reduced-form vector autoregressive model. They find that the so "purged" news shocks (which are obtained by removing the financial uncertainty shocks component) generate stronger positive responses of economic activity, while the negative responses to financial uncertainty shocks are deeper in the medium term, something which is explained by the absence of "good uncertainty" (news-related) effects on technology.

A challenge in quantifying and interpreting the business cycle effects of uncertainty shocks is that of defining the shocks of interest in the first place. In empirical studies (e.g., VAR studies), uncertainty shocks are often conceptually different with respect to those modeled within the context of DSGE frameworks. For instance, in many VAR-based studies uncertainty is modeled using proxies or indicators such as the implied or realized volatility of stock market returns. On the other hand, DSGE frameworks often model uncertainty shocks as second-moment shocks capturing innovations to the volatility of stochastic processes, e.g., of technology and/or households' discount factor. Hence, a gap between theory and empirics tends to be present in the literature. Part of the reaction to this gap has been that of building up models that match the empirical evidence better. For instance, Fernández-Villaverde et al. (2015) estimate fiscal policy rules with time-varying volatility to recover fiscal uncertainty shocks. They use such shocks as "observables" in a VAR to estimate the business cycle effects of fiscal uncertainty. Then, they feed the estimated fiscal rules into a medium-scale new Keynesian model of the business cycle and match its impulse responses with those of the VAR. Hence, conceptually, in this paper the VAR and the DSGE framework refer to the same uncertainty object. Another example is Basu and Bundick (2017), who estimate a VAR in which uncertainty is captured by the VXO. Then, they propose a nonlinear micro-founded DSGE framework in which the uncertainty shock is a shock to households' discount factor. However, their model also features equities whose returns' implied volatility - which is, the "model-implied VXO" - can be meaningfully matched to the response of the VXO in the VAR to calibrate the size of the uncertainty shock in their framework.[2]

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[2]To be precise, they estimate their DSGE framework by matching the impulse responses of a battery of macroeconomic indicators (VXO included) as well as some selected moments. Also, their VAR works well as an auxiliary model in their direct inference approach because the uncertainty shock in their model turns out to be the relevant driver of the volatility of the model-implied VXO. In other words,

A different, somewhat complementary reaction to the difficulty of matching theoretical and empirical concepts regarding uncertainty has been that of constructing different measures of uncertainty with the same empirical strategy and study the similarities and differences among them. A prominent example is the paper by Ludvigson et al. (2021b). Building on Jurado et al. (2015), Ludvigson et al. (2021b) employ a data-rich approach and a state-of-the-art empirical framework to model the common volatility of the unpredictable components of a large number of US time series. Their measures of financial and macroeconomic uncertainty (which are plotted in Figure 1 of this paper) as well as their estimate of real uncertainty offer different interpretations of the concept of uncertainty depending on the data they are built upon. Studying the heterogeneities in these measures is important to have a sense on how uncertainty originates in an economic system. At the same time, similarities in these series (e.g., the peak they all display during the great recession) document robust stylized facts that macroeconomic models should ideally be able to replicate, perhaps with a broad, encompassing "uncertainty shock" concept.

Before closing this takeaway, it is worth noting that survey data on households may be fruitfully employed to identify the effects of uncertainty shocks. Coibion et al. (2021) quantify the effects of exogenous changes in the level of macroeconomic uncertainty perceived by European households on their spending decisions. To achieve identification, they employ randomized information treatments that provide different types of inflation on the first and second-moments of future economic growth. In this way, they generate exogenous changes in households' perceptions of macroeconomic uncertainty. Then, they use follow-up surveys to compare treated households' spending decisions with respect to those of the control group. They find that higher macroeconomic uncertainty induces households to reduce their spending on different types of goods (non-durables, durables, services). They also find that uncertainty reduces households' investment in mutual funds.

Identification of uncertainty shocks is likely to represent a florid research territory for the years to come.

2.3   Uncertainty is harmful for trade

Uncertainty shocks have been documented to be one of the drivers of trade. Using US data, Novy and Taylor (2020) show that, in response to a jump in the VXO, both

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the other two shocks they model - a first-moment disturbance to the discount factor, and a first-moment technology shock - are only marginally important for the volatility of the model-implied VXO.

industrial production and imports decline, but the peak response of the latter is about 5 times larger. Using a model of international trade that assumes higher fixed costs associated to imports of foreign inputs with respect to domestically produced ones, they show that firms optimally adjust their inventories by cutting their foreign orders more in response of an increase in uncertainty. In the aggregate, this response leads to a bigger contraction in international trade flows than in domestic economic activity.

Interestingly, the response of trade of uncertainty shocks is actually unclear from a theoretical standpoint, because different channels can be at work. Baley et al. (2020) 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 et al. (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 et al. (2020) 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. Constantinescu et al. (2019) exploit EPU data for 18 countries and 24 years and estimate the effects of jumps in EPU for global trade in a panel setting. A one percent increase in uncertainty is associated with a 0.02 percentage point reduction in the growth of goods and services trade. Given the huge increase in policy uncertainty since mid-2018, such estimate implies that up to one percentage point decline in world trade growth may be attributed to policy uncertainty. 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. However, as stressed by Constantinescu et al. (2019), the type of uncertainty one considers matters. In fact, while finding a clearly negative relationship between EPU and overall trade, they also find that the relationship between uncertainty and trade is much more blurred if one considers the proxy for trade uncertainty recently developed by Ahir et al. (2022). Constantinescu et al. (2019) point out that the reason for this different evidence may rely on the way trade uncertainty is constructed. First, the measure constructed by Ahir et al. (2022), which is based on the presence of the words "uncertainty" and "trade" in proximity within press articles, does not distinguish between negative and positive uncertainty realizations (e.g., the conclusion of a new trade liberalization agreement could be confounded with a jump in uncertainty). Second, an increase in trade uncertainty affecting certain countries (say, the US and China) could actually be beneficial for other countries due to uncertainty-induced trade diversion. The improvement on the existing uncertainty indicators is certainly a necessary step to do in the future.

2.4   The impact of uncertainty on inflation 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. Haque and Magnusson (2021) find that this conclusion is robust to admitting parameter instability in a VAR modeling inflation, uncertainty, and a battery of other macroeconomic indicators. Going back to Leduc and Liu's (2016) framework, Fasani and Rossi (2018) show that the negative response of inflation in their model can become positive when modeling interest rate inertia. In particular, degrees of interest rate smoothing in line with the Taylor rule-related empirical evidence (see Clarida et al. (2000), Castelnuovo (2003, 2007), Coibion and Gorodnichenko (2011, 2012), and Ascari et al. (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 et al. (2015), Mumtaz and Theodoridis (2015), Basu and Bundick (2017)). An analysis on the relative role of price vs. wage stickiness is proposed by Born and Pfeifer (2021).

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. De Santis and Van der Veken (2021) separately identify uncertainty and financial shocks in their VAR analysis by imposing a mix of sign and narrative restrictions. They find that uncertainty shocks are recessionary but inflationary, while financial shocks are recessionary and deflationary. Lopez and Mitchener (2021) analyze uncertainty during the post-WWI period. They relate such uncertainty - particularly high in Germany, Austria, Poland, and Hungary - to the

protracted political negotiations over reparations payments, the apportionment of the Austro-Hungarian debt, and border disputes. They find a strong association between jumps in exchange rate uncertainty (a proxy for political uncertainty) and hyperinflation. Differently, in countries whose economic fundamentals at that time were similar but uncertainty was substantially lower (such as, e.g., France and the Netherlands), hyperinflation did not materialize.

An in-depth analysis on the transmission channels operating in a new-Keynesian model with nominal rigidities and search-and-matching frictions on the labor market and the effect of uncertainty shocks on inflation via such channels is offered by Freund and Rendahl (2020). Oh (2020) shows that the response of inflation to an uncertainty shock may depend on the structural source of price rigidity one relies upon when working with a new Keynesian framework, i.e., Rotemberg-type and Calvo-type price rigidities. He shows that these two schemes generate different dynamics in response to uncertainty shocks, with inflation responding positively under Calvo (due to precautionary pricing) and negatively under Rotemberg. This calls for an investigation on the relative importance of these two schemes when it comes to modeling rigidities in a given economy (for an example with US data, see Ascari et al. (2011)). Turning to open economies, Ghironi and Ozhan (2020) show that interest rate uncertainty can discourage short-term inflows via portfolio risk and precautionary saving channels, while a markup channel generates net foreign direct investment-inflows under imperfect exchange rate pass-through. The authors investigate the effects of policy uncertainty across different scenarios (irreversible foreign direct investments, different currencies related to export invoicing, different degrees of risk aversion of outside agents, and the presence of an effective lower bound in the rest of the world). A common prediction of Ghironi and Ozhan's model is that policy uncertainty is inflationary. More work is needed to understand the response of inflation to uncertainty shocks.

A note related to the response of inflation to uncertainty is the role that uncertainty plays in inducing price rigidity. Ilut et al. (2020) employ an ambiguity aversion framework to rationalize price rigidity. The story goes as follows. Firms are uncertain about their competitive environment. This uncertainty implies two things. First, firms have to learn about the shape of their demand function from past observations of the quantities they sold. Because of this learning process, kinks in the expected profit function materialize in correspondence of previously observed prices, making those prices both sticky and more likely to realize again,. Second, nominal rigidity arises as an implication of uncertainty about the relationship between aggregate and industry-level

inflation. Working with an estimated version of their model, Ilut et al. (2020) show that their framework is able to match a variety of micro-level pricing facts that are typically challenging to match jointly. Another implication of their model is that nominal shocks generate larger real effects than in standard models.

2.5 The effects of uncertainty shocks are state-dependent

Caggiano et al. (2014), Nodari (2014), Caggiano et al. (2017a), Chatterjee (2019a), Colombo and Paccagnini (2021), and Caggiano et al. (2022) find that the effects of uncertainty shocks are stronger when an economy is already in a low-growth state. This might be due to the fact that recessions are associated with a tightening of financial conditions (Alessandri and Mumtaz (2019)) or an increase in uncertainty (Jackson et al. (2018)). Another possible explanation regards the labor market. Cacciatore and Ravenna (2021) 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 et al. (2022) work with a nonlinear Interacted VAR à la Pellegrino (2018, 2021) and a narrative identification strategy to estimate the effects uncertainty shocks during the Great Recession. They find them to be substantially larger than in normal times, and interpret this fact via an estimated nonlinear DSGE model in which risk aversion is large (for related contributions, see Bretscher et al. (2018) and Caggiano et al. (2021b)). Then, they run counterfactual simulations and show that the more aggressive monetary policy response to business cycle fluctuations (with respect to the one estimated to be in place in normal times) successfully curbed the output loss that would otherwise materialize. Andreasen et al. (2021) use a similar nonlinear framework and identification strategy to separate the effects of uncertainty shocks in recessions vs. expansions. They find them to be significantly larger in recessions. Working with an estimated nonlinear DSGE framework with recursive preferences and sticky prices approximated at a third order around the stochastic steady state (the proposed solution of such a model represents a contribution to the literature *per se*), they show that firms' stronger upward nominal pricing bias in recessions - due to higher inflation volatility and a higher stochastic discount factor - is behind the larger impact of uncertainty shocks on real activity when output growth is low. A somewhat related paper is Diercks et al. (2020). They show that sequences of uncertainty shocks - an hypothesis they support with an empirical

analysis - may importantly exacerbate the severity of recessions in a model in which a state-dependent precautionary motive is present. They also show that, in a model approximated around the deterministic steady-state, such a state-dependence arise just when the approximation is taken at least up to the fourth order. Dibiasi (2018) extends Bloom et al.'s (2018) model to accommodate for time-varying irreversibility, which he empirically documents to be countercyclical (i.e., the degree of irreversibility is larger in recessions). He then shows that the just-mentioned micro-founded real business cycle model goes a long way in replicating the stronger real effects of uncertainty shocks found in the literature exactly thanks to the time-varying degree of irreversibility present in his model. State-dependence complements the time-dependent analysis on the real effects of uncertainty shocks that some authors have recently put forth (see, e.g., Mumtaz and Theodoridis (2018)). Turning to the oil market, Nguyen et al. (2021) investigate the uncertainty-dependent and sign-dependent effects of supply, aggregate demand and oil-specific demand shocks. Working with a nonlinear framework that allows for these shocks to have different effects in regimes characterized by different levels of oil price uncertainty, they find that both supply shocks and oil-specific demand shocks have negligible impacts in periods of low oil price uncertainty, but they have sizeable effects in a high-oil-price-uncertainty regime.

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 et al. (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 of the central bank to set the real interest rate as low as desired. Caggiano et al. (2017b) 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. Haque et al. (2021) employ a time-varying parameter VAR to investigate the effects of financial uncertainty shocks on investment. They find such effects to be larger in presence of the zero lower bound than during the great moderation. 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 et al. (2019)). (For contrasting evidence, see Debortoli et al. (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

19

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 issue is investigated 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.

It is worth noting that the literature cited so far has been after the cyclical effects of uncertainty shocks. However, a different strand of the literature has attempted to tackle puzzles in the data that relate to the medium-term cycles. Bianchi et al. (2018) find that post-WWII US data show distinct patterns of comovements between stock prices, debt issuance and shareholder payout not only at a cyclical level, but also at medium-term cycle frequencies. The latter fact is not easily replicable with standard macro-finance frameworks. Interestingly, Bianchi et al. (2018) show that an ambiguity aversion interpretation of the data is possible. In other words, one can assume that: i) the representative household be averse to Knightian uncertainty (ambiguity) and choose asset holdings to keep a worst case expected return on equity aligned with the riskless interest rate; ii) the representative firm face adjustment costs that encourage dividend smoothing and an upward sloping marginal cost of debt, i.e., issuing additional debt be cheaper than raising equity at low levels of debt, but eventually become more expensive as debt increases. Shareholders maximize the value of the firm by choosing both optimal investment and determining optimal leverage and payout ratios. Bianchi et al. (2018) investigate the response of households and firms to variations in uncertainty, and show that changes in uncertainty endogenously generate the short and medium-run comovement of stock prices, debt and payout observed in the data. Importantly, dropping ambiguity aversion is shown to make the model significantly worse in fitting the dynamics of the data, in particular those of payout and equity value.

2.6 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 et al. (2014), Gilchrist et al. (2014), Bonciani and van Roye (2016), Arellano et al. (2019), Brand et al. (2019), Alfaro et al.

(2019), Chatterjee (2019b), and Chatterjee et al. (2020) 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 et al. (2019) - captures the additional output effects due to financial frictions that materialize after a exogenous increase in uncertainty. Alfaro et al. (2019) 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 et al. (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 et al. (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 optimally manage 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 speak in favor of modeling uncertainty and financial frictions in empirical frameworks. Caldara et al. (2016) employ 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 et al. (2019) work 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). Caggiano et al. (2021a) exploit the different behavior of EBP during the Black Monday (where it decreased) vs. the great recession (where it increased) to separate EBP shocks from financial uncertainty shocks (financial volatility increased in both events). Moreover, they use ratio restrictions to separately identify shocks to financial uncertainty and shocks to macroeconomic uncertainty. Working

with counterfactual simulations that assume that uncertainty shocks do not have an impact on EBP, and contrasting the counterfactual response of real activity to the factual one (which is consistent with a positive increase in the cost of credit in response to an uncertainty shock), they estimate the finance uncertainty multiplier to be equal to 2. Reassuringly, in spite of the striking differences in the two econometric approaches used by the authors, this estimate lines up with the one by Alfaro et al. (2019). Choi et al. (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 et al. (2016), who focus on the role of banking frictions and find them to be relevant for the transmission of EPU shocks.

Nonlinear effects of uncertainty shocks due to credit or financial frictions more in general have been documented by a few authors. 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. Lhussier and Tripier (2021) 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. Turning to micro-data, Alessandri and Bottero (2020) investigate the response of the supply of bank credit to changes in economic uncertainty by working with a rich monthly dataset that includes all loan applications submitted by a sample of 650,000 Italian firms between 2003 and 2012. An increase in aggregate uncertainty is documented to: i) decrease banks' likelihood to accept new credit applications; ii) lengthen the waiting time faced by firms before their loans is released; iii) make banks less reactive to changes in the short-term interest rate (something that weakens the banking channel of monetary policy). All else being equal, uncertainty exerts a stronger impact on poorly capitalized

lenders and geographically distant borrowers.

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, future research will hopefully be informative on the relative importance of uncertainty shocks vs. other shocks in presence of financial frictions (e.g., news shocks as in Görtz et al. (2020) and Cascaldi-Garcia and Galvão (2021)), which is relevant from a modeling as well as policy standpoint.

2.7 Uncertainty shocks exert stronger effects 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 macro-economic 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 (2019a) 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 (2019b) interprets this fact with a higher degree of financial frictions estimated for the set of emerging economies she consider. Bhattarai et al. (2020) 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 et al. (2020) attribute such heterogeneity to different monetary policy responses by Latin American countries to US uncer-

tainty shocks. An analysis of central bank minutes confirms that Latin American EMEs pay less attention to smoothing capital flows. Ahir et al. (2022) 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. Ahir et al. (2022) find that innovations in WUI 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.

Fernández-Villaverde et al. (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.

An important point made by Groshenny et al. (2021) is that different types of uncertainty have a different effect on open economies. The authors employ a panel VAR to model data of a variety of emerging countries and estimate the impact of financial uncertainty, global economic policy uncertainty, and trade policy uncertainty shocks on their trade flows. They find that global economic and trade policy uncertainty shocks substantially and persistently reduce the degree of openness of these economies, while financial uncertainty shock exert a negligible effect, and mostly in the very short-run. As pointed out Groshenny et al. (2021), the effect of global economic policy and trade uncertainties is problematic, because the shrinkage of trade openness for these countries is likely to be associated with a reduction in their overall wealth.

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 is 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)).

2.8 Macroeconomic policies are weaker in presence of uncertainty

Pellegrino (2018, 2021) works with nonlinear Interacted VAR models and finds that monetary policy shocks affect the US and Euro area business cycle more weakly in periods of high uncertainty. In his empirical framework, which allows uncertainty to endogenously respond to macroeconomic shocks, the response of uncertainty to a monetary policy shock is found to be significant. A similar finding is proposed by Aastveit et al. (2017), and - with different types of nonlinear frameworks - by Eickmeier et al. (2016) and Castelnuovo and Pellegrino (2018). The 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 et al. (2022) 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 et al. (2018)). De Pooter et al. (2021) find that a monetary policy shock is followed by a stronger response of the medium-to-long end of the term structure of interest rates when monetary policy uncertainty is low. Digging deeper, they find that primary dealers are more active in adjusting their positions in the US Treasury market and their exposure to interest rates when policy uncertainty is low. A somewhat connected literature is the one on the effects of monetary policy shocks on financial and macroeconomic volatility. Bekaert et al. (2013) estimate recursive VARs for the US economy and finds that a monetary policy shock increases financial volatility. This result is driven by the increase both in risk and uncertainty, with the response of the former being stronger than the latter.

The literature has also investigated the connection between uncertainty and fis-

cal policy. Ricco et al. (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 et al. (2015)), perhaps due 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 (2021)).

The impact of uncertainty on the effectiveness of macroeconomic policies seems to represent an important research avenue. This is potentially true also when it comes to macro-financial policies designed to reduce fluctuations in asset prices. This statement is supported by recent evidence on the role of uncertainty as an element "filtering" the effects of shocks on agents' portfolio decisions. Schmalz and Zhuk (2019) propose and empirically support a Bayesian learning model that predicts that investors react more strongly to news in downturns than in upturns when they are uncertain about individual assets' risk loadings.

2.9 Monetary policymakers act as risk managers

Evans et al. (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 et al. (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. (2021b). 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 et al. (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 et al. (2000), Ascari et al. (2011), Coibion and Gorodnichenko (2011, 2012). Then, is the evidence in favor of a systematic response to measures of uncertainty a genuine one, or is it spurious and due to an omitted variable problem? Further investigations are needed to address this question.

2.10 Macroeconomic policies can 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 et al. (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 (2020) 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 et al. (2016), Husted et al. (2020) 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. To the extent that monetary (and fiscal) policy moves are influenced by business cycle shocks, these findings are consistent with those in Caldara et al. (2021b), who find that a business cycle shock can importantly affect uncertainty and risk. Fasani et al. (2022) employ a proxy-FAVAR framework to estimate the business cycle effects of monetary policy uncertainty shocks. As instrument, they employ the residual from the regression of the conditional volatility of 1-year swap rate 1-month ahead taken by Carlston and Ochoa (2016) over monetary policy surprises on FOMC meeting days. They consider the three measures of policy surprises produced by Rogers et al. (2018). Their FAVAR impulse responses point to a recessionary effect due to the increase in monetary policy uncertainty, with a decrease in firms' entry and a decrease in exit. They show that these stylized facts can be replicated with a DSGE framework in which firms' entry and exit is endogenous. Interestingly, the effects of monetary policy uncertainty may be nonlinear. Dahlhaus and Sekhposyan (2020) use survey data to derive a measure of monetary policy uncertainty which they then model with a battery of macroeconomic indicators to gauge the effects of a monetary policy uncertainty shock. They find such a shock to be more powerful in phases of monetary policy easing than during tightenings. Creal and Wu (2017) involve long term rates and work with a term structure model that allows for second moments of macroeconomic indicators and yields to exert first-order effects on the modeled variables. Their empirical analysis points to the existence of two factors, which they interpret at monetary policy uncertainty and term premium uncertainty. Also in their framework, uncertainty is shown to have recessionary effects.

Central banks' policy liquidity is also an element surrounded by uncertainty. Jasova et al. (2021) investigate the role played by the 2011 very Long-Term Refinancing Operation, which implied a reduction in lender of last resort-related policy uncertainty. Working with a novel granular dataset that perfectly matches the ECB monetary policy and market operations data, private repo market haircuts data, firm credit registry and banks' security holdings in Portugal, they find that banks more affected by the reduction in such an uncertainty deleveraged at a slower pace. They show that this had a positive and economically sizable impact on lending and real activity.

As anticipated above, fiscal policy uncertainty is also present in a number of countries. Baker et al. (2016) rank fiscal policy as the first driver of the elevated level of

economic policy uncertainty during and after the Great Recession. Fernández-Villaverde et al. (2015) estimate stochastic volatility processes for US capital taxes, labor taxes, and government expenditures. When coupling these estimated processes with a non-linear DSGE framework, they find that a jump in fiscal policy uncertainty is clearly detrimental for the US business cycle. Ricco et al. (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. A contribution on the role of political uncertainty in the US in the aftermath of the global financial crisis is Born and Pfeifer (2014a).

Anzuini et al. (2017) estimate a fiscal policy rule with Italian data allowing for the volatility of the fiscal policy shocks to vary over time. Then, they model said volatility series with a number of macroeconomic indicators via a VAR framework, and find that a shock to their fiscal policy uncertainty measure is one of the drivers of the Italian business cycle (with a jump in uncertainty exerting a negative impact on real activity). Belianska et al. (2021) document the effects of government spending uncertainty in the Euro area. They first estimate a stochastic volatility model on European government consumption and propose a measure of government spending uncertainty which they plug into a VAR to show that an increase in uncertainty generates significantly negative, persistent responses of real GDP, consumption, and investment. Then, they build up a new Keynesian model with financial frictions related to the construction of a portfolio of equity and long-term government bonds. They show that the imperfect substitutability between these two assets generates a "portfolio effect" that acts as a multiplier of the real effects of fiscal uncertainty shocks.

An event that has attracted a lot of attention is the Brexit referendum held in June 2018 and the uncertainty injected in the UK system and at a global level by UK's decision to leave the European Union. 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 et al. (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 June 2016 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 et al. (2020) 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. Following Jurado et al.'s (2015) econometric strategy, Redl (2020) 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. Working with text data, Hassan et al. (2020) investigate the propagation of uncertainty shocks at the firm level. They find significant effects on firms in 81 countries, with substantial losses of their market value and a dramatic reduction in their hiring and productive investment. Finally, it is worth noting that uncertainty can facilitate political reforms that would not otherwise be implemented. Bonfiglioli et al. (2021) exploit exogenous differential variations in countries' exposure to foreign

volatility shocks to identify the causal effects of financial volatility on the adoption of reforms. They find this effect to be positive, i.e., financial uncertainty increases the likelihood of political reforms - namely, an increase in deregulation indices related to a variety of sectors.

3 Uncertainty spillovers and global uncertainty

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.

Before doing so, a note is in order. In dealing with uncertainty spillovers or global uncertainty, one has to take a stand on what is "domestic" and what is "foreign". While conceptually this separation is neat, empirically it is very tricky. For instance, are measures of financial volatility in the US - such as the VIX, or the VXO - truly domestic? As a matter of fact, the VIX is often used as a proxy for the global financial cycle or the global risk appetite (see, e.g., Miranda-Agrippino and Rey (2020)). Moreover, the VIX has a correlation of 0.86 with the global financial uncertainty index recently put forth by Caggiano and Castelnuovo (2022). The difficulty of drawing a line in today's financial environment that is characterized by a variety of interconnections among different stock markets worldwide is tangible. Hence, while below some papers are classified as dealing with uncertainty spillovers and others as focusing on global uncertainty, in light of the correlations discusses above, one should take such classifications with a grain of salt. With this caveat in mind, we now turn to uncertainty spillovers.

3.1 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 et al. (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 et al. (2020a) 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 et al. (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 et al. (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. Liu and Sheng (2019) build a measure of US macroeconomic uncertainty by exploiting the information contained in the forecasts collected by the survey of professional forecasters. A VAR analysis points to a significant spillover effect going from US uncertainty to real GDP (which responds negatively to jumps in US uncertainty) in Brazil, Russia, India, and China.

Fernández-Villaverde et al. (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 indi-

cated above (although their estimates point to a milder response of real activity than the one documented in Fernández-Villaverde et al. (2011)). Mumtaz and Theodoridis (2015) 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. Using Australia as a case-study, Tran (2021) investigates the real effects of commodity price uncertainty (related to China's shifting demand of commodities). His VAR analysis reveals that commodity price uncertainty exerts a larger business cycle effect than financial, economic, and trade policy uncertainties. He interprets the effects of commodity price uncertainty via a nonlinear medium-scale new Keynesian model which allows for household's precautionary savings.

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 et al. (2020) 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 et al. (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.

3.2 Global uncertainty

A related strand of the literature has recently investigated the macroeconomic consequences of shocks to global uncertainty. Figure 2 plots three measures of global uncertainty, i.e., the global economic policy uncertainty (GEPU) measure proposed by Baker et al. (2016) and Davis (2016); the global financial uncertainty (GFU) measure recently proposed by Caggiano and Castelnuovo (2022); and the trade policy uncertainty (TPU) measure proposed by Caldara et al. (2020). These three measures display interesting heterogeneities. For instance, the global peak of GFU materializes in correspondence of the Great Recession, and its second spike is clearly related to the advent of the COVID-19 pandemic. A "reverse ordering" between these two events is signalled by GEPU, whose global peak clearly corresponds to the early phase of the pandemic. Quite interestingly, the TPU index does not move much during the Great Recession, but increases in association with the Trump election and massively increases in correspondence of the US-China trade war and then during the pandemic.

These and other indices of global uncertainty have been employed to gauge the global effects of uncertainty shocks. Ahir et al. (2022) propose a world uncertainty index (WUI) based on the machine-driven reading of the Economist Intelligence Unit country reports. They find a jump in WUI equal to a 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 (2022) 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).

Berger et al. (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 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 et al. (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. Dibiasi and Sarferaz (2020) carefully work with initial releases and final estimates of macroeconomic indicators to estimate the conditional volatility of the error corresponding to the unpredictable part of revisions in GDP growth for 39 countries. Weighting country-specific uncertainty estimates, they then construct a measures of global uncertainty. Working with country-specific VARs as well as a VAR for the G7 aggregate, they show that unexpected changes in their uncertainty measures are (temporarily) recessionary. Then, they use their newly created international set of indicators to investigate the role of labor adjustment costs in transmitting uncertainty shocks. They do so by splitting the set of countries in their dataset into countries characterized by a high employment protection legislation and countries that feature a low employment protection legislation. Working again with a VAR analysis, they show that the degree of labor protection plays a crucial role for the real effects for uncertainty shocks, with a larger real effect recorded for the countries affected by a higher employment protection. Working with differently calibrated versions of Bloom et al.'s (2018) model - the crucially calibrated parameter being that regulating firing costs, which they take as a proxy for the costs related to employment protection - they show that such a framework is able to rationalize their empirical findings.

Mumtaz and Theodoridis (2017) 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 uncer-

tainty 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 et al. (2019b) 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 et al. (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. Ozturk and Sheng (2018) employ Consensus Forecast data over the period 1989-2014 to construct measures of macroeconomic uncertainty for 45 countries. A weighted average of such country-specific uncertainty indicators is then interpreted as global uncertainty. Common uncertainty shocks produce the large and persistent negative response in real economic activity, whereas the contributions of idiosyncratic uncertainty shocks is found to be negligible. Working with a large-scale Bayesian VAR model with factor stochastic volatility and volatility-in-mean effects, Cuaresma et al. (2019) investigate to what extent global uncertainty shocks are a driver of business cycle fluctuations in G7 countries. They find shocks to their indicator of global uncertainty - which is strongly connected to global equity price volatility - to be behind part of the business cycle fluctuations in the countries considered in their study.

Caggiano and Castelnuovo (2022) propose a new index of global financial uncertainty (GFU) by modeling monthly volatilities of stock market returns, exchange rate returns, and long-term government bond yields of 42 countries for the 1992-2019 sample with a dynamic factor framework à la Moench et al. (2013) that controls for regional and country-specific effects. The GFU index is found to spike in correspondence of well identified episodes of global financial markets turmoil. Then, Caggiano and Casteln-

uovo (2022) run a VAR analysis jointly modeling the GFU index and state-of-the-art measures of global financial cycle and global industrial production. GFU shocks are identified with a novel combination of narrative, ratio, and sign restrictions. Their VAR suggests that the cumulative world output loss recorded during and after the global financial crisis would have been 20% lower in absence of GFU shocks. Bonciani and Ricci (2020) 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 (2021) 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 et al. (2020a) 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. Carriero et al. (2019b) estimated a sophisticated multivariate model with stochastic volatility that allows for a common component of the conditional variance of the modeled series. They model inflation of 20 industrialized countries, and find substantial commonality in the inflation volatilities, which has increased in the last two decades. They point to Chinese PPI and oil inflation as the two major drivers of this commonality since the early '90s.

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 et al. (2020) 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 Uncertainty and COVID-19

The advent of COVID-19 has brought along a huge uncertainty on the economic outlook of a variety of countries, as displayed in Figure 2 and already documented by the literature (see Dietrich et al. (2020), Baker et al. (2020c), Ludvigson et al. (2021a), and Meyer et al. (2022)). But how large are the consequences of the COVID-19-related uncertainty from a business cycle standpoint? This Section offers short summaries on selected contributions.

Working with an interacted VAR à la Pellegrino (2021), Pellegrino et al. (2021) model Euro area aggregates allowing for the impact of uncertainty shocks to depend on the state of the average outlook for the economy measured by survey data. They find the recessionary and deflationary impact of uncertainty shocks on real activity to be three times larger during pessimistic times. Then, they used the estimated IVAR to

simulate the business cycle impact of a sequence of uncertainty shocks that replicates the increase in the observed VSTOXX - an index of implied financial volatility - since the beginning of the COVID-19 pandemic in February 2020. Their analysis predicts industrial production to drop about 9.2% (on an yearly basis) in the fourth quarter of 2020. This huge drop is due to the combination of a very large uncertainty shock and a very negative economic outlook. As far as policy is concerned, their findings speak in favor of the unprecedented fiscal and monetary policy responses to the pandemic. From a normative standpoint, policymakers should communicate as clearly as possible in order to boost confidence and ensure that extraordinary measures are taken when rare negative events take place.

Altig et al. (2021a) analyze a variety of economic uncertainty indicators for the United States and the United Kingdom before and during the COVID-19 pandemic. In spite of the very different nature of such indicators (implied stock market volatility, EPU à la Baker et al. (2016), indicators based on Twitter data, subjective uncertainty about business growth, disagreement among forecasters on future GDP growth, and an estimated measure of macro uncertainty based on a forecasting framework), all of them point to a spectacular jump in uncertainty during the pandemic, with many of them recording their global peak values conditional on the available data (although the growth rate of such indicators differs greatly from one to another). Financial indicators responded more quickly and temporarily, while broader measures of uncertainty responded less rapidly but more persistently. Running recursive VARs, the authors document a dramatic fall in industrial production (ranging between 12% to 19%) in response to a jump in uncertainty comparable in size to the one observed at the beginning of the pandemic. A similar strategy is followed by Gieseck and Rujin (2020), who find that the uncertainty shock due to COVID-19 could be responsible for dampening the expected rebound in activity in the Euro area by a cumulative 5% until mid-2021. Caggiano et al. (2020b) estimate a tri-variate VAR that models the world industrial production measure proposed by the OECD and updated by Baumeister and Hamilton (2019), the global financial cycle measure put forth by Miranda-Agrippino and Rey (2020), and the VIX as a proxy for global financial uncertainty. Then, they simulate the response of world industrial production to a jump in uncertainty similar in size to the one observed in the data in March 2020. They estimate the cumulative world industrial production loss over one year to be equal to 14%. These dramatic figures are confirmed by the VAR analysis by Baker et al. (2020a), which is based on the VAR estimated by Baker et al. (2020b) on quarterly data for 38 countries for the period 1987-2017.

After documenting the skyrocketing uncertainty affecting the US economy right after the materialization of the pandemic according to a variety of indicators, they work with the above-mentioned VAR and calibrate the uncertainty shock to replicate the dynamics of stock market volatility observed during the first months of the pandemic. Their estimated 90% confidence interval points to the possibility of a 20 percent year-on-year contraction of the US real GDP.

Miescu and Rossi (2021) identify a COVID-19 shock by extracting it from a VAR analysis conducted with a selection of the daily data available in the dataset put together by Chetty et al. (2021). In particular, they work with information around days characterized by large jumps in financial markets directly due to COVID-19-related news and announcements as categorized by Baker et al. (2021) and major national newspapers. What they find is that around these days economic volatility is significantly higher than the one recorded in non-event days, a difference that they attribute to a single shock termed "COVID-19-induced shock". Digging deeper, they show that this shock can structurally be interpreted as an uncertainty shock, which is further shown to be recessionary.

Carriero et al. (2020b) build on Carriero et al. (2018) and estimate a VAR that allows for heteroskedasticity and in which the volatilities of the error terms share two common factors - which the authors interpret as macroeconomic uncertainty and financial uncertainty - on top of idiosyncratic components. Importantly, their machinery allows both types of uncertainty to exert a contemporaneous impact on the real and financial cycles. One of the versions of the framework they propose is specifically designed to accommodate for the abrupt changes in the volatility of several indicators they model due to the pandemic. In particular, they allow for outliers in volatility to control for the impact of such extreme observations. Carriero et al. (2020b) confirm that both macroeconomic and financial uncertainty reached unprecedented levels during the COVID-19 pandemic, and such a large increase of uncertainty contributed to the recession. However, they also point out that such a contribution is estimated to be small compared to the overall deterioration of the macro-financial conditions.

A natural question about the uncertainty triggered by the pandemic is on the future of work. Leduc and Liu (2020a) notice that, while humans are susceptible to the virus, robots are not. Hence, all else being equal, firms could have an incentive to switch to more automated processes to reduce the risk of running periods of low productivity due to the infection of part of their employees. On the other hand, uncertainty reduces aggregate demand and negatively affects the returns from capital, therefore reducing the

value of new investment in automation. Leduc and Liu (2020a) investigate this tension with a new-Keynesian DSGE framework in which firms have to decide if to adopt a robot to perform a set of tasks - only non-automated tasks translate into vacancies for hiring workers. In this sense, robots represent a labor-substituting technology. They find that job uncertainty stimulates automation, which mitigates the negative effects of increased uncertainty on real activity. From a policy standpoint, uncertainty-driven automation is deflationary and associated to a deterioration of employment in their model, a prediction in line with their previous VAR analysis (Leduc and Liu (2016), Leduc and Liu (2020b)).

Finally, an interesting question raised by the advent of the COVID-19 pandemic regards supply chains. In general, being part of the global value chain can be a way to deal with uncertainty and reduce external risks (for an analysis focused on Chinese export firms, see Wang et al. (2022)). However, the difficulty of finding a wide range of goods going from the more obvious ones (hand sanitizers) to the slightly less obvious ones (toilet paper) during different phases of the pandemic has unveiled the fragility of the current structure of the supply chains in presence of an aggregate shock. Jiang et al. (2021) investigate the design of a robust global supply chain in presence of uncertainty shocks, where "uncertainty" here refers to the "unknown unknowns", i.e., a situation in which firms do not know the distribution of the shocks they are facing. The investigation is conducted by appealing to a robust control approach in which a min-max strategy is designed for firms to avoid the dramatic scenario of a collapse of the global supply chain. This calls for moving away from the "Just-in-Case" strategies (a competitor of the "Just-in-Time" approach to manage inventories) adopted to reduce the dependency of a firm from suppliers in presence of negative shocks hitting the chain to a novel "Just-in-Worst-Case" approach where the uncertainty surrounding suppliers' ability to provide goods leads a firm to dramatically change its decisions regarding the supply chain it refers to (e.g., via a drastically different choice of the geographical location of the suppliers). Interestingly, Jiang et al.'s (2021) model replicates the probability matching behavior predicted by evolutionary psychology models where foraging species allocate resources to maximize their survival probability while reducing that of competing species to grab their resources. Further discussions on the role of risk for the design of global supply chains are contained in Baldwin and Freeman (2021).

5 Conclusions and avenues for future research

This survey has reviewed the most recent empirical research on the role of domestic uncertainty, global uncertainty, and the uncertainty induced by the COVID-19 pandemic. 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 presented some of the contributions on the macroeconomic and financial effects of the COVID-19 pandemic shock.

In closing his survey, Bloom (2014) wrote: *"[...] there is still much about uncertainty about which we remain uncertain."* Since then, the profession has made huge steps in terms of understanding the uncertainty-business/financial cycles connections, and this survey has been at attempt to acknowledge these advances. At the same time, much is still to be learned. Many areas represent fruitful avenues for future research. Let us provide a few instances.

Sectoral uncertainty. Recent contributions have tried to isolate the role of sectoral uncertainty to have a better understanding on which sectors are mostly responsible for the negative business cycle effects of uncertainty shocks. Segal (2019) constructs measures of TFP volatility for the consumption and investment sectors. He shows that the former is associated with a bust in real activity, while the latter with a boom. He proposes a quantitative two-sector DSGE framework that features sticky prices and Epstein-Zin preferences. His model is able to replicate his stylized facts: consumption volatility brings real activity (consumption and investment) down due to precautionary savings, which weaken aggregate demand and - in his demand-driven economy - output. Differently, investment volatility incentivizes firms to cumulate capital and create a buffer to smooth consumption and investment spending in case negative TPF shocks realize. Ma and Samaniego (2019) work with firm-level forecast errors on earnings-per-share to construct measures of aggregate and sectoral-specific uncertainty. They find that industry uncertainty measures share of common factor that closely follows aggregate uncertainty, while also containing sector-specific information. Uncertainty measured among financial firms is documented to have greater economic impact that uncertainty coming from non-financial sectors. Castelnuovo et al. (2021) employ data on industrial production coming from a variety of production sectors in the US to estimate a hierarchical model with stochastic volatility that allows for a common component as well as sector-specific ones. They document that different sectors (in particular,

durables and nondurables) experience a somewhat different evolution of uncertainty over time. Moreover, a VAR exercise in which they control for aggregate uncertainty reveals that while a shock to the level of uncertainty affecting durables is recessionary, an uncertainty shock to nondurables is found to be expansionary. These findings point to the importance of working with sectoral data to understand the different dynamics triggered by uncertainty shocks in different sectors (characterized, for instance, by different non-convex adjustment costs).

Accounting for indicator-specific uncertainty also seems to be relevant. Jo and Sekkel (2019) work with survey forecasts on the US economy and show that an uncertainty measure extracted as a common component from a factor stochastic volatility model peaks in correspondence of three big recessions (1973-1975, 1980, and 2007-2009). Differently, other recessions are characterized by increases in indicator-specific uncertainties. Sectoral data can represent a precious source of information to dig deeper and gain a better understanding on the channels responsible of the transmission of uncertainty shocks to the real economy.

Vulnerable growth. Recent papers have advanced the idea that uncertainty shocks may have nonlinear effects on the business cycle. As discussed in the text, to our knowledge this has first been shown by Caggiano et al. (2014) conditional on the state of the business cycle (an uncertainty shock exerts stronger real effects when the economy is in a recession); by Caggiano et al. (2017b) conditional on the monetary policy regime in place (uncertainty shocks have a more severe impact on real activity when the zero lower bound is binding); and by Alessandri and Mumtaz (2019) conditional on the financial cycle (the real effects of uncertainty shocks are stronger in presence of financial stress). A nascent strand of the literature has extended these nonlinear investigations to the "growth-at-risk" literature (Adrian et al. (2019)). Hengge (2019) shows that, when adding uncertainty to predictive quantile regression for the growth rate of output that feature financial conditions as covariate, macroeconomic uncertainty turns out to be a significant regressor of the left-tail of the GDP growth conditional density. Moreover, macroeconomic uncertainty is found to carry a larger weight than financial conditions in the optimal predictive density, a result that holds true for a large sample of countries. Jovanovic and Ma (2022) document similar empirical evidence for the United States, and interpret it via a microfounded framework in which rapid adoption of new technology may generate higher economic uncertainty and cause a decline in productivity. Forni et al. (2021a) combine a quantile regressions approach with a VAR approach to study the effects of "good" uncertainty (characterized as the uncertainty related to quantiles of the

conditional density of real activity over the median) and "bad" uncertainty (captured by quantiles of the conditional density of real activity below the median). They find shocks to bad uncertainty to be recessionary, while those to good uncertainty are documented to be mildly expansionary. Castelnuovo and Mori (2022) work with a mixed-frequency quantile regressions approach and predict the conditional density of real GDP growth with monthly data on financial conditions. They show that measures of uncertainty and skewness derived from selected quantiles of such a conditional density (an approach recently implemented by, e.g., Salgado et al. (2019) and Forni et al. (2021a)) may significantly differ from those derived from a conditional density estimated only with quarterly data. These difference have implications for the computation of the impulse responses to uncertainty and skewness shocks, with the impact of uncertainty (skewness) shocks that turns out to be underestimated (overestimated) if monthly information of financial conditions in not taken into account when predicting the conditional density of output growth. A paper offering a unifying framework to study tail risks, first-moment shocks, and uncertainty is Caldara et al. (2021a). The link between nonlinear effects of uncertainty shocks and growth-at-risk appears to be a promising research avenue.

Optimal policies. The optimal response to uncertainty shocks is still to be identified from a theoretical standpoint. 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. Obviously, the answer on how to optimally tackle the macroeconomic effects of uncertainty shocks may also depend on the underlying drivers of uncertainty and the type of uncertainty faced by policymakers. What is driving uncertainty? Is fiscal policy uncertainty the main driver of the business cycle? Are central banks reducing or increasing uncertainty with their communications? Is macroeconomic uncertainty one of the main drivers of the business cycle? Or is financial uncertainty behind swings in real GDP, consumption, investment, unemployment? Is uncertainty a demand shock or a supply shock? How does inflation respond to uncertainty shocks? Addressing these questions is crucial for the optimal design of macroeconomic policies aiming at reducing inefficient business cycle fluctuations due to uncertainty shocks.

Some researchers have already tried to tackle the question concerning the design of an optimal macroeconomic policy in presence of uncertainty. Basu and Bundick (2017) show that, in a new-Keynesian framework with time-varying volatility affecting households' discount factor, a central bank tracking the natural real interest rate is able to restore the efficient allocation of resources because it "kills" the countercyclical

markup mechanism behind the recessionary effects of uncertainty shocks. This result is confirmed by simulations conducted by Pellegrino et al. (2022) in a model estimated to replicate the recessionary effects induced by the large jump in uncertainty materialized in the US during the Great Recession. Cho et al. (2021) show that such a result can also be obtained via a Taylor rule that features an extremely aggressive systematic policy response to fluctuations in inflation. The common intuition behind the results documented in these three papers is that monetary policy can "kill" firms' precautionary pricing incentive and shut down the countercyclical markup channel responsible for the inefficient allocation of resources after an uncertainty shock. Cho and Oh (2021) show that identifying the source of the uncertainty shock is crucial to optimally design monetary policy. If the uncertainty shock regards future productivity, optimal monetary policy can achieve the joint stabilization of inflation and the output gap. Differently, a cost-push uncertainty shock implies a trade-off between stabilizing inflation and real activity. Favara et al. (2021) exploit the staggered introduction of anti-recharacterization laws (i.e., laws that strengthened creditors' rights to repossess collateral allocated to special purpose vehicles) in US states to assess if better access to debt markets can mitigate the effects of uncertainty on corporate policies. They find a positive answer, i.e., firms that face more uncertainty after the passage of the law are found to hoard less cash and increase payouts, leverage, and investment in intangible assets. Their findings point to the desirability of policies designed facilitate firms' access to debt markets, something that could shield themselves against fluctuations in uncertainty and foster investment in intangible capital. Gross and Hansen (2021) analytically derive an n-order accurate approximation of optimal policy for a wide class of nonlinear DSGE frameworks that seems to be promising for studying the optimal monetary and fiscal policy response to various types of uncertainty shocks.

Climate change uncertainty. The IMF identifies "three Cs" currently injecting uncertainty in the economic systems around the globe: COVID-19, cryptocurrencies, and climate change (International Monetary Fund (2021)). Focusing on the latter, climate-related risks are particularly difficult to assess because their probability to occur is not necessarily well reflected in past data. Moreover, there is substantial uncertainty on the magnitude of their impact at a global level, and on the "if" and "when" on the possible materialization of tail risks. How relevant is climate change uncertainty? This is a nascent literature that has already produced interesting research. First off, it is important to stress that climate change uncertainty is relevant in this context on top of the effects caused by an increase in the level of the global temperature. Alessandri

and Mumtaz (2021) estimate a panel VAR with stochastic volatility for 133 countries between 1961 and 2005. They find the ex-ante temperature risk (i.e., the volatility of the residual component of annual temperatures that cannot be predicted via past data) to have increased steadily over time in all regions in their dataset. Moreover, they show that this risk matters from a macroeconomic standpoint. Controlling for the level of the temperature, an increase of one degree (Celsius) of the latter's volatility is found to be responsible of an average drop in real GDP growth of 0.9 percent, and an increase in the volatility of real GDP growth of 1.3 percent. Turning to policy, Fried et al. (2021) investigate the consequences of having uncertainty surrounding the imposition of a carbon tax in the future. They do so by developing a model characterized by agents investing in long-lived, sector-specific assets (coal power plants, wind farms). Inference on firms' beliefs about the probability of a future carbon tax is conducted by using data on observed internal carbon prices, i.e., carbon prices levied by firms on themselves. The main findings are the following: i) climate policy risk induces firms to tilt their investment portfolio towards cleaner technologies, which also implies a lower level of investment overall; ii) the consequent reduction in emission due to the risk of facing an (uncertain) future carbon tax is far from negligible. Hence, ignoring climate policy risk when modeling the climate change effects on investment may lead to overstate welfare costs and emissions reductions related to the actual implementation of a carbon tax policy. Following the strategy popularized by Baker et al. (2016), Gavriilidis (2021) builds up an index of climate policy uncertainty (CPU) by relying on the frequency of articles in eight major newspapers in the US reporting climate change-related keywords. He shows that such index correlates with well-known events related to climate policy (e.g., policymakers' speeches about climate change or decisions related to carbon taxes). Then, he runs a VAR analysis and shows that unexpected changes in CPU are correlated with changes in carbon dioxide emissions.

There is still much about uncertainty about which we remain uncertain. The research agenda on uncertainty will certainly be an exciting ones for many years to come.

References

Aastveit, K. A., Natvik, G. J., and Sola, S. (2017). Economic uncertainty and the influence of monetary policy. *Journal of International Money and Finance*, 76:50–67.

Abberger, K., Dibiasi, A., Siegenthaler, M., and Sturm, J.-E. (2018). The effects of policy uncertainty on investment: Evidence from the unexpected acceptance of a far-reaching referendum in switzerland. *European Economic Review*, 104:38–67.

Adrian, T., Boyarchenko, N., and Giannone, D. (2019). Vulnerable growth. *American Economic Review*, 109(4):1263–1289.

Ahir, H., Bloom, N., and Furceri, D. (2019). Caution: Trade uncertainty is rising and can harm the global economy. available at https://voxeu.org/article/trade-uncertainty-rising-and-can-harm-global-economy.

Ahir, H., Bloom, N., and Furceri, D. (2022). The world uncertainty index. National Bureau of Economic Reserach Working Paper No. 29763.

Alessandri, P. and Bottero, M. (2020). Bank lending in uncertain times. *European Economic Review*, 128(103503).

Alessandri, P., Gazzani, A., and Vicondoa, A. (2020). Uncertainty matters: evidence from a high-frequency identification strategy. Bank of Italy Working Paper No. 1284.

Alessandri, P. and Mumtaz, H. (2019). Financial regimes and uncertainty shocks. *Journal of Monetary Economics*, 101:31–46.

Alessandri, P. and Mumtaz, H. (2021). The macroeconomic cost of climate volatility. available at https://sites.google.com/site/hmumtaz77/.

Alexopoulos, M. and Cohen, J. (2015). The power of print: Uncertainty shocks, markets, and the economy. *International Review of Economics and Finance*, 40(C):8–28.

Alfaro, I., Bloom, N., and Lin, X. (2019). The finance uncertainty multiplier. available at https://nbloom.people.stanford.edu/research.

Alloza, M. (2018). Is fiscal policy more effective in uncertain times or during recessions? Banco de España Working Paper No. 1730.

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., Davis, S. J., Leather, J., Meyer, B., Mihaylov, E., Mizen, P., Parker, N., Renault, T., Smietanka, P., and Thwaites, G. (2021a). Economic uncertainty before and during the covid-19 pandemic. *Journal of Public Economics*, 191(104274).

Altig, D., Barrero, J. M., Bloom, N., Davis, S. J., Meyer, B., and Parker, N. (2021b). Surveying business uncertainty. *Journal of Econometrics*, forthcoming.

Andreasen, M., Caggiano, G., Castelnuovo, E., and Pellegrino, G. (2021). Why does risk matter more in recessions than in expansions? University of Padova Working Paper No. 275.

Angelini, G., Bacchiocchi, E., Caggiano, G., and Fanelli, L. (2019). Uncertainty across volatility regimes. *Journal of Applied Econometrics*, 34(3):437–455.

Angelini, G., Costantini, M., and Easaw, J. (2018). Uncertainty and spillover effects across the euro area. Cardiff Economics Working Paper E2018/15.

Angelini, G. and Fanelli, L. (2019). Exogenous uncertainty and the identification of structural vector autoregressions with external instruments. *Journal of Applied Econometrics*, 34(6):951–971.

Antolín-Díaz, J. and Rubio-Ramírez, J. F. (2018). Narrative sign restrictions. *American Economic Review*, 108(10):2802–2829.

Anzuini, A., Rossi, L., and Tommasino, P. (2017). Fiscal policy uncertainty and the business cycle: Time series evidence from italy. Bank of Italy Working Paper No. 1151.

Arellano, C., Bai, Y., and Kehoe, P. J. (2019). Financial markets and fluctuation in volatility. *Journal of Political Economy*, 127(5):2049–2103.

Ascari, G., Castelnuovo, E., and Rossi, L. (2011). Calvo vs. rotemberg in a trend inflation world: An empirical investigation. *Journal of Economic Dynamics and Control*, 35:1852–1867.

Auerbach, A. and Gorodnichenko, Y. (2012). Measuring the output responses to fiscal policy. *American Economic Journal: Economic Policy*, 4(2):1–27.

Auerbach, A. and Gorodnichenko, Y. (2013). Output spillovers from fiscal policy. *American Economic Review Papers and Proceedings*, 103(3):141–146.

Bacchiocchi, E., Castelnuovo, E., and Fanelli, L. (2018). Gimme a break! identification and estimation of the macroeconomic effects of monetary policy shocks in the u.s. *Macroeconomic Dynamics*, 22(6):1613–1651.

Bacchiocchi, E. and Fanelli, L. (2015). Identification in structural vector autoregressive models with structural changes with an application to u.s. monetary policy. *Oxford Bulletin of Economics and Statistics*, 77(6):761–779.

Bachmann, R. and Bayer, C. (2013). "wait-and-see" business cycles. *Journal of Monetary Economics*, 60(6):704–719.

Bachmann, R., Carstensen, K., Lautenbacher, S., , and Schneider, M. (2021). Uncertainty and change: Survey evidence of firms' subjective beliefs. NBER Working Paper No. 29430.

Bachmann, R., Elstner, S., and Sims, E. (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics*, 5(2):217–249.

Bachmann, R. and Moscarini, G. (2012). Business cycles and endogenous uncertainty. RWTH Aachen University and Yale University, mimeo.

Bachmann, R. and Sims, E. (2012). Confidence and the transmission of government spending shocks. *Journal of Monetary Economics*, 59(3):235–249.

Baker, S., Bloom, N., Davis, S., and Sammon, M. (2021). What triggers stock market jumps? NBER Working Paper No. 28687.

Baker, S., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131(4):1539–1636.

Baker, S., Bloom, N., Davis, S. J., and Kost, K. J. (2019). Policy news and stock market volatility. NBER Working Paper No. 25720.

Baker, S., Bloom, N., Davis, S. J., and Terry, S. J. (2020a). Covid-induced economic uncertainty. available at https://nbloom.people.stanford.edu/.

Baker, S., Bloom, N., and Terry, S. J. (2020b). Using disasters to estimate the impact of uncertainty. available at https://nbloom.people.stanford.edu/research.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., and Viratyosin, T. (2020c). The unprecedented stock market reaction to covid-19. available at https://nbloom.people.stanford.edu/research.

Baldwin, R. and Freeman, R. (2021). Risks and global supply chains: What we know and what we need to know. NBER Working Paper No. 29444.

Baley, I. and Blanco, J. A. (2019). Firm uncertainty cycles and the propagation of nominal shocks. *American Economic Journal: Macroeconomics*, 11(1):276–337.

Baley, I., Veldkamp, L., and Waugh, M. E. (2020). Can global uncertainty promote international trade? *Journal of International Economics*, 126(103347).

Basu, S. and Bundick, B. (2015). Endogenous volatility at the zero lower bound: Implications for stabilization policy. Federal Reserve Bank of Kansas City Research Working Paper No. 15-01.

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

Baumeister, C. and Hamilton, J. D. (2019). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. *American Economic Review*, 109(5):1873–1910.

Bekaert, G., Engstrom, E., and Xu, N. R. (2021). The time variation in risk appetite and uncertainty. *Management Science*, forthcoming.

Bekaert, G., Hoerova, M., and Lo Duca, M. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, 60:771–788.

Belianska, A., Eyquem, A., and Poilly, C. (2021). The transmission channels of government spending uncertainty. Aix-Marseille University, mimeo.

Benati, L. (2019). Economic policy uncertainty, the great recession, and the great depression. University of Bern, mimeo.

Benigno, G., Benigno, P., and Nisticò, S. (2012). Risk, monetary policy and the exchange rate. in D. Acemoglu and M. Woodford (eds.): NBER Macroeconomics Annual, vol. 26, University of Chicago Press:247–309.

Berger, D., Dew-Becker, I., and Giglio, S. (2020). Uncertainty shocks as second-moment news shocks. *Review of Economic Studies*, 87:40–76.

Berger, D. and Vavra, J. (2019). Shocks versus responsiveness: What drives time-varying dispersion? *Journal of Political Economy*, 127(5):2104–2142.

Berger, T., Grabert, S., and Kempa, B. (2016). Global and country-specific output growth uncertainty and macroeconomic performance. *Oxford Bulletin of Economics and Statistics*, 78(5):694–716.

Berger, T., Grabert, S., and Kempa, B. (2017). Global macroeconomic uncertainty. *Journal of Macroeconomics*, 53(C):42–56.

Bhattarai, S., Chatterjee, A., and Park, W. Y. (2020). Global spillover effects of us uncertainty. *Journal of Monetary Economics*, 114:71–89.

Bianchi, F., Ilut, C., and Schneider, M. (2018). Uncertainty shocks, asset supply and pricing over the business cycle. *Review of Economic Studies*, 85(2):810–854.

Bianchi, F., Kung, H., and Tirskikh, M. (2019). The origins and effects of macro-economic uncertainty. Duke University and London Business School, available at https://sites.google.com/view/francescobianchi/home.

Binding, G. and Dibiasi, A. (2017). Exchange rate uncertainty and firm investment plans: Evidence from swiss survey data. *Journal of Macroeconomics*, 51:1–27.

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

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, 28(2):153–176.

Bloom, N. (2017). Observations on uncertainty. *Australian Economic Review*, 50(1):79–84.

Bloom, N., Bunn, P., Chen, S., Mizen, P., Smietanka, P., and Thwaites, G. (2019). The impact of brexit on uk firms. NBER Working Paper No. 26218.

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

Bonciani, D. and Oh, J. (2020). The long-run effects of uncertainty shocks. Bank of England Staff Working Paper No. 802.

Bonciani, D. and Oh, J. (2021). Unemployment risk, liquidity traps, and monetary policy. available at https://sites.google.com/view/joonseokoh/.

Bonciani, D. and Ricci, M. (2020). The international effects of global financial uncertainty shocks. *Journal of International Money and Finance*, 109(102236).

Bonciani, D. and van Roye, B. (2016). Uncertainty shocks, banking frictions, and economic activity. *Journal of Economic Dynamics and Control*, 73:200–219.

Bonfiglioli, A., Crinò, R., and Gancia, G. (2021). Economic uncertainty and structural reforms: Evidence from stock market volatility. *Quantitative Economics*, forthcoming.

Bontempi, M. E., Frigeri, M., Golinelli, R., and Squadrani, M. (2021). Eurq: A new web search-based uncertainty index. *Economica*, 88(352):969–1015.

Bordo, M. D., Duca, J. V., and Koch, C. (2016). Economic policy uncertainty and the credit channel: Aggregate and bank level u.s. evidence over several decades. *Journal of Financial Stability*, 26:90–106.

Born, B., Müller, G. J., Schularick, M., and Sedlacek, P. (2020). The costs of economic nationalism: Evidence from the brexit experiment. *Economic Journal*, 129(623):2722–2744.

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

Born, B. and Pfeifer, J. (2014b). Risk matters: The real effects of volatility shocks: Comment. *American Economic Review*, 104(12):4231–4239.

Born, B. and Pfeifer, J. (2021). Uncertainty-driven business cycles: assessing the markup channel. *Quantitative Economics*, 12(2):587–623.

Brand, T., Isoré, M., and Tripier, F. (2019). Uncertainty shocks and firm creation: Search and monitoring in the credit market. *Journal of Economic Dynamics and Control*, 99:19–53.

Bretscher, L., Hsu, A., and Tamoni, A. (2018). Risk aversion and the response of the macroeconomy to uncertainty shocks. London Business School, Georgia University of Technology, and London School of Economics, mimeo.

Brianti, M. (2020). Financial shocks, uncertainty shocks, and monetary policy trade-offs. available at https://sites.google.com/site/marcobrianticeconomics/.

Bundick, B., Herriford, T., and Smith, A. L. (2017). Forward guidance, monetary policy uncertainty, and the term premium. Federal Reserve Bank of Kansas City Working Paper No. 17-07.

Cacciatore, M. and Ravenna, F. (2021). Uncertainty, wages, and the business cycle. *Economic Journal*, 131(639):2792–2823.

Caggiano, G. and Castelnuovo, E. (2022). Global uncertainty. Monash University and University of Padova, mimeo.

Caggiano, G., Castelnuovo, E., Colombo, V., and Nodari, G. (2015). Estimating fiscal multipliers: News from a nonlinear world. *Economic Journal*, 125(584):746–776.

Caggiano, G., Castelnuovo, E., Delrio, S., and Kima, R. (2021a). Financial uncertainty and real activity: The good, the bad, and the ugly. *European Economic Review*, 136(103750).

Caggiano, G., Castelnuovo, E., and Figueres, J. M. (2017a). Economic policy uncertainty and unemployment in the united states: A nonlinear approach. *Economics Letters*, 151:31–34.

Caggiano, G., Castelnuovo, E., and Figueres, J. M. (2020a). Economic policy uncertainty spillovers in booms and busts. *Oxford Bulletin of Economics and Statistics*, 82(1):125–155.

Caggiano, G., Castelnuovo, E., and Groshenny, N. (2014). Uncertainty shocks and unemployment dynamics: An analysis of post-wwii u.s. recessions. *Journal of Monetary Economics*, 67:78–92.

Caggiano, G., Castelnuovo, E., and Kima, R. (2020b). The global effects of covid-19-induced uncertainty. *Economics Letters*, 194(109392).

Caggiano, G., Castelnuovo, E., and Nodari, G. (2018). Risk management-driven policy rate gap. *Economics Letters*, 171:235–238.

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

Caggiano, G., Castelnuovo, E., and Pellegrino, G. (2017b). Estimating the real effects of uncertainty shocks at the zero lower bound. *European Economic Review*, 100:257–272.

Caggiano, G., Castelnuovo, E., and Pellegrino, G. (2021b). Uncertainty shocks and the great recession: Nonlinearities matter. *Economics Letters*, 198(109669).

Caldara, D., Cascaldi-Garcia, D., Cuba-Borda, P., and Loria, F. (2021a). Understanding growth-at-risk: A markov-switching approach. Federal Reserve Board, mimeo.

Caldara, D., Fuentes-Albero, C., Gilchrist, S., and Zakrajšek, E. (2016). The macroeconomic impact of financial and uncertainty shocks. *European Economic Review*, 88:185–207.

Caldara, D. and Herbst, E. (2018). Monetary policy, real activity, and credit spreads: Evidence from bayesian proxy svar. *American Economic Journal: Macroeconomics*, 11(1):157–192.

Caldara, D. and Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, 112(4):1194–1225.

Caldara, D., Iacoviello, M., Molligo, P., Prestipino, A., and Raffo, A. (2020). The economic effects of trade policy uncertainty. *Journal of Monetary Economics*, 103:38–59.

Caldara, D., Scotti, C., and Zong, M. (2021b). Macroeconomic and financial risks: A tale of mean and volatility. Board of Governors of the Federal Reserve System, International Finance Discussion Papers 1326.

Campbell, J. Y., Lettau, M., Malkiel, B. G., and Xu, Y. (2001). Have individual stocks become more volatile? an empirical exploration of idiosyncratic risk. *Journal of Finance*, 1:1–43.

Canova, F. and Menz, T. (2011). Does money have a role in shaping domestic business cycles? an international investigation. *Journal of Money, Credit and Banking*, 43(4):577–607.

Carlston, B. and Ochoa, M. (2016). Macroeconomic announcements and investor beliefs at the zero lower bound. Board of Governors of the Federal Reserve System, mimeo.

Carrière-Swallow, Y. and Céspedes, L. F. (2013). The impact of uncertainty shocks in emerging economies. *Journal of International Economics*, 90:316–325.

Carriero, A., Clark, T. E., and Marcellino, M. (2018). Measuring uncertainty and its impact on the economy. *Review of Economics and Statistics*, 100(5):799–815.

Carriero, A., Clark, T. E., and Marcellino, M. (2019a). The identifying information in vector autoregressions with time-varying volatilities: An application to endogenous uncertainty. Queen Mary University of London, Federal Reserve Bank of Cleveland, and Bocconi University, mimeo.

Carriero, A., Clark, T. E., and Marcellino, M. (2020a). Assessing international commonality in macroeconomic uncertainty and its effects. *Journal of Applied Econometrics*, 35:273–293.

Carriero, A., Clark, T. E., Marcellino, M., and Mertens, E. (2020b). Measuring uncertainty and its effects in the covid-19 era. Queen Mary - University of London, Federal Reserve Bank of Cleveland, Bocconi University, and Deutsche Bundesbank, mimeo.

Carriero, A., Corsello, F., and Marcellino, M. (2019b). The global component of inflation volatility. CEPR Working Paper No. 13470.

Carriero, A., Mumtaz, H., Theodoridis, K., and Theophilopoulou, A. (2015). The impact of uncertainty shocks under measurement error: A proxy svar approach. *Journal of Money, Credit and Banking*, 47(6):1223–1238.

Casarin, R., Foroni, C., Marcellino, M., and Ravazzolo, F. (2018). Uncertainty through the lenses of a mixed-frequency bayesian panel markov switching model. *Annals of Applied Statistics*, 12(4):2559–2586.

Cascaldi-Garcia, D. and Galvão, A. (2021). News and uncertainty shocks. *Journal of Money, Credit and Banking*, 53(4):779–811.

Cascaldi-Garcia, D., Sarisoy, C., Londono, J. M., Rogers, J., Datta, D., Ferreira, T., Grishchenko, O., Jahan-Parvar, M. R., Loria, F., Ma, S., Rodriguez, M., and Zer, I. (2021). What is certain about uncertainty? *Journal of Economic Literature*, forthcoming.

Castelnuovo, E. (2003). Taylor rules, omitted variables, and interest rate smoothing in the US. *Economics Letters*, 81(1):55–59.

Castelnuovo, E. (2007). Taylor rules and interest rate smoothing in the euro area. *Manchester School*, 75(1):1–16.

Castelnuovo, E. (2012). Estimating the evolution of money's role in the u.s. monetary business cycle. *Journal of Money, Credit and Banking*, 44(1):23–52.

Castelnuovo, E. (2019). Yield curve and financial uncertainty: Evidence based on us data. *Australian Economic Review*, 52(3):323–335.

Castelnuovo, E., Lim, G., and Pellegrino, G. (2017). A short review of the recent literature on uncertainty. *Australian Economic Review*, 50(1):68–78.

Castelnuovo, E. and Mori, L. (2022). Uncertainty, skewness, and the business cycle through the midas lens. University of Padova, mimeo.

Castelnuovo, E. and Nisticò, S. (2010). Stock market conditions and monetary policy in a DSGE model for the u.s. *Journal of Economic Dynamics and Control*, 34(9):1700–1731.

Castelnuovo, E. and Pellegrino, G. (2018). Uncertainty-dependent effects of monetary policy shocks: A new keynesian interpretation. *Journal of Economic Dynamics and Control*, 93:277–296.

Castelnuovo, E. and Tran, T. D. (2017). Google it up! a google trends-based uncertainty index for the united states and australia. *Economics Letters*, 161:149–153.

Castelnuovo, E., Tuzcouglu, K., and Uzeda, L. (2021). Sectoral uncertainty. Bank of Canada and University of Padova, mimeo.

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

Chatterjee, P. (2019a). Asymmetric impact of uncertainty in recessions - are emerging countries more vulnerable? *Studies in Nonlinear Dynamics and Econometrics*, 23(2):1–27.

Chatterjee, P. (2019b). Uncertainty shocks, financial frictions and business cycle asymmetries across countries. University of New South Wales, mimeo.

Chatterjee, P., Gunawan, D., and Kohn, R. (2020). The interaction between credit constraints and uncertainty shocks. University of New South Wales and University of Wollongong, mimeo.

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., and Team, T. O. I. (2021). How did covid-19 and stabilization policies affect spending and employment? a new real-time economic tracker based on private sector data. NBER Working Paper No. 27431.

Cho, D., Han, Y., Oh, J., and Rogantini Picco, A. (2021). Optimal monetary policy and uncertainty shocks. *Journal of Macroeconomics*, 69(103343).

Cho, D. and Oh, J. (2021). The source of uncertainty and optimal monetary policy. available at https://sites.google.com/view/joonseokoh/.

Choi, S., Furceri, D., Huang, Y., and Loungani, P. (2018). Aggregate uncertainty and sectoral productivity growth: The role of credit constraints. *Journal of International Money and Finance*, 88:314–330.

Choi, S. and Yoon, C. (2019). Uncertainty, financial markets, and monetary policy over the last century. Yonsei University Working Paper 2019-142.

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

Clarida, R., Galí, J., and Gertler, M. (2000). Monetary policy rules and macroeconomic stability: Evidence and some theory. *Quarterly Journal of Economics*, 115:147–180.

Clark, T. E., McCracken, M. W., and Mertens, E. (2020). Modeling time-varying uncertainty of multiple-horizon forecast errors. *Review of Economics and Statistics*, 102(1):17–33.

Coibion, O., Georgarakos, D., Gorodnichenko, Y., Kenny, G., and Weber, M. (2021). The effect of macroeconomic uncertainty on household spending. National Bureau of Economic Research Working Paper No. 28625.

Coibion, O. and Gorodnichenko, Y. (2011). Monetary policy, trend inflation and the great moderation: An alternative interpretation. *American Economic Review*, 101:341–370.

Coibion, O. and Gorodnichenko, Y. (2012). Why are target interest rate changes so persistent? *American Economic Journal: Macroeconomics*, 4(4):126–162.

Colombo, V. (2013). Economic policy uncertainty in the us: Does it matter for the euro area? *Economics Letters*, 121(1):39–42.

Colombo, V. and Paccagnini, A. (2021). The asymmetric effects of uncertainty shocks. mimeo.

Constantinescu, I. C., Mattoo, A., and Ruta, M. (2019). Policy uncertainty, trade, and global value chains: Some facts, many questions. World Bank Policy Research Working Paper No. 9048.

Creal, D. D. and Wu, C. (2017). Monetary policy uncertainty and economic fluctuations. *International Economic Review*, 58(4):1317–1354.

Cuaresma, J. C., Huber, F., and Onorante, L. (2019). The macroeconomic effects of international uncertainty. European Central Bank Working Paper No. 2302.

Dahlhaus, T. and Sekhposyan, T. (2020). Survey-based monetary policy uncertainty and itsasymmetric effects. Bank of Canada and University of Austin, Texas, mimeo.

Danielsson, J., Valenzuela, M., and Zer, I. (2018). Learning from history: Volatility and financial crises. *Review of Financial Studies*, 31(7):2774–2805.

Davis, S. J. (2016). An index of global economic policy uncertainty. NBER Working Paper No. 22740.

De Pooter, M., Favara, G., Modugno, M., and Wu, J. (2021). Monetary policy uncertainty and monetary policy surprises. *Journal of International Money and Finance*, 112(102323).

De Santis, R. A. and Van der Veken, W. (2021). Business cycle fluctuations: Financial shocks versus uncertainty shocks. European Central Bank, mimeo.

Debortoli, D., Galí, J., and Gambetti, L. (2019). On the empirical (ir)relevance of the zero lower bound constraint. in: (Eds.) Martin S. Eichenbaum, Erik Hurst, and Jonathan A. Parker, NBER Macroeconomics Annual, 34, 141-170, University of Chicago Press, Chicago.

Den Haan, W., Freund, L. B., and Rendahl, P. (2021). Volatile hiring: Uncertainty in search and matching models. *Journal of Monetary Economics*, 123:1–18.

Dibiasi, A. (2018). Non-linear effects of uncertainty. KOF ETH Zurich Swiss Economic Institute, mimeo.

Dibiasi, A. and Sarferaz, S. (2020). Measuring macroeconomic uncertainty: A cross-country analysis. available at https://sites.google.com/tcd.ie/andreasdibiasi/research.

Diercks, A. M., Hsu, A., and Tamoni, A. (2020). When it rains it pours: Cascading uncertainty shocks. available at https://andreatamoni.meltinbit.com/.

Dietrich, A., Kuester, K., Muller, G., and Schoenle, R. (2020). News and uncertainty about covid-19: Survey evidence and short-run economic impact. available at http://keithkuester.eu/.

Eickmeier, S., Metiu, N., and Prieto, E. (2016). Time-varying volatility, financial intermediation and monetary policy. CAMA Working Paper No. 32/2016.

Esady, V. (2019). Real and nominal effects of monetary shocks under time-varying disagreement. CESifo Working Paper No. 7956.

Evans, C., Fisher, J. D. M., Gourio, F., and Krane, S. (2015). Risk management for monetary policy near the zero lower bound. *Brookings Papers on Economic Activity*, Spring:141–196.

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

Falck, E., Hoffmann, M., and Hürtgen, P. (2021). Disagreement about inflation expectations and monetary policy transmission. *Journal of Monetary Economics*, 118:15–31.

Fasani, S., Mumtaz, H., and Rossi, L. (2022). Monetary policy uncertainty and firm dynamics. *Review of Economic Dynamics*, forthcoming.

Fasani, S. and Rossi, L. (2018). Are uncertainty shocks aggregate demand shocks? *Economics Letters*, 167:142–146.

Favara, G., Giannetti, M., and Gao, J. (2021). Uncertainty, access to external finance, and firm precautionary behavior. *Journal of Financial Economics*, 141(2):436–453.

Fernández-Villaverde, J. and Guerrón-Quintana, P. (2020). Uncertainty shocks and business cycle research. *Review of Economic Dynamics*, 37(1):S118–S146.

Fernández-Villaverde, J., Guerrón-Quintana, P., Kuester, K., and Rubio-Ramírez, J. F. (2015). Fiscal volatility shocks and economic activity. *American Economic Review*, 105(11):3352–3384.

Fernández-Villaverde, J., Guerrón-Quintana, P., Rubio-Ramírez, J. F., and Uribe, M. (2011). Risk matters: The real effects of volatility shocks. *American Economic Review*, 101:2530–2561.

Figueres, J. M. (2015). News on state-dependent fiscal multipliers: The role of confidence. University of Padova Marco Fanno Working Paper No. 202.

Forni, M., Gambetti, L., and Sala, L. (2021a). Downside and upside uncertainty shocks. available at http://pareto.uab.es/lgambetti/.

Forni, M., Gambetti, L., and Sala, L. (2021b). Macroeconomic uncertainty and vector autoregressions. available at http://pareto.uab.es/lgambetti/research3.htm.

Freund, L. and Rendahl, P. (2020). Unexpected effects: Uncertainty, unemployment, and inflation. CEPR Discussion Paper No. 14690.

Fried, S., Novan, K., and Peterman, W. B. (2021). The macro effects of climate policy uncertainty. Federal Reserve Bank of San Francisco Working Paper No. 6.

Furlanetto, F. (2011). Does monetary policy react to asset prices? some international evidence. *International Journal of Central Banking*, 7(3):91–111.

Furlanetto, F., Ravazzolo, F., and Sarferaz, S. (2019). Identification of financial factors in economic fluctuations. *Economic Journal*, 129:311–337.

Garratt, A., Lee, K., and Shields, K. (2018). The role of uncertainty, sentiment and cross-country interactions in g7 output dynamics. *Canadian Journal of Economics*, 51(2):391–418.

Gavriilidis, K. (2021). Measuring climate policy uncertainty. University of Stirling, mimeo.

Ghironi, F. and Ozhan, G. K. (2020). Interest rate uncertainty as a policy tool. NBER Working Paper No. 27084.

Gieseck, A. and Rujin, S. (2020). The impact of the recent spike in uncertainty on economic activity in the euro area. ECB Economic Bulletin No. 6.

Gilchrist, S., Sim, J. W., and Zakrajšek, E. (2014). Uncertainty, financial frictions, and investment dynamics. Boston University and Federal Reserve Board of Governors, mimeo.

Gilchrist, S. and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, 102(4):1692–1720.

Görtz, C., Tsoukalas, J. D., and Zanetti, F. (2020). News shocks under financial frictions. *American Economic Journal: Macroeconomics*, forthcoming.

Grimme, C. and Stöckli, M. (2018). Measuring macroeconomic uncertainty in germany. *CESifo Forum*, 19(1):46–50.

Groshenny, N., Heid, B., and Sewak, T. (2021). Does uncertainty matter for trade flows of emerging economies? University of Le Mans and University of Adelaide, mimeo.

Gross, I. and Hansen, J. (2021). Optimal policy design in nonlinear dsge models: An n-order accurate approximation. *European Economic Review*, 140(103918).

Handley, K. and Limão, N. (2017). Policy uncertainty, trade and welfare: Theory and evidence for china and the united states. *American Economic Review*, 107(9):2731–2783.

Haque, Q. and Magnusson, L. M. (2021). Uncertainty shocks and inflation dynamics in the u.s. *Economics Letters*, 202:109825.

Haque, Q., Magnusson, L. M., and Tomioka, K. (2021). Empirical evidence on the dynamics of investment under uncertainty in the us. *Oxford Bulletin of Economics and Statistics*, 83(5):1193–1217.

Hassan, T. A., Hollander, S., van Lent, L., and Tahoun, A. (2020). The global impact of brexit uncertainty. NBER Working Paper No. 26609.

Hengge, M. (2019). Uncertainty as a predictor of economic activity. Working Paper HEIDWP19-2019.

Huang, Z., Tong, C., Qiu, H., and Shen, Y. (2018). The spillover of macroeconomic uncertainty between the u.s. and china. *Economics Letters*, 171(C):123–127.

Husted, L., Rogers, J., and Sun, B. (2020). Monetary policy uncertainty. *Journal of Monetary Economics*, 115:20–36.

Ilut, C. and Saijo, H. (2021). Learning, confidence, and business cycles. *Journal of Monetary Economics*, 117:354–376.

Ilut, C., Valchev, R., and Vincent, N. (2020). Paralyzed by fear: Rigid and discrete pricing under demand uncertainty. *Econometrica*, 88(5):1899–1938.

International Monetary Fund (2021). Global financial stability report. October.

Ireland, P. (2001). Money's role in the monetary business cycle. NBER Working Paper No. 8115.

Ismailov, A. and Rossi, B. (2018). Uncertainty and deviations from uncovered interest rate parity. *Journal of International Money and Finance*, 88:242–259.

Istrefi, K. and Mouabbi, S. (2018). Subjective interest rate uncertainty and the macroeconomy: A cross-country analysis. *Journal of International Money and Finance*, 88:296–313.

Jackson, L. E., Kliesen, K. L., and Owyang, M. T. (2018). The nonlinear effects of uncertainty shocks. Federal Reserve Bank of St. Louis Working Paper No. 2018-035A.

Jasova, M., Mendicino, C., and Supera, D. (2021). Policy uncertainty, lender of last resort and the real economy. *Journal of Monetary Economics*, 118:381–398.

Jiang, B., Rigobon, D. E., and Rigobon, R. (2021). From just in time, to just in case, to just in worst-case: Simple models of a global supply chain under uncertain aggregate shocks. NBER Working Paper No. 29345.

Jo, S. and Sekkel, R. (2019). Macroeconomic uncertainty through the lens of professional forecasters. *Journal of Business and Economic Statistics*, 37(3):436–446.

Johannsen, B. K. (2014). When are the effects of fiscal policy uncertainty large? Board of Governors of the Federal Reserve System, Finance and Economics Discussion Series 2014-40.

Jovanovic, B. and Ma, S. (2022). Uncertainty and growth disasters. *Review of Economic Dynamics*, 44:33–64.

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

Kang, W., Ratti, R. A., and Vespignani, J. (2017). The impact of global uncertainty on the global economy, and large developed and developing economies. Globalization and Monetary Policy Institute Working Paper No. 303.

Kehrig, M. (2015). The cyclical nature of the productivity distribution. Duke University, mimeo.

Klößner, S. and Sekkel, R. (2014). International spillovers of policy uncertainty. *Economics Letters*, 124:508–512.

Knight, F. H. (1921). Risk, uncertainty, and profit. Boston, MA: Hart, Schaffner & Marx; Houghton Mifflin Company.

Koren, M. and Tenreyro, S. (2007). Volatility and development. *Quarterly Journal of Economics*, 122(1):243–287.

Kozeniauskas, N., Orlik, A., and Veldkamp, L. (2018). What are uncertainty shocks? *Journal of Monetary Economics*, 100:1–15.

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

Leduc, S. and Liu, Z. (2020a). Can pandemic-induced job uncertainty stimulate automation? Federal Reserve Bank of San Francisco Working Paper No. 19.

Leduc, S. and Liu, Z. (2020b). The uncertainty channel of the coronavirus. Federal Reserve Bank of San Francisco Economic Letter No. 2020-07.

Lhussier, S. and Tripier, F. (2021). Regime-dependent effects of uncertainty shocks: A structural interpretation. *Quantitative Economics*, 12:1139–1170.

Liu, P., Theodoridis, K., Mumtaz, H., and Zanetti, F. (2019). Changing macroeconomic dynamics at the zero lower bound. *Journal of Business and Economic Statistics*, 37:391–404.

Liu, Y. and Sheng, X. S. (2019). The measurement and transmission of macroeconomic uncertainty: Evidence from the u.s. and bric countries. *International Journal of Forecasting*, 35:967–979.

Lopez, J. A. and Mitchener, K. J. (2021). Uncertainty and hyperinflation: European inflation dynamics after world war i. *Economic Journal*, 131(633):450–475.

Ludvigson, S. C., Ma, S., and Ng, S. (2021a). Covid19 and the macroeconomic effects of costly disasters. *American Economic Review Papers and Proceedings*, 111:366–370.

Ludvigson, S. C., Ma, S., and Ng, S. (2021b). Uncertainty and business cycles: Exogenous impulse or endogenous response? *American Economic Journal: Macroeconomics*, 13(4):369–410.

Lütkepohl, H. and Milunovich, G. (2016). Testing for identification in svar-garch models. *Journal of Economic Dynamics and Control*, 73:241–258.

Ma, X. and Samaniego, R. (2019). Deconstructing uncertainty. *European Economic Review*, 119:22–41.

Maggi, G. and Limão, N. (2015). Uncertainty and trade agreements. *American Economic Journal: Microeconomics*, 7(4):1–42.

Meinen, P. and Röhe, O. (2017). On measuring uncertainty and its impact on investment: Cross-country evidence from the euro area. *European Economic Review*, 92(C):161–179.

Meinen, P. and Röhe, O. (2018). To sign or not to sign? on the response of prices to financial and uncertainty shocks. *Economics Letters*, 171:189–192.

Meyer, B., Mihaylov, E., Barrero, J. M., Davis, S. J., Altig, D., and Bloom, N. (2022). Pandemic-era uncertainty. IZA DP No. 15229.

Miescu, M. and Rossi, R. (2021). Covid-19-induced shocks and uncertainty. *European Economic Review*, 139(103893).

Miescu, M. S. (2018). Uncertainty shocks in emerging economies: a global to local approach for identification. Queen Mary University of London, mimeo.

Miranda-Agrippino, S. and Rey, H. (2020). Us monetary policy and the global financial cycle. *Review of Economic Studies*, 87(6):2754–2776.

Moench, E., Ng, S., and Potter, S. (2013). Dynamic hierarchical factor models. *Review of Economics and Statistics*, 95(5):1811–1817.

Moore, A. (2017). Measuring economic uncertainty and its effects. *Economic Record*, June:1–26.

Mumtaz, H. and Musso, A. (2021). The evolving impact of global, region-specific and country-specific uncertainty. *Journal of Business and Economic Statistics*, 39(2):466–481.

Mumtaz, H. and Surico, P. (2018). Policy uncertainty and aggregate fluctuations. *Journal of Applied Econometrics*, 33:319–331.

Mumtaz, H. and Theodoridis, K. (2015). The international transmission of volatility shocks: An empirical analysis. *Journal of the European Economic Association*, 13(3):512–533.

Mumtaz, H. and Theodoridis, K. (2017). Common and country specific economic uncertainty. *Journal of International Economics*, 105:205–216.

Mumtaz, H. and Theodoridis, K. (2018). The changing transmission of uncertainty shocks in the us: An empirical analysis. *Journal of Business and Economic Statistics*, 36(2):239–252.

Mumtaz, H. and Theodoridis, K. (2020). Dynamic effects of monetary policy shocks on macroeconomic volatility. *Journal of Monetary Economics*, 114:262–282.

Mumtaz, H. and Zanetti, F. (2013). The impact of the volatility of monetary policy shocks. *Journal of Money, Credit and Banking*, 45(4):535–558.

Nakamura, E., Sergeyev, D., and Steinsson, J. (2017). Growth-rate and uncertainty shocks in consumption: Cross-country evidence. *American Economic Journal: Macroeconomics*, 9(1):1–39.

Nakata, T. (2017). Uncertainty at the zero lower bound. *American Economic Journal: Macroeconomics*, 9(3):186–221.

Nguyen, B. H., Okimoto, T., and Tran, T. D. (2021). Uncertainty-dependent and sign-dependent effects of oil market shocks. *Journal of Commodity Markets*, forthcoming.

Nodari, G. (2014). Financial regulation policy uncertainty and credit spreads in the u.s. *Journal of Macroeconomics*, 41:122–132.

Novy, D. and Taylor, A. M. (2020). Trade uncertainty. *Review of Economics and Statistics*, 102:749–765.

Oh, J. (2020). The propagation of uncertainty shocks: Rotemberg versus calvo. *International Economic Review*, 61(3):1097–1113.

Orlik, A. and Veldkamp, L. (2014). Understanding uncertainty shocks and the role of black swans. NBER Working Paper No. 20445.

Ozturk, E. O. and Sheng, X. S. (2018). Measuring global and country-specific uncertainty. *Journal of International Money and Finance*, 88(C):276–295.

Paccagnini, A. and Parla, F. (2021). Identifying high-frequency shocks with bayesian mixed-frequency vars. University College Dublin and Central Bank of Ireland, mimeo.

Pastor, L. and Veronesi, P. (2012). Uncertainty about government policy and stock prices. *Journal of Finance*, 64(4):1219–1264.

Pastor, L. and Veronesi, P. (2017). Explaining the puzzle of high policy uncertainty and low market volatility. Vox, 25 May 2017.

Pellegrino, G. (2018). Uncertainty and the real effects of monetary policy shocks in the euro area. *Economics Letters*, 162:177–181.

Pellegrino, G. (2021). Uncertainty and monetary policy in the us: A journey into non-linear territory. *Economic Inquiry*, 59:1106–1128.

Pellegrino, G., Castelnuovo, E., and Caggiano, G. (2022). Uncertainty and monetary policy during the great recession. available at https://sites.google.com/site/efremcastelnuovo/home.

Pellegrino, G., Ravenna, F., and Züllig, G. (2021). The impact of pessimistic expectations on the effects of covid-19-induced uncertainty in the euro area. *Oxford Bulletin of Economics and Statistics*, 83:841–869.

Piffer, M. and Podstawski, M. (2018). Identifying uncertainty shocks using the price of gold. *Economic Journal*, 128(616):3266–3284.

Ponomareva, N., Sheen, J., and Wang, B. Z. (2019). Does monetary policy respond to uncertainty? evidence from australia. *Australian Economic Review*, 52(3):336–343.

Popp, A. and Zhang, F. (2016). The macroeconomic effects of uncertainty shocks: The role of the financial channel. *Journal of Economic Dynamics & Control*, 69:319–349.

Ramey, V. A. and Zubairy, S. (2018). Government spending multipliers in good times and in bad: Evidence from u.s. historical data. *Journal of Political Economy*, 126(2):850–901.

Redl, C. (2017). The impact of uncertainty shocks in the u.k. Bank of England Staff Working Paper No. 695.

Redl, C. (2020). Uncertainty matters: Evidence from close elections. *Journal of International Economics*, 124(103296).

Ricco, G., Callegari, G., and Cimadomo, J. (2016). Signals from the government: Policy uncertainty and the transmission of fiscal shocks. *Journal of Monetary Economics*, 82:107–118.

Rivolta, G. and Trecroci, C. (2021). Measuring the effects of u.s. uncertainty and monetary conditions on eme's macroeconomic dynamics. Università Cattolica del Sacro Cuore - Milan and University of Brescia, mimeo.

Rogantini Picco, A. and Oh, J. J. (2020). Macro uncertainty and unemployment risk. available at https://sites.google.com/view/annarogantini/home.

Rossi, B. and Sekhposyan, T. (2015). Macroeconomic uncertainty indices based on nowcast and forecast error distributions. *American Economic Review Papers and Proceedings*, 105(5):650–655.

Rossi, B. and Sekhposyan, T. (2017). Macroeconomic uncertainty indices for the euro area and its individual member countries. *Empirical Economics*, 53(1):41–62.

Rossi, B., Sekhposyan, T., and Soupre, M. (2019). Understanding the sources of macroeconomic uncertainty. Universitat Pompeu Fabra and Texas A&M University, mimeo.

Salgado, S., Guvenen, F., and Bloom, N. (2019). Skewed business cycles. National Bureau of Economic Research Working Paper No. 26565.

Saltzman, B. and Yung, J. (2018). A machine learning approach to identifying different types of uncertainty. *Economics Letters*, 171:58–62.

Schmalz, M. C. and Zhuk, S. (2019). Revealing downturns. *Review of Financial Studies*, 32(1):338–373.

Schwert, W. G. (1989). Why does stock market volatility change over time? *Journal of Finance*, 44(5):1115–1153.

Scotti, C. (2016). Surprise and uncertainty indexes: Real-time aggregation of real-activity macro surprises. *Journal of Monetary Economics*, 82:1–19.

Segal, G. (2019). A tale of two volatilities: Sectora uncertainty, growth, and asset prices. *Journal of Financial Economics*, 134:110–140.

Seneca, M. (2018). Risk shocks and monetary policy in the new normal. Bank of England Staff Working Paper No. 606.

Sheen, J. and Wang, B. Z. (2019). Understanding macroeconomic disagreement. Macquarie University, mimeo.

Shields, K. and Tran, T. D. (2019). Uncertainty in a disaggregate model: A data richapproach using google search queries. CAMA Working Paper No. 83.

Steinberg, J. B. (2019). Brexit and the macroeconomic impact of trade policy uncertainty. *Journal of International Economics*, 117:175–195.

Straub, L. and Ulbricht, R. (2021). Endogenous uncertainty and credit crunches. available at https://scholar.harvard.edu/straub.

Swanson, E. T. (2019). The federal reserve is not very constrainedby the lower bound on nominal interest rates. University of California, Irvine, mimeo.

Tran, T. D. (2021). The macroeconomic effects of commodity price uncertainty. CAMA Working Paper No. 09.

Tran, T. D., Vehbi, T., and Wong, B. (2019). Measuring uncertainty for new zealand using a data-rich approach. *Australian Economic Review*, 52(3):344–352.

Vavra, J. (2014a). Inflation dynamics and time-varying volatility: New evidence and an ss interpretation. *Quarterly Journal of Economics*, 129(1):215–258.

Vavra, J. (2014b). Time-varying phillips curves. NBER Working Paper No. 19790.

Wang, X., Wu, H., Li, L., and Liu, L. (2022). Uncertainty, gvc participation and the export of chinese firms. *Journal of Economic Survey*, 36(3):634–661.
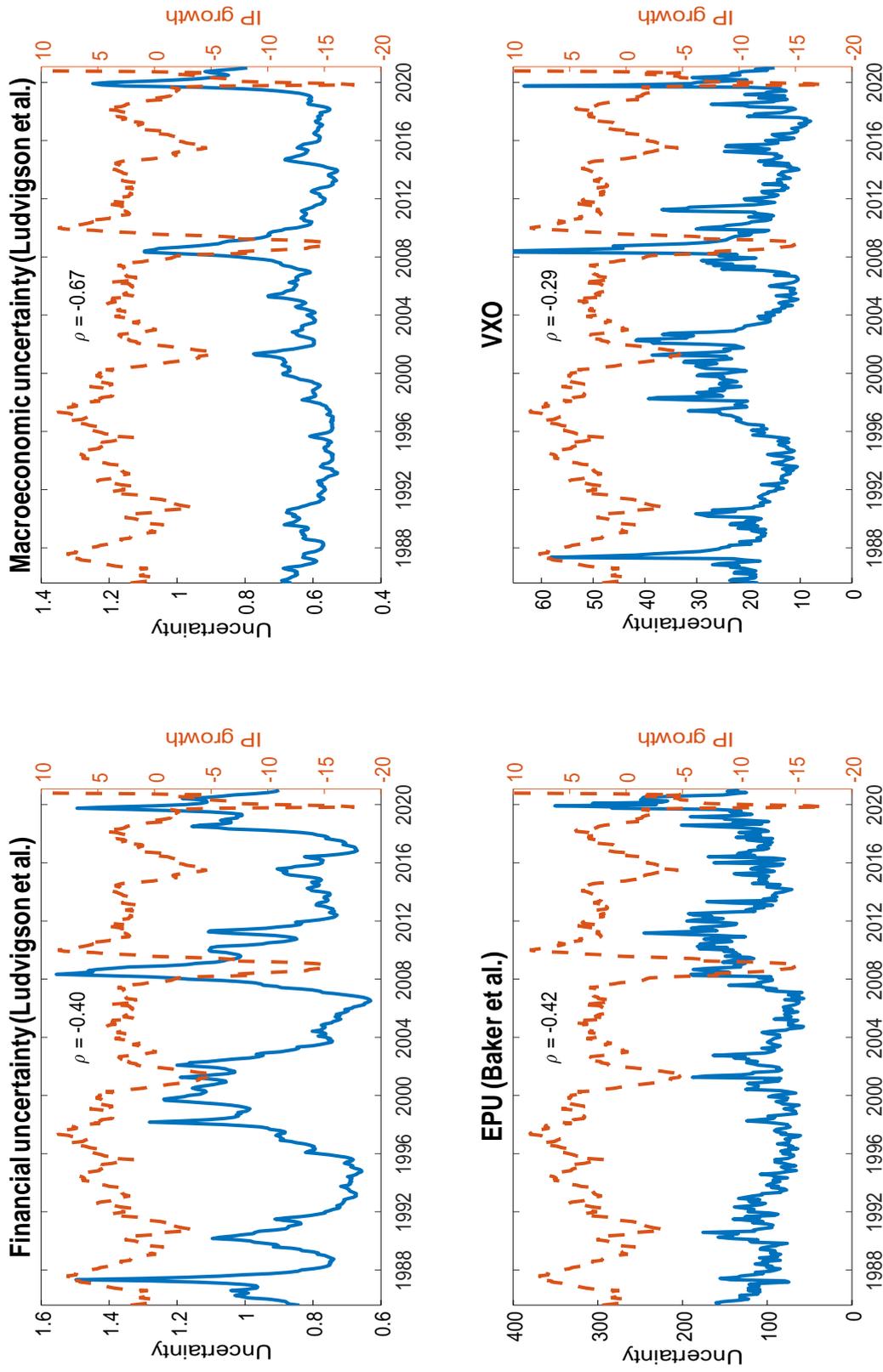
Figure 1: **Measures of US uncertainty.** Sample: 1986M1-2021M6. Solid lines: Uncertainty Measures. Dashed lines: Industrial Production (y-o-y growth rate). Financial and macroeconomic uncertainty constructed as a weighted average of estimated volatilities of forecast errors of a variety of (respectively) financial and macroeconomic indicators as documented in Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2021), forecast horizon = one month. Economic Policy Uncertainty measure based on survey data, tax code expiration data, and data coming from selected newspapers as explained in Baker, Bloom, and Davis (2016). VXO: Measure of implied financial volatility (horizon = one month) constructed by the Federal Reserve Bank of Chicago.
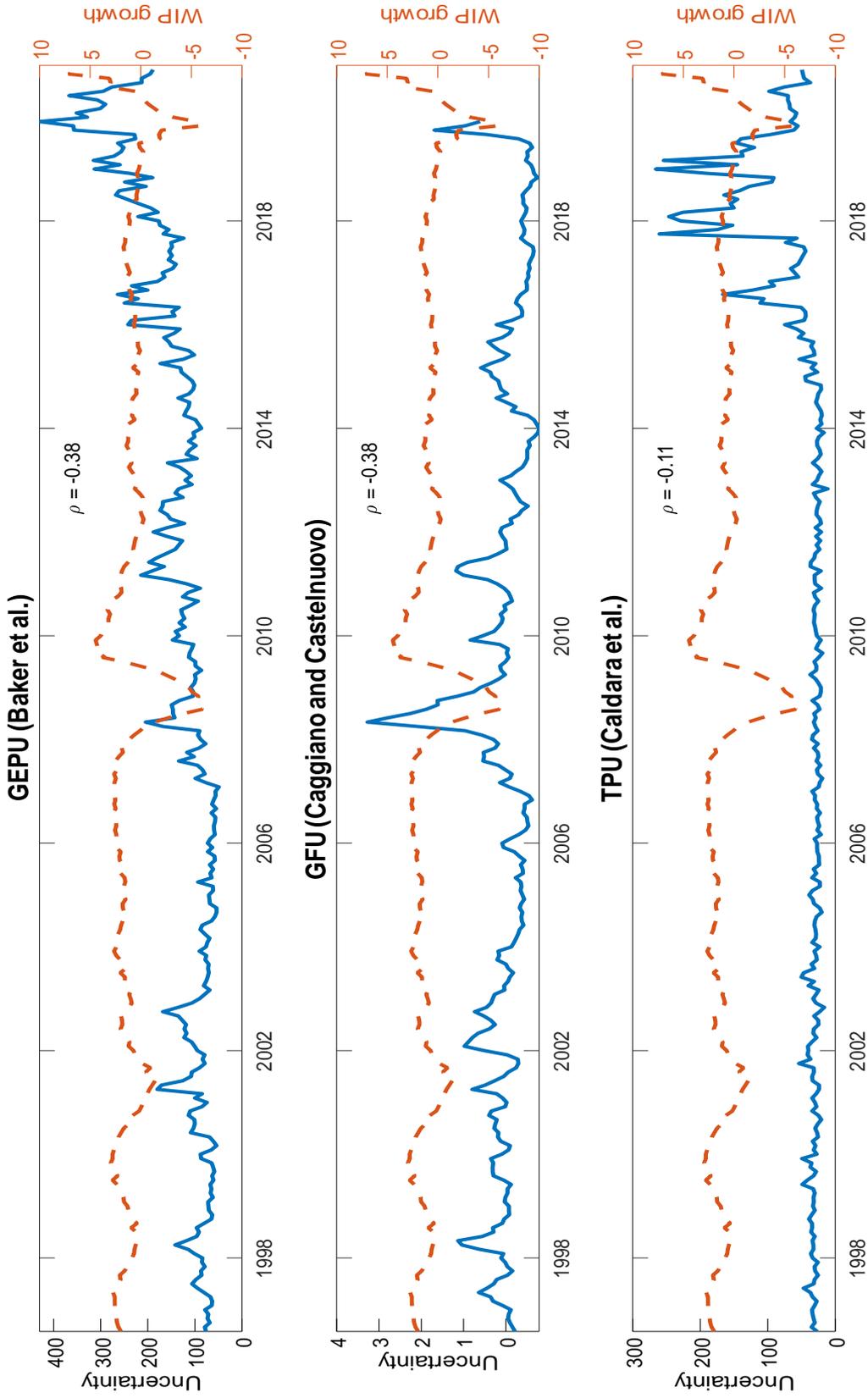
Figure 2: **Measures of global uncertainty.** Sample: 1997M1-2021M5 (with the exception of GFU, which stops in 2020M5)). Solid lines: Uncertainty measures. Dashed lines: World Industrial Production (y-o-y growth rate). WIP measure taken from Baumeister and Hamilton (2019). GEPU: Global Economic Policy Uncertainty index proposed by Baker, Bloom, and Davis (2016). GFU: Global Financial Uncertainty measure estimated by Caggiano and Castelnuovo (2021). TPU: Trade Policy Uncertainty index developed by Caldara et al. (2020).