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TRANSMISSION CHAINS OF ECONOMIC UNCERTAINTY ON MACROECONOMIC ACTIVITY: NEW EMPIRICAL EVIDENCE

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This paper investigates the macroeconomic impact of uncertainty by using three recently constructed US economic uncertainty proxies. Emphasis is placed on examining the informational value of these indicators and their ability to better predict economic activity. We focus on the direct and/or indirect transmission chains of economic uncertainty on US macroeconomic aggregates, the magnitude of the forecast improvement induced by economic uncertainty and the strength of the observed dynamic relations. Our results show that macroeconomic uncertainty can help in forecasting key macroeconomic aggregates across multiple horizons, and this predictive power is economically and statistically significant. The two macroeconomic uncertainty measures anticipate industrial production and consumption directly, and investment and employment indirectly, with a time-delay. The transmission chains for investment include consumption and the stock market as intermediate variables, and for employment consumption and investment. No substantial evidence of feedback effects from real activity to macroeconomic uncertainty is found. Moreover, asymmetry in macroeconomic uncertainty is found to be important. Upside and downside uncertainty produce significant macroeconomic effects, yet downside uncertainty produces the strongest impact. Results from a "news-based" economic policy uncertainty measure are weaker.

Keywords: Economic Uncertainty, Macroeconomic Activity, Transmission Chains, Multi-Horizon Causality, Causality Measure

1. INTRODUCTION

The role of economic uncertainty in macroeconomic activity is intensely discussed in recent years, especially after the Great Recession that was followed by

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a slow recovery of the US economy. A large body of the literature suggests that increased uncertainty has negatively affected several macroeconomic outcomes, including, e.g., investment, employment, consumption, and output. Policy makers also argue that uncertainty has played an important role during the last recession or in driving the slow recovery, as discussed in a number of reports of the Federal Reserve Open Market Committee (2008) or the International Monetary Fund (2012).[1]

An important question arising is how is economic uncertainty defined and measured. Economic uncertainty is difficult to quantify. As stated by Bloom (2014), "Uncertainty is an amorphous concept. It reflects uncertainty in the minds of consumers, managers, and policymakers about possible futures. It is also a broad concept, including uncertainty over the path of macro phenomena like GDP growth, micro phenomena like the growth rate of firms, and noneconomic events like war and climate change... Our measures of uncertainty are far from perfect and in fact are best described as proxies rather than real measures."

Until recently, the most common proxies of uncertainty have been the stock market volatility, cross-sectional dispersion of firm profits (or sales) or stock returns, or cross-sectional dispersion of subjective survey-based forecasts. According to Jurado et al. (2015), common uncertainty proxies may be closely linked to the typical theoretical notion of uncertainty only under special conditions. For instance, stock market volatility (i.e., financial market uncertainty) might change even if there is no change in uncertainty about economic fundamentals, while cross-sectional dispersion in firm profits or sales can change due to heterogeneity in the cyclicality of firms' business activity. Hence, there has been a need for constructing new uncertainty measures that might be more related to or are better proxies for "macroeconomic activity" uncertainty or "economic policy" uncertainty. Given that there is no objective measure of uncertainty, a growing number of studies have focused on the construction of new proxies of economic uncertainty during the years following the recent financial crisis.[2]

Three recently constructed uncertainty proxies based on this argument are the economic policy uncertainty (EPU) index of Baker et al. (2013), and the macroeconomic uncertainty indices of Jurado et al. (2015) and Rossi and Sekhposyan (2015). These proxies are built using different methodological or conceptual approaches and reflect several aspects of economic policy or macroeconomic uncertainty. EPU mainly constitutes a newspaper-based indicator of policy uncertainty, although further components reflecting fiscal or monetary uncertainty are considered. The macroeconomic uncertainty proxies are both based on the concept of (un)predictability, yet each indicator is constructed based on a different methodological approach and different sets of economic series. The Rossi and Sekhposyan (2015) measures further consider asymmetry in uncertainty, distinguishing between downside (negative) or upside (positive) uncertainty. Empirical work on the informational value of these uncertainty indices and their impact on the macroeconomy is limited, particularly for the Jurado et al. (2015) and Rossi and Sekhposyan (2015) proxies that have been constructed during the last year.

Hence, there is a need for a detailed examination of the dynamic relationships between these various uncertainty proxies and the real economy.

The contribution of this paper is twofold. First, we assess the macroeconomic impact of economic uncertainty by employing these three recent uncertainty proxies, which have not yet been widely used in empirical analysis. Emphasis is placed on examining the informational value of these indicators and their ability to better predict economic activity. Our empirical analysis further highlights direct effects or indirect transmission chains (effects) of economic uncertainty on US macroeconomic fluctuations, by employing the dynamic causality methodology of Dufour et al. (2006). The method uncovers potential multiple channels (causal chains) through which predictive information might be transmitted when considering high dimensional VAR's.[3] This paper is the first that investigates dynamic causation between economic uncertainty and key macroaggregates, and, more precisely, which chains are observed from economic uncertainty to the macrovariables, the presence of causal delays in these effects or their direct or indirect nature. Importantly, the dynamic causality method uncovers links in all directions. We thus also examine whether there are feedback effects from real activity variables to economic uncertainty.

The Dufour et al. (2006) method is based on the concept of Granger (1969) causality, which is defined in terms of predictability providing evidence on whether a set of variables contains useful information for improving the forecasts of another set of variables. Hence, our results of direct or indirect, multiple causal chains and relations are interpreted in terms of (in-sample) improved predictability and not as real causal effects. The dynamic causality results are useful because they can show that either a "mechanism" or an "expectation phenomenon" encompassed in the economic uncertainty indices is sufficiently important to allow forecasting of key macroeconomic aggregates [Dufour et al. (2012)].

Second, we measure the strength of the observed dynamic relations, in order to assess the magnitude of the forecast improvement from each economic uncertainty index to the macrovariables. Given that different causality relations may coexist, it is important to examine their relative importance which may differ substantially [Dufour et al. (2012)]. In case of feedback effects, it is also important to examine which link matters most, in terms of direction and time horizon [Zhang et al. (2016)]. The Dufour et al. (2006) method provides evidence on the presence of direct or indirect effects but cannot quantify the observed causality relations. Dufour and Taamouti (2010) have developed causality measures at different horizons that quantify the strength of dynamic causal relations and, given that they are estimated at different horizons, they capture indirect causal effects that are apparent after several periods. Within our empirical framework, the measures can be interpreted as the proportional reduction in the variance of the forecast error of each macrovariable obtained by introducing economic uncertainty to the information set.

Our empirical results show that macroeconomic uncertainty plays an important role in macroeconomic activity, and can help in forecasting key macroeconomic aggregates across multiple horizons. The two macroeconomic uncertainty indices help to anticipate industrial production, consumption, investment, and employment, both at short-run and long-run horizons. Uncertainty anticipation effects on industrial production and consumption are direct and last for several months ahead. The effects on investment and employment are indirect, occurring with a time-delay. For example, 3-month-ahead macrouncertainty anticipates investment and employment with a 3-month and 6-month delay, respectively. Dynamic causality reveals that the transmission chains for investment include consumption and the stock market as intermediate variables, and for employment consumption and investment. The evidence of feedback effects from real activity to economic uncertainty is negligible.

The causality measures (CM) suggest that the predictive power or the magnitude of the forecast improvement induced by macroeconomic uncertainty is economically and statistically significant. Evidence of indirect transmission channels is further supported by the CM; the measures are not statistically significant at horizon one, in cases where direct noncausality is not rejected. In addition, asymmetry in macroeconomic uncertainty is important when it is taken into account. Upside and downside uncertainty produce significant macroeconomic effects, yet downside uncertainty produce the strongest impact on the macroaggregates. On the other hand, the information content of the mainly “news-based” EPU index is weaker. In most cases, dynamic causality results and CM are not statistically significant and/or sizeable from an economic point of view.

The structure of the paper is the following: Section 2 offers an overview of the existing literature on the role of uncertainty in economic activity. Section 3 describes the data and the employed methodologies, while Section 4 presents our results. Section 5 discusses the empirical results, and robustness of the results is examined in Section 6. Finally, Section 7 concludes. Technical details are available in the online supplemental appendix.

2. RELATED LITERATURE

The theoretical literature emphasizes two major transmission channels for the effects of uncertainty on economic activity. The first channel focuses on the “real options” effect. From the firms’ perspective, high uncertainty about the future makes firms more cautious about their investment plans, especially when individual investment plans are irreversible [Bernanke (1983), Bloom (2009)]. Hence, firms will prefer to wait and postpone or delay investment and hiring until business conditions become clearer. Consumers’ response to high uncertainty is similar, since it is more valuable to wait and postpone (reduce) consumption, particularly for durable goods, during more uncertain times. The second channel emphasizes the “risk aversion” effect. Risk averse consumers tend to increase precautionary savings in times of high uncertainty, which leads to a decrease in consumption spending [Carroll and Samwick (1998)]. In addition, financial frictions (constraints) raise firms’ borrowing costs due to increasing risk premia.

Firms' ability to borrow is reduced, which can lead to a decline in investment and output growth [Gilchristet al. (2014)]. Bloom (2014) offers a detailed discussion on the theoretical literature for the effects of uncertainty.

Existing empirical literature on the role of uncertainty in economic activity includes a considerable amount of studies during the last 5 years. Most of these studies use stock market volatility or cross-sectional dispersion proxies for uncertainty. Alexopoulos and Cohen (2009) employ a VAR model and find negative responses of US economic activity (e.g., output, employment, investment) to positive stock market volatility shocks (i.e., unanticipated increases in volatility).[4] Beetsma and Giuliodori (2012) further split their sample in two sub-samples and find significant changes in the macroeconomic responses to stock market volatility shocks over time. Responses are found to be smaller during the second sub-sample.

Bachmann et al. (2013) construct a measure of US business uncertainty based on the cross-sectional dispersion in firms' subjective expectations, and employ an SVAR model where the identification scheme assumes that uncertainty shocks influence economic activity in the short-run, yet their effects vanish in the long-run.[5] The authors find little statistical or economic significance for the impact of uncertainty shocks to aggregate economic activity once imposing restrictions on the long-run effects of uncertainty on economic activity. Cesa-Bianchi et al. (2014) employ a global VAR to study the interrelationship between economic activity and financial markets volatility, and further assume that both variables are driven by a similar set of common factors. The authors provide evidence of volatility being a symptom rather than a cause of economic instability.

Caggiano et al. (2014) examine the impact of stock market volatility shocks on macroeconomic aggregates, particularly on US unemployment dynamics, by employing a nonlinear (logistic smooth transition, LSTAR) VAR model. The authors find strong asymmetric real effects of uncertainty shocks over the business cycle. More precisely, they find that the responses of unemployment are substantially larger during recessions than the ones predicted by linear VAR models, which are not able to isolate recessionary and nonrecessionary phases.[6] A nonlinear LSTAR model consisting of high uncertainty and low uncertainty regimes is employed in Jones and Enders (2016). In line with Caggiano et al. (2014), the authors find that positive uncertainty shocks induce higher responses in several macroaggregates than negative uncertainty shocks.

Meinen and Röhe (2017) compare several uncertainty proxies based on evidence obtained from linear VAR-models and impulse responses for four European countries. In their study, the authors construct uncertainty measures based on the approaches of Jurado et al. (2015) and Rossi and Sekhposyan (2015) for Germany, France, Italy, and Spain, and conclude that the responses of investment are substantially negative across all countries under several uncertainty measures. In their recent study, Henzel and Rengel (2016) employ a dynamic factor model and distinguish US macroeconomic uncertainty based on two obtained factors, which are interpreted as business cycle uncertainty and oil and commodity price uncertainty, respectively. The authors estimate impulse responses from linear VAR models and find that both types of uncertainty induce significant drops in economic activity, yet the effects of oil and commodity price uncertainty are larger and more persistent.[7]

Finally, Baker et al. (2013), Jurado et al. (2015), and Rossi and Sekhposyan (2015) construct macroeconomic or EPU measures (explained in detail in the next section), and use these measures to examine the effects of economic uncertainty on real activity based on standard (linear) VAR models, where impulse responses (and forecast error variance decomposition) are estimated based on identifying assumptions concerning the direction of contemporaneous linkages between the variables. All these studies find that economic uncertainty innovations substantially (negatively) affect macroeconomic activity, yet the number of included variables or variable ordering differ in each study.

3. EMPIRICAL INVESTIGATION

3.1. Economic Uncertainty Proxies

In our empirical analysis, we consider the following proxies of US economic uncertainty: (i) the EPU index of Baker, Bloom, and Davis (henceforth BBD), (ii) the measures of Jurado, Ludvigson, and Ng (henceforth JLN) of $h = 1, 3, 12$-period ahead macrouncertainty, termed $\mathrm{U}_t(1)$, $\mathrm{U}_t(3)$, and $\mathrm{U}_t(12)$, respectively, and (iii) the macroeconomic downside, upside and overall uncertainty indices of Rossi and Sekhposyan (2015, henceforth RS), based on 4-quarter-ahead forecasts, termed U_{t+4}^{-}, U_{t+4}^{+}, and $\mathrm{U}_{t+4}^{\mathrm{overall}}$, respectively.[8]

These uncertainty proxies are designed to reflect several aspects of EPU or macroeconomic activity uncertainty, yet they differ considerably from a conceptual (narrative analysis vs. econometric approach) or methodological perspective (factor models and conditional volatility vs. unconditional historical distribution of forecast errors). As discussed below in more detail, the major data source of EPU is newspaper article counts. JLN macrouncertainty indices are based on a broad set of economic and financial time series, while, on the other hand, the RS measures are built based on a single series [real gross domestic product (GDP) growth], which is considered as the informative proxy for the state of the business cycle and its comparison with the Survey of Professional Forecasters. All measures are standardized for comparison (demeaned and divided by their standard deviations) and are depicted in Figure 1.

The BBD index reflects movements in policy-related economic uncertainty since 1985, and, more precisely, uncertainty about fiscal, monetary and regulatory conditions. The index combines four components that quantify: (a) the frequency of newspaper article references to “policy uncertainty” (i.e., frequency of articles containing the words “uncertain” or “uncertainty,” and “economy” or ”economics,” and “policy” words, e.g., “deficit,” “Federal Reserve,” “regulation,” “congress,” “legislation” or “White House,” across 10 leading US newspapers), (b) the extent of disagreement among economic forecasters about future government purchases,

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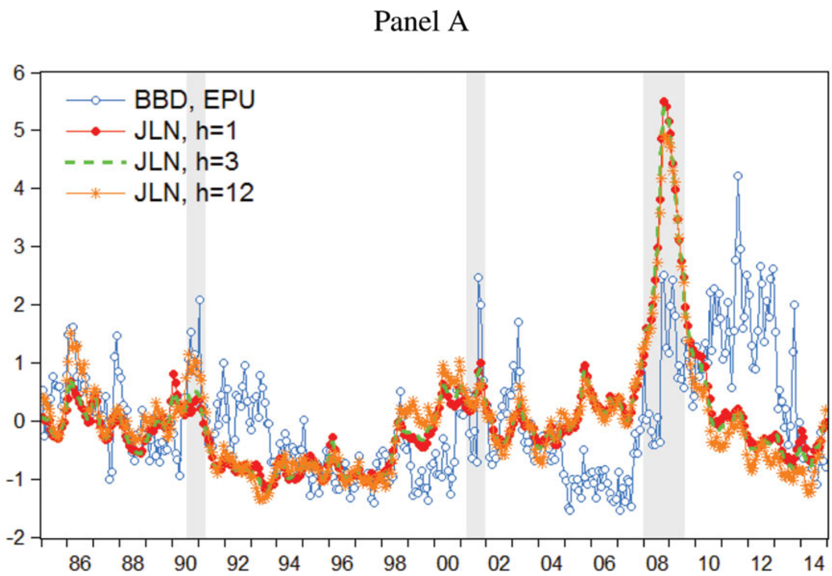

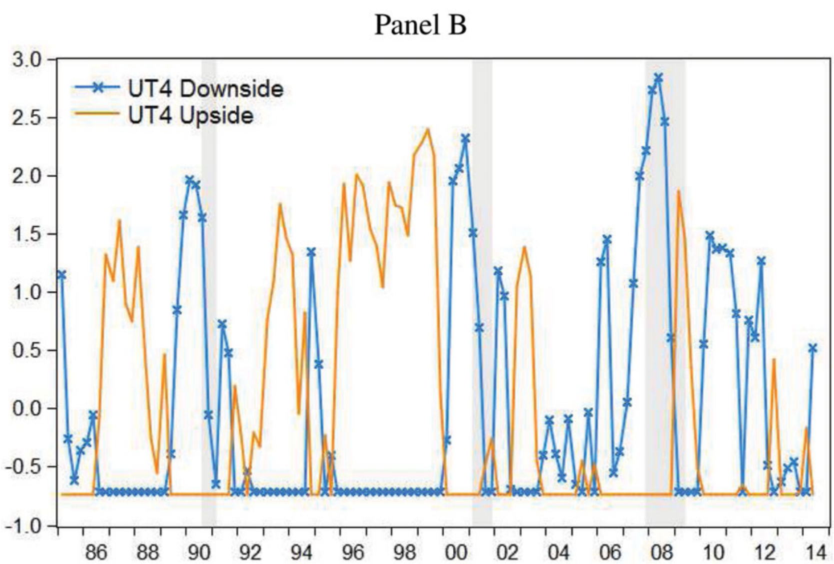

FIGURE 1. Panel A shows Baker et al. (2013) economic policy uncertainty (EPU), and Jurado et al. (2015) macrouncertainty $U_t(1)$, $U_t(3)$, $U_t(12)$, for the period 1985m01–2014m12 (monthly data). Panel B shows Rossi and Sekhposyan (2015) macrodownside U^-_{t+4} and macroupside U^+_{t+4} uncertainty for the period 1985q1–2014q2 (quarterly data). All series are normalized (demeaned and divided by their standard deviations). National Bureau of Economic Research (NBER) recession periods are depicted as shaded areas in both panels. (a) Panel A. (b) Panel B.

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(c) the extent of disagreement about future inflation, and (d) the revenue effects of scheduled tax code provisions. The EPU index spikes during several events, including, e.g., Black Monday, Gulf Wars I and II, presidential elections, the Lehman Bankruptcy, and the Eurozone debt crisis (Figure 1). BBD employ a recursive structural VAR model and find that positive innovations in EPU are followed by a decline in both industrial production and employment over several months after the uncertainty shock, implying potentially damaging economic effects of policy uncertainty.

JLN econometric estimates of macrouncertainty are designed to depict information on whether the entire (macro)economy has become more or less predictable, i.e., more or less uncertain. Based on this argument, the authors employ a broad set of macroeconomic and financial time series to construct their proxies. In their framework, $U_t(h)$ macroeconomic uncertainty is not related to uncertainty in any single series, but instead it is related to the common variation in uncertainty across many economic series.

In brief, the basic steps of the JLN approach are the following. First, the authors estimate individual series' forecasts (i.e., estimates of the forecastable component) based on a diffusion index model, using factors extracted from the large set of macroeconomic and financial time series (132 and 147, respectively). Then, a parametric stochastic volatility model for the one-step ahead prediction errors of each series is estimated to obtain conditional volatilities. Using these estimates, conditional volatilities at $h > 1$ are computed recursively, yielding individual series' uncertainty at horizon h. Finally, $U_t(h)$ macroeconomic uncertainty is defined as the equally-weighted average of individual series' uncertainties. Notice that while the whole set of macroeconomic and financial economic series is used to estimate the factors, individual uncertainties are considered only for the macroeconomic series, so that the financial series are not overrepresented and do not dominate the broad measure of macroeconomic uncertainty $U_t(h)$.

The $U_t(h)$ measures provide an inherent differentiation between macroeconomic uncertainty and the individual series' forecastable variations, and they further avoid dependence on the structure of specific theoretical models or on variations of specific observable economic indicators. JLN estimate macrouncertainty for three horizons ($h = 1$, 3, and 12 months) and find that important uncertainty episodes appear far more infrequently than indicated by popular uncertainty proxies, but when they do occur, they are larger, more persistent, and more correlated with real activity. Panel A of Figure 1 presents time series plots of monthly EPU, and of $U_t(1)$, $U_t(3)$, $U_t(12)$ macroeconomic uncertainty for the period 1985 onward. It reveals that the EPU and $U_t(h)$ proxies are countercyclical, rising in recessions and falling in expansions. The EPU index spikes more often than $U_t(h)$, while $U_t(h)$ uncertainty episodes occur more infrequently. The most striking episode, particularly for $U_t(h)$, corresponds to the 2007–2009 financial crisis and the Great Recession. The two measures exhibit correlation, yet EPU is substantially more volatile than $U_t(h)$. A notable difference is the persistent level break that EPU exhibits in the postcrisis period. The figure shows that it is only after 2013 that the normalized levels of EPU and $U_t(h)$ converge.

The RS macroeconomic uncertainty index is formed on a quarterly basis and is also based on the concept of (un)predictability. In contrast to JLN, RS use only a single indicator (real GDP growth) as an informative proxy for the overall business cycle. The RS index is based on the cumulative density of the forecast errors evaluated at the actual realized forecast error. The authors compare the h-step-ahead realized forecast error of the cyclical component of real GDP with its historical forecast error distribution (forecast error realization relative to its ex-ante probability). A forecast error realization in the empirical distribution tails corresponds to a highly uncertain macroeconomic environment.[9] The RS uncertainty measure is, by construction, between zero and one, $U_{t+h} \in (0, 1)$. A value close to one indicates a much higher realized value than the expected value, while the opposite holds for values close to zero. U_{t+h} is based on nowcasts and on 4-quarter ahead GDP growth forecasts, yet the latter is less noisy and more informative about recessions. In our analysis, we follow RS and use the uncertainty proxies based on 4-quarters ahead forecasts, U_{t+4}.

RS focus on asymmetry in uncertainty by distinguishing between downside $U^-_{t+4} = 1/2 + \max\{1/2 - U_{t+4}, 0\}$ and upside $U^+_{t+4} = 1/2 + \max\{U_{t+4} - 1/2, 0\}$ uncertainty, which may not be of the same importance affecting the macroeconomy in a different way. Downside uncertainty is related to "negative" unexpected news, e.g., lower GDP growth than expected, and upside macrouncertainty is related to "positive" unexpected outcomes, e.g., higher GDP than expected. U^{overall}_{t+4} uncertainty is defined as $U^{\text{overall}}_{t+4} = \max\{U^+_{t+4}, U^-_{t+4}\}$. By construction, the indices are between one-half and one.

Panel B of Figure 1 shows plots of the RS downside and upside macrouncertainty. The RS downside uncertainty proxy leads or coincides with US recessions, while upside uncertainty is also observed, e.g., in late 1990s, a period associated with significant economic expansion. RS compare their index with JLN and BBD and find that downside and upside uncertainty is more correlated, positively and negatively, respectively, with JLN. The authors employ a recursive structural VAR and find that both downside and upside uncertainty have large—similar in magnitude and opposite in sign—effects on output.

To summarize, despite the differences in the methodological or conceptual approach and the data used to construct each measure, all these proxies focus on macroeconomic uncertainty that reflects ambiguity about the future state of the economy, as opposed to microeconomic uncertainty, which is typically based on cross-sectional variation in time that reflects dispersion across sectoral production or productivity, profits, returns, or firm sales. By construction, the EPU index focuses more or "picks" up economic policy uncertainty, while the JLN and RS measures point acutely toward uncertainty about the future evolution of economic activity. Further evidence on the differences among several uncertainty measures may be found in Meinen and Röhe (2017).

3.2. Benchmark VAR Model

Our empirical analysis is based on a seven-variable VAR model that includes real industrial production (as a proxy for output), employment, real personal consumption expenditure (PCE) and real gross private domestic investment as macroeconomic aggregates, the S&P 500 price index to control for the stock market, the effective federal funds rate to control for interest rates/monetary policy and the (standardized) economic uncertainty measures described in the preceding section, one at a time.[10] The benchmark VAR(p) model we estimate is

$$\underset{K\times 1}{Y_t} = \mu(t) + \sum_{k=1}^{p} \pi_k Y_{t-k} + u_t,\ t = 1, \ldots, T, \tag{1}$$

where $Y_t = (y_{1,t}, \ldots, y_{K,t})'$, $\mu(t) = \delta_0 + \delta_1 t$ is a deterministic linear trend, u_t is a K-dimensional zero mean white noise process with $E(u_t u_t') = \Sigma_u$ a nonsingular and positive definite matrix. Our sample spans the period 1985m1–2014m12 and consists of 360 monthly observations. When we employ the RS macrouncertainty measures, data are in quarterly frequency covering the period 1985q1–2014q2, while real GDP is used instead of industrial production. Detailed information on the VAR variables and data sources may be found in the online Appendix A1.[11]

3.3. Dynamic Causality at Different Horizons

Economic uncertainty proxies may contain predictive information for real aggregates that is transmitted directly or indirectly, implying a causal delay of uncertainty effects on macroeconomic aggregates that would otherwise remain undetected. Evidence on direct or indirect transmission chains can be uncovered by employing the dynamic (multihorizon) causality method of Dufour, Pelletier, and Renault (henceforth DPR). The DPR method is based on the definition of (non)-causality at a given horizon h, and (non)-causality up to any given horizon h introduced in Dufour and Renault (1998). The authors define conditional noncausality with auxiliary variables, which may induce indirect causal links and transmit indirect causality between variables at horizons higher than one, even if there is no direct causality at horizon one.

Starting from a VAR(p) model as in (1), the procedure is based on ordinary least squares (OLS) estimation of the following autoregression of order p at horizon h, named (p, h)-autoregression by DPR:

$$Y_{t+h} = \mu^{(h)}(t) + \sum_{k=1}^{p} \pi_k^{(h)} Y_{t+1-k} + \sum_{k=p+1}^{d} \pi_k^{(h)} Y_{t+1-k} + v_{t+h}^{(h)},\ t = 0, \ldots, T-h, \tag{2}$$

where Y_{t+h} is composed of the conditional prediction of (1) at any horizon h given the available information at time t, and the projection error term $v_{t+h}^{(h)} = \sum_{j=0}^{h-1} \psi_j u_{t+h-j}$ follows a moving average MA($h-1$) process for $h \geq 2$, where

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the coefficient matrices ψ_h are the impulse response coefficients of the process, with $\psi_0 = I_K$, $\psi_h = \pi_1^{(h)}$ for $1 \leq h < T$, and d is the largest order of integration for the Y_t vector process. The order of integration determines the number of extra lags to insert to the levels specification when Y_t is nonstationary, based on Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996).

Notice that the DPR method can be applied to both stationary ($d = 0$) and nonstationary ($d = 1$) integrated VAR processes, which may involve unspecified cointegrating relationships. Standard unit root tests applied to the system variables suggest that there are I(1) nonstationary variables in our VAR model.[12] Hence, a specification question arises whether the nonstationary variables should be differenced (i.e., considering growth rates) before estimating the (p, h)-autoregression (even though DPR allows for both stationary and nonstationary frameworks). Sims et al. (1990) argued that differencing (or considering cointegrating relations) might not be necessary even if the variables contain a unit root, and showed that the VAR OLS estimates are consistent and asymptotically normally distributed under general conditions even when the series are integrated or cointegrated.

As it is discussed in Enders (2010) and Ramey (2016), among others, the less harmful approach seems to be the VAR-in-levels model (along with some deterministic trends) as long as the imposition of first differencing or cointegration is not required for structural identification. One of the main arguments against the adoption of first differencing is that information about the co-movements in the data will be excluded, e.g., the long-run tendencies between the series will not be captured. An additional drawback of differencing or adopting error-correction mechanisms is that if the restrictions imposed are misspecified then parameter estimates are biased.[13] Based on these arguments, in our analysis, we estimate the (p, h)-autoregressions in levels form.

Following OLS estimation of (2), the null hypothesis of noncausality ($\underset{h}{\nrightarrow}$) from variable $y_{j,t}$ to variable $y_{i,t}$ at horizon h takes the form of a set of zero restrictions on certain elements of the coefficient matrices $\pi_k^{(h)} = (\pi_{ij,k}^{(h)})_{i,j}$ for $k = 1, 2, \ldots, p$,

$$H_0\left(y_j \underset{h}{\nrightarrow} y_i\right) : \pi_{ij,k}^{(h)} = 0,\ k = 1, 2, \ldots, p. \tag{3}$$

For example, if variable $y_{j,t}$ does not cause variable $y_{i,t}$ at horizon h, then the corresponding coefficients $\pi_{ij,k}^{(h)}$ in the $y_{i,t}$-equation should be zero for all lags $k = 1, 2, \ldots, p$. The noncausality hypothesis in (3) is tested through a Wald type statistic $W[H_0(h)] \overset{d}{\rightarrow} \chi_p^2$. Since prediction errors $v_{t+h}^{(h)}$ follow an MA$(h-1)$ process, the Newey–West procedure is employed to obtain HAC estimates for the variance–covariance matrix of coefficients $\hat{\pi}_k^{(h)}$.[14] In the case of $I(1)$ nonstationarity, $d = 1$ and the Wald test is applied to the appropriate subset of matrix coefficients $\pi_k^{(h)}$ for $1 \leqslant k \leqslant p$.[15] The statistical significance of $W[H_0(h)]$ is assessed via a parametric bootstrap method suggested by DPR, given that the χ_p^2 asymptotic distribution is not reliable in finite samples.[16]

Causality testing from variable $y_{j,t}$ to variable $y_{i,t}$ (variables of immediate interest) at horizon h is conditional on the remaining $K-2$ variables in Y_t (auxiliary variables in that context). In addition, nonrejection of the null hypothesis (3) for horizons $h = 1, 2, \ldots, (K-2)\,p+1$ is sufficient to obtain noncausality at all horizons, while noncausality up to horizon H can be obtained from the nonrejection of the null hypothesis for $h = 1, 2, \ldots, H$.

Based on Dufour and Renault (1998), noncausality from $y_{j,t}$ to $y_{i,t}$ at horizon $h+1$ occurs when: (a) there is noncausality from $y_{j,t}$ to $y_{i,t}$ at $h = 1$ and (b) the composed effects that run first from $y_{j,t}$ to $y_{z,t}$ at $h = 1$ and then from $y_{z,t}$ to $y_{i,t}$ at horizon h are zero. Thus, even if $y_{j,t}$ does not cause $y_{i,t}$ at horizon $h = 1$ (no direct causality), causality at horizons $h > 1$ can be justified through causal chains of indirect transmission if $y_{j,t}$ causes at least one of the auxiliary variable(s) $y_{z,t}$, $z \neq i, j$ at $h = 1$ and the auxiliary variable(s) $y_{z,t}$ cause $y_{i,t}$ at horizon $h \geq 1$. Schematically, if $y_{j,t} \underset{h=1}{\rightarrow} y_{z,t}$ and $y_{z,t} \underset{h}{\rightarrow} y_{i,t}$ then $y_{j,t} \underset{h+1}{\rightarrow} y_{i,t}$.

3.4. Measuring Causality at Different Horizons

The dynamic causality method is based on pure significance tests and the obtained results are only suggestive about whether economic uncertainty helps to forecast the macroaggregates, although the analysis goes beyond the benchmark Granger causality tests since it reveals potential causal delays and transmission chains of economic uncertainty on macroeconomic activity. Dynamic causality tests might reject the noncausality hypothesis, e.g., from economic uncertainty to investment, suggesting that uncertainty helps to anticipate the latter, yet this effect might not be large from an economic viewpoint or relative to other anticipating effects. Hence, it is important to assess the magnitude of the forecast improvement and distinguish the relative strength of observed dynamic causal relations. Dufour and Taamouti (2010, henceforth DT) have developed multihorizon short-run and long-run CM that quantify the strength of bivariate relationships within a multivariate framework. “Short-run” refers to low horizon values h and “long-run” to high values for the underlying horizon, although a precise threshold is not available.

More precisely, the DT conditional CM with auxiliary variables are developed for different horizons and are able to capture and quantify (a) indirect causal effects through the auxiliary variables, which are apparent only after several periods if there is no (direct) causality at horizon one, and (b) both direct effects at horizon one and indirect effects at horizons higher than one, in case both are present. For example, if economic uncertainty significantly improves predictability of industrial production both directly, at $h = 1$, and indirectly via some of the other system variables, the CM at horizons $h > 1$ assesses forecast improvement induced by both direct and indirect effects. Notice, however, that although conditional CM can account for indirect effects between two variables at higher horizons, yet they do not easily provide information on the presence of specific causal links. This is complemented by the DPR significance tests that can uncover such causal chains induced by the auxiliary variables.

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DT (2010, Sect. 6) provide a framework to assess unconditional and conditional (on a vector of variables) CM under the assumption of stationarity of the underlying vector process. They construct CM that presuppose a linear invertible underlying process, which includes vector autoregressive (VAR), vector moving average (VMA), and mixed (VARMA) models of finite order as special cases. The (parametric) CM are defined in terms of reduced form impulse response coefficients in the VMA representation of a VAR model. At given horizon h, the eight-step residual-based bootstrap confidence intervals—described in detail in DT (2010, Sect. 8)—are employed for statistical inference.

In our empirical implementation, CM are computed based on VAR-in-level models (after subtracting a linear deterministic trend), as in the dynamic DPR causality tests and along the lines discussed in Section 3.2 in favor of the VAR-in-levels approach. Arguably, if the vector time series Y_t has nonstationary I(1) components, the Wold MA representation does not exist, however, impulse response coefficients can be computed from the VAR-in-levels coefficients by recursions, as in the stationary case [Lütkepohl (2011)]. The same holds true for forecast error variance–covariance matrices represented as nonlinear functions of impulse response coefficients upon which the DT CM are built. OLS-based estimation of impulse-response coefficients (and forecast error variance decompositions) is consistent at any given horizon h except in the long run (asymptotically) as shown by Phillips (1998). As horizon $h \to \infty$, the forecast MSEs will be unbounded and forecast uncertainty may become extremely large [Lütkepohl (2006)]. However, as discussed in Section 3.2, first differencing would result in throwing away too much information. Based on our results, discussed in the following sections, (i) CM statistical significance is in agreement with the DPR dynamic causality results, and (ii) CM estimates converge slowly to zero as horizon h increases. All our statistically significant results adhere to short- or medium-run horizons and none can be attributed to nonstationarity.

For our purposes, let $Y_t^m = (Y_{1,t}^m, Y_{2,t}^m, Y_{3,t}^m)'$ denote the $K \times 1$ detrended vector process of Y_t that appears in (1). Let $Y_{1,t}^m$ and $Y_{2,t}^m$ be 1×1 and assume our interest in assessing the strength of causal relation from $Y_{2,t}^m$ to $Y_{1,t}^m$ at a given horizon $h > 0$ conditional on a set of auxiliary, relevant variables $Y_{3,t}^m$. In our application, $Y_{2,t}^m$ will denote an uncertainty variable while $Y_{1,t}^m$ will denote a real macroeconomic aggregate.

A VAR(p) model for Y_t^m is estimated with least squares to obtain autoregressive parameter matrix estimates $\hat{\pi}_k$, $k = 1, \ldots, p$ and the variance–covariance matrix $\hat{\Sigma}_{u|p}$ of the error term. We compute the coefficient matrices $\hat{\Psi}_j$, $j = 0, \ldots, h-1$, $\hat{\Psi}_0 = I_K$, by recursive substitution based on $\hat{\pi}_k$, $k = 1, \ldots, p$ and then the unconstrained forecast error variance–covariance matrix at horizon h.[17]

$$\hat{\Sigma}_p(h) = \sum_{j=0}^{h-1} \hat{\Psi}_j \hat{\Sigma}_{u|p} \hat{\Psi}_j'.$$

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Similarly, we estimate with least squares a constrained VAR(p) model for $Y_{0,t}^m = (Y_{1,t}^m, Y_{3,t}^m)'$, and we keep estimates $\tilde{\pi}_k$, $k = 1, \ldots, p$ and $\tilde{\Sigma}_{e|p}$ to construct $\tilde{\Psi}_j$, $j = 0, \ldots, h-1$, $\tilde{\Psi}_0 = I_K$ and the constrained forecast error variance–covariance matrix

$$\tilde{\Sigma}_{0|p}(h) = \sum_{j=0}^{h-1} \tilde{\Psi}_j \tilde{\Sigma}_{e|p} \tilde{\Psi}_j'.$$

The conditional CM estimate is given by

$$\hat{C}_L(h) = \hat{C}_L\left(Y_{2,t}^m \underset{h}{\rightarrow} Y_{1,t}^m\right) = \ln\left(\frac{\tilde{\sigma}_{0|p}^{(1,1)}(h)}{\tilde{\sigma}_p^{(1,1)}(h)}\right),$$

where $\tilde{\sigma}_{\bullet}^{(1,1)}(h)$ denotes the top left element of matrices $\tilde{\Sigma}_{0|p}(h)$ and $\hat{\Sigma}_p(h)$, respectively.

We consider the same lag order p for unconstrained and constrained models to facilitate comparison of the forecast error variance, as in Dufour and Taamouti (2010) and Dufour et al. (2012). For comparison purposes, the lag p is the same as the lag chosen for the dynamic causality analysis, based on a number of criteria discussed in the next section. In order to approximate the finite sample distribution of $\hat{C}_L(h)$ and the corresponding confidence interval at given horizons $h > 0$, we employ the eight-step residual-based bootstrap approach that DT propose using 2,000 replications.[18]

Estimated CM, $\hat{C}_L(h)$, quantify the causal effect from economic uncertainty ($Y_{2,t}^m$) to each of the key macrovariables ($Y_{1,t}^m$) at horizon h conditional on the set of relevant variables ($Y_{3,t}^m$). Higher values for $\hat{C}_L(h)$ indicate stronger causality from uncertainty to macroaggregates. The measure can be interpreted as the horizon specific proportional reduction in the variance of the forecast error of each macrovariable obtained by taking into account the history of economic uncertainty.

DT also define unconditional CM obtained by eliminating the auxiliary variables from the information set. Unconditional measures are based on bivariate models and, as such, indirect causal links cannot be uncovered. The bivariate system and corresponding Granger causality results are vulnerable to the omitted variable(s) problem or the hidden variable(s) criticism discussed, e.g., in Lütkepohl (1982) and Hill (2007). For example, spurious (Granger) causality might arise between the variables of a bivariate framework due to omitted, hidden variables that may be driving the system, while, on the other hand, noncausality in a bivariate system does not preclude causation in higher dimensional systems (indirect causality) when the omitted variables help to identify causal relations, e.g., Dufour et al. (2012) and Zhang et al. (2016). In our empirical analysis, we also compute unconditional measures to examine how the forecast improvement induced by economic uncertainty for each macroaggregate might change in the absence of auxiliary variables that, based on the dynamic causality results, appear to transmit indirect causality.

4. EMPIRICAL RESULTS

4.1. Dynamic Causality

Table 1 presents DPR dynamic causality results with JLN $U_t(3)$ macrouncertainty and BBD's EPU.[19] Table 2 shows results with RS macroeconomic downside and upside uncertainty. To preserve space, we report horizons in which the null hypothesis of noncausality is rejected at least at the 10% significance level. Our complete set of results with simulated p-values is tabulated in online Appendix B (Tables B1, B2, B3). We follow Ivanov and Kilian (2005) to choose the optimal number of lags for each VAR(p) model with monthly data based on the AIC criterion, and for each VAR(p) with quarterly data based on the HQC criterion.[20] All (p, h)-autoregressions include a linear trend. Maximum order of integration is equal to one.[21] Finally, bootstrap p-values are computed from $N = 999$ replications.[22]

Jurado, Ludvigson, Ng macrouncertainty. $U_t(3)$ JLN macrouncertainty helps to anticipate all four macroeconomic variables. Improved predictability is observed both at short horizons (short-run) and at higher horizons (long-run), while, further, the effects of macrouncertainty to PCE and industrial production are direct, beginning at horizon $h = 1$ and lasting for 5 months and 15 months, respectively.[23] Particularly regarding PCE, this result suggests no delay but rather a quick consumers' response to macrouncertainty.

The effects from macrouncertainty to investment and employment are indirect and occur with a 3-month and 6-month delay, respectively. These effects are observed for $h = 4$–18 months for investment, and $h = 7$–23 months for employment. Evidence on the transmission chains reveals that uncertainty effects on investment and employment are transmitted through consumption and the stock market.

More precisely, for the case of investment the first chain includes the direct effects of $U_t(3)$ on consumption expenditure (horizons $h = 1$–5), and the direct effects of consumption expenditure on investment ($h = 1$–8 months). According to this chain, the predictive content of uncertainty is transmitted through consumption; macroeconomic uncertainty anticipates consumption expenditure, which in turn anticipates investment. The second chain includes the direct (short-lived) effect of macrouncertainty on stock prices at horizons $h = 1$–3 and the effects of S&P 500 on investment ($h = 1$–14 months). By including the stock price index in the VAR model, we can ensure—to some extent—that the predictive content of macrouncertainty for the macroaggregates does not primarily reflect potential forward looking behavior of the macrouncertainty measures. Such content is captured by stock price movements.

Since the employed DPR method examines predictability of macroeconomic aggregates by economic uncertainty, the transmission chains cannot be related to (or identify) the channels emphasized by the theoretical literature and cannot be interpreted in terms of real causal effects. However, our empirical results support the "real options" or the "risk aversion" effect, which emphasizes the role of uncertainty in consumption, investment, and employment (through the first

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TABLE 1. Dufour et al. (2006) dynamic causality: Uncertainty measures, macrouncertainty $U_t(3)$ and economic policy uncertainty (EPU)

	Predicted						
$p = 5$ lags	$U_t(3)$	S&P 500	EFFR	PCE	INV	EMP	IP
Predictor							
$U_t(3)$		1–3	5–8	1–5,7,11–13,17,19,21	4–18	7–23	1–15
S&P 500	–		–	1,7,10,12,15,19	1–14	12	1–17
PCE	–	9–26	1–16		1–8	5–6,8,13,16	2–3,20–26
INV	–	17,20–22	–	1–6,11–17,21		4	1–2,20–22,24–25

	Predicted						
$p = 4$ lags	EPU	S&P 500	EFFR	PCE	INV	EMP	IP
Predictor							
EPU		1–3	1–5,11,14–20	–	1–3	4	–
S&P 500	1–4		4	1–21	1–21	7–19	1–21
PCE	4,10–12	10–21	2–13		1–8	6,8	1–4
INV	–	5,18–21	–	1–7,14–17,19–21		4–7,16,21	1–2,7–10,12–17,19–21

Notes: The null hypothesis is that the"predictor" does not cause the"predicted" variable at horizon $h = 1, \ldots, h$ max. h max is 21 for the VAR with EPU and 26 with $U_t(3)$. Reported horizons signify cases in which the null hypothesis of noncausality is rejected at least at the 10% significance level. Variables' abbreviations: $U_t(3)$: Jurado et al. (2015) macroeconomic uncertainty, EPU: Baker et al. (2013) economic policy uncertainty, S&P 500: Standard & Poor's 500 stock price index, EFFR: effective federal funds rate, PCE: real personal consumption expenditure, INV: real gross private domestic investment, EMP: employment, IP: industrial production.

TABLE 2. Dufour et al. (2006) dynamic causality: Uncertainty measures, downside $U^{-}_{t+h}(4)$ and upside $U^{+}_{t+h}(4)$ macrouncertainty

	Predicted						
$p = 2$ lags	$U^{-}_{t+h}(4)$	S&P 500	EFFR	PCE	INV	EMP	GDP
Predictor							
$U^{-}_{t+h}(4)$		1–8	2–7	1–8	1–7	2–9	1–8
S&P 500	7–9		1	5,10–11	1–4,6,8	4–8	3,11
PCE	–	–	–		1–2	6–8	1–3
INV	–	5	10–11	2–5,7–11		4,6–11	6–11

	Predicted						
$p = 2$ lags	$U^{+}_{t+h}(4)$	S&P 500	EFFR	PCE	INV	EMP	GDP
Predictor							
$U^{+}_{t+h}(4)$		1–4,8	5–11	1–7	2–5	2–7	1–7
S&P 500	1–2,8		1–2	10–11	1–4	3–4,11	2–3,11
PCE	–	3,5–6	1–2		1–2	–	1–4
INV	–	4–8	–	2–11		3–4,7–11	1–11

Notes: The null hypothesis is that the "predictor" does not cause the"predicted" variable at horizon $h = 1, \ldots, 11$. Reported horizons signify cases in which the null hypothesis of noncausality is rejected at least at the 10% significance level. Variables' abbreviations: U^{-}_{t+h} (4): Rossi and Sekhposyan (2015) downside uncertainty, U^{+}_{t+h} (4): Rossi and Sekhposyan upside uncertainty, S&P 500: Standard & Poor's 500 stock price index, EFFR: effective federal funds rate, PCE: real personal consumption expenditure, INV: real gross private domestic investment, EMP: employment, GDP: real gross domestic product.

chain), and the financial frictions channel, which emphasizes the role of financial frictions in investment or output (through the second chain).[24]

Predictive information from uncertainty to employment is transmitted mainly via consumption expenditure, and also via investment. The first chain includes the direct effects of $U_t(3)$ on consumption expenditure, and the effects of consumption on employment at least for horizons 5–6,[25] and the second chain includes the effects of $U_t(3)$ on consumption, consumption on investment, and the effects of investment to employment.[26]

Focusing on the possibility of feedback effects from real activity to macroeconomic uncertainty, industrial production is the only real macrovariable that contains short-run predictive information for economic uncertainty. Evidence of feedback effects from industrial production to $U_t(1)$, $U_t(3)$, $U_t(12)$ is observed at $h = 1$, $h = 1$, and $h = 1 - 5$, respectively, though CM (discussed in the next section) reveal that this effect is not statistically significant or sizeable from an economic viewpoint. The monetary policy variable (federal funds rate) also produces some short-lived ($h = 1$ or $h = 1, 2$) statistically significant DPR results of predictive ability on macrouncertainty. In general, the macroeconomic aggregates included in our VAR are not found to have predictive power for JLN macroeconomic uncertainty.[27]

The causal delay from macrouncertainty to real aggregates is shortened by 1-horizon (or 1 month on average), as forecast horizon increases. The effects from $U_t(1)$, $U_t(3)$, $U_t(12)$ to investment occur with a 4-months, 3-months, 2-months delay, respectively, and to employment with a 7-months, 6-months, 4-months delay, respectively. JLN show that the importance of the macrouncertainty estimates grows as the forecast horizon increases and that the fraction of the individual series uncertainty driven by common macrouncertainty $U_t(h)$ is much higher for $U_t(3)$, $U_t(12)$ than for $U_t(1)$. Our DPR results show that a higher macrouncertainty (forecast) horizon in $U_t(h)$ induces "faster" effects on real activity.

Finally, the observed direct effects from $U_t(3)$ to industrial production do not preclude the presence of indirect effects as well at horizons higher than $h = 1$ via the following causal chains: $U_t(3) \rightarrow$ PCE $\rightarrow$ investment $\rightarrow$ industrial production, or $U_t(3) \rightarrow$ S&P 500 $\rightarrow$ industrial production.

Rossi and Sekhposyan downside and upside uncertainty. The (p, h)-autoregressions are now based on quarterly data and significant horizons correspond to quarters. Table 2 shows that downside uncertainty U^{-}_{t+4} anticipates all macroaggregates, the S&P 500 and federal funds rate as well. As a general rule, observed results are in agreement with JLN results. The effects to investment, GDP and consumption are direct and last 7, 8, and 8 quarters, respectively.[28] Uncertainty effects on employment are still indirect and occur with a 1-quarter delay, for horizons $h = 2$ to $h = 9$. Transmission chains are still present and include consumption and investment as intermediate variables. One difference pertains to the S&P 500 price index, whose predictive content for the macroaggregates is now weaker, especially for GDP and investment.

Similar statistical significance results are obtained when using U^{+}_{t+4} upside uncertainty. Hence, not only downside uncertainty associated with unexpectedly negative news or outcomes, but also upside uncertainty associated with unexpectedly positive news [considered in Rossi and Sekhposyan (2015)] bears predictive content for the macrovariables. Although DPR results cannot measure the magnitude of such predictive content, they point toward the presence of asymmetries. In the next section, estimated CM reveal which type of uncertainty produces stronger effects.

Overall uncertainty (U^{overall}_{t+4}) does not anticipate any of the macroaggregates across horizons.[29] The same result (in terms of impulse responses) is obtained in Rossi and Sekhposyan (2015) and Meinen and Röhe (2017). Rossi and Sekhposyan (2015) find only marginal effects of overall uncertainty on output, whereas downside and upside uncertainty induce significantly larger effects. Meinen and Röhe (2017) find higher negative effects on investment when considering downside uncertainty than overall uncertainty. By construction, overall uncertainty U^{overall}_{t+4} combines both upside and downside uncertainty in such a way that positive and negative shock effects "cancel out" at the overall level. The methodological approach of the other two measures does not distinguish positive and negative outcomes by treating them symmetrically (for example, the JLN measure is based on the forecast errors variance).

Baker, Bloom, Davis economic policy uncertainty. The predictive ability of EPU diminishes significantly compared to that of JLN and RS measures. As Table 1 shows, EPU helps to anticipate investment directly at short-run horizons, $h = 1$–3, and employment indirectly via investment, yet only at $h = 4$. On the other hand, it does not contain any—direct or indirect—predictive information for consumption expenditure and industrial production. DPR tests do not reject the null of no-causality at any horizon and causal chains via other variables cannot be established. When EPU is included in the (p, h)-autoregression, it is the S&P 500, which significantly anticipates all four real variables, directly across any horizon for consumption, investment and industrial production and indirectly for employment from horizon $h = 7$ onward.

Notice that the second part of the previously established causal chain via consumption is still present. Consumption expenditure anticipates investment, industrial production, and employment (at some horizons). The first part of the potential causal chain, however, i.e., EPU anticipation effects on consumption expenditure, is not observed.[30] This is a case of a "broken" causal chain.

4.2. Causality Measures

We now turn to the estimated CM $\hat{C}_L(h)$, and we assess and compare the magnitude and strength of the observed causal relations at different horizons and directions. Each graph of Figure 2 shows the conditional CM as a function of the horizon, along with the 90% bootstrap percentile confidence intervals. A conditional CM is statistically significant when the interval does not include zero. Higher values for $\hat{C}_L(h)$ imply stronger causality, whereas statistical significance at $h > 1$ implies indirect causality, if there is no causality at $h = 1$.

The CM patterns show that the degree of the observed causal relations from economic uncertainty to macroeconomic activity or the magnitude of the forecast improvement obtained by including economic uncertainty to the information set is substantially large when the macroeconomic uncertainty proxies of JLN and RS are considered. Moreover, both short-run and long-run effects are important, as implied by the magnitude of these effects across multiple horizons. Importantly, the CM results are in agreement to the dynamic causality results. Evidence of the indirect transmission channels is reinforced as CM confidence bands include zero at horizons $h = 1$ at which the dynamic causality results do not reject direct noncausality.

Among the RS macroeconomic uncertainty proxies, U^{-}_{t+4} downside uncertainty produces the strongest impact in absolute terms (four upper graphs in Figure 2). The CM are sizeable from an economic viewpoint (i.e., the strength of forecast improvement is large) and statistically significant across multiple horizons for all macroaggregates, e.g., $h = 1$–12 for GDP (direct, highest value attained at $h = 3$),

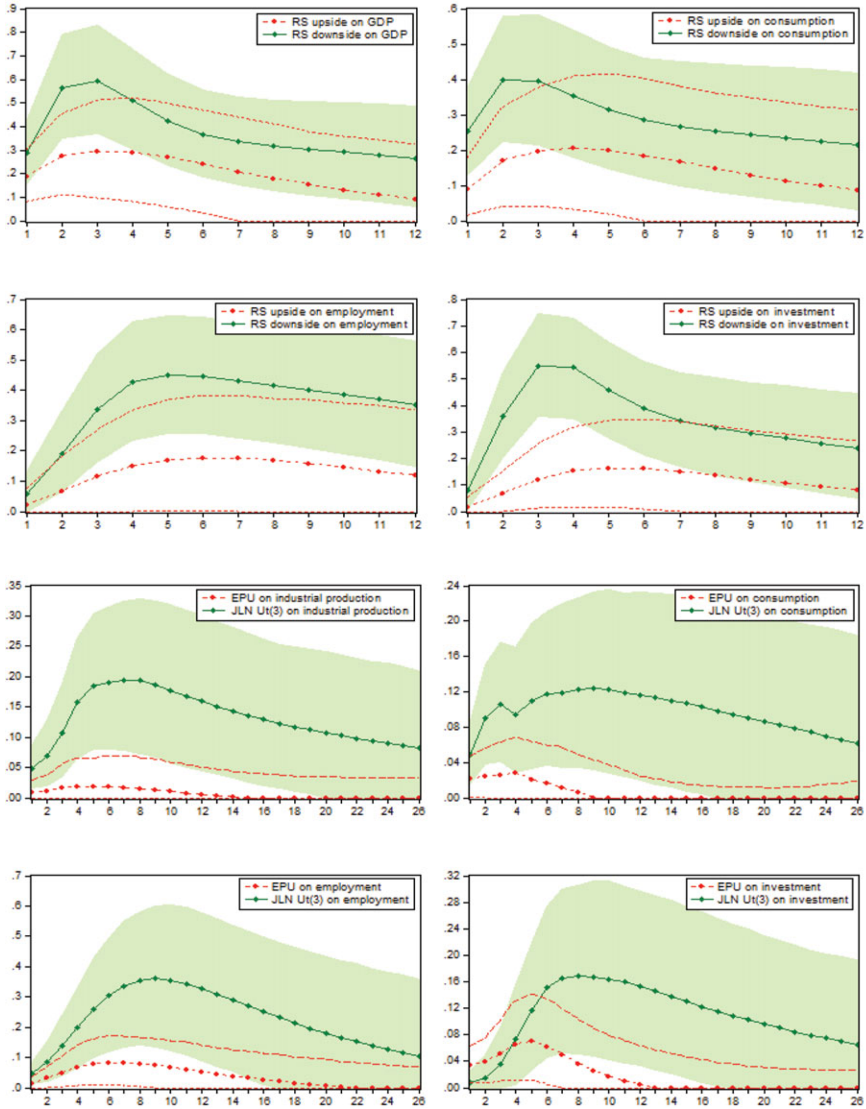

FIGURE 2. Conditional causality measures up to 12 quarters for RS downside and upside macrouncertainty; up to 26 months for JLN Ut(3) macrouncertainty and BBD economic policy uncertainty (EPU). In total, 90% bootstrap percentile confidence intervals shown as shaded areas or dashed lines.

$h = 1$–12 for consumption (direct, highest value at $h = 2$), $h = 1$–12 for investment (direct, highest value at $h = 3$) and $h = 2$–12 for employment (indirect, highest value attained at $h = 5$). The CM for employment is not statistically significant at horizon one, confirming the indirect effects also observed in the dynamic causality

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results. Among the macroaggregates, U^-_{t+4} produces CM that are larger (i.e., the highest value) for GDP and investment.

Upside uncertainty U^+_{t+4} also produces important effects, albeit of smaller magnitude compared to downside uncertainty. Estimated CM imply direct causality for GDP (h = 1–6) and consumption (h = 1–5), while further they capture the indirect effects of upside uncertainty on investment (h = 3–6) and employment (h = 5–6) observed in the dynamic causality results. Hence, as in DPR results, upside "positive news" uncertainty does have significant macroeconomic effects, and asymmetry in the effects of macrouncertainty, as proxied by Rossi and Sekhposyan (2015), is observed. In this case, the degree of forecast improvement is larger for GDP and consumption. Finally, CM for overall uncertainty are not statistically significant or sizeable at any horizon, a result which is also in agreement to DPR results.[31]

The CM of JLN $U_t(3)$ macrouncertainty are also statistically significant and sizeable from an economic viewpoint across several horizons (four lower graphs in Figure 2). The strongest effects are observed for industrial production (h = 1–19) and employment (h = 1–16). Corresponding CM attain their highest value at horizons $h = 7$ and $h = 9$, respectively. The CM captures the indirect effects of uncertainty to investment; the measure is not statistically significant at horizons 1–3, turning significant at $h = 4$ and attaining the highest value at $h = 8$. CM patterns further confirm the direct effects of uncertainty on industrial production and consumption, observed in the DPR results. There are some cases with JLN $U_t(3)$ where there is a difference with the dynamic causality results. One example is employment, where estimated CM imply that uncertainty effects occur substantially earlier, suggesting a smaller causal delay and a quicker response of employment to macroeconomic uncertainty.

The EPU estimated CM for industrial production and consumption are not sizeable nor statistically significant at any horizon. The measures are statistically significant in the cases of investment (h = 1–6) and employment (h = 4–7); however, these results are also not sizeable from an economic viewpoint compared to those produced by the other uncertainty indices. In line with the DPR results, the information content of EPU in predicting real activity is rather limited.

Unconditional causality results are summarized in Figure 3, where we preserve space and clarity by excluding confidence intervals for the conditional measures and by reducing the number of graphs to focus on measures that presented the maximum difference compared across horizons. Unconditional CM imply a higher strength of the bivariate macroeconomic uncertainty—macroaggregates relationships in the absence of auxiliary variables.[32] Figure 3 shows that the ability of macrouncertainty in forecasting each of the macroeconomic aggregates is magnified once variables that induce indirect causal links (based on DPR results) are excluded, while, further, all measures are now statistically significant from horizon one.

For instance, the effects of JLN $U_t(3)$ uncertainty to investment are substantially higher and "direct" in the bivariate model. Once consumption and the S&P 500 are

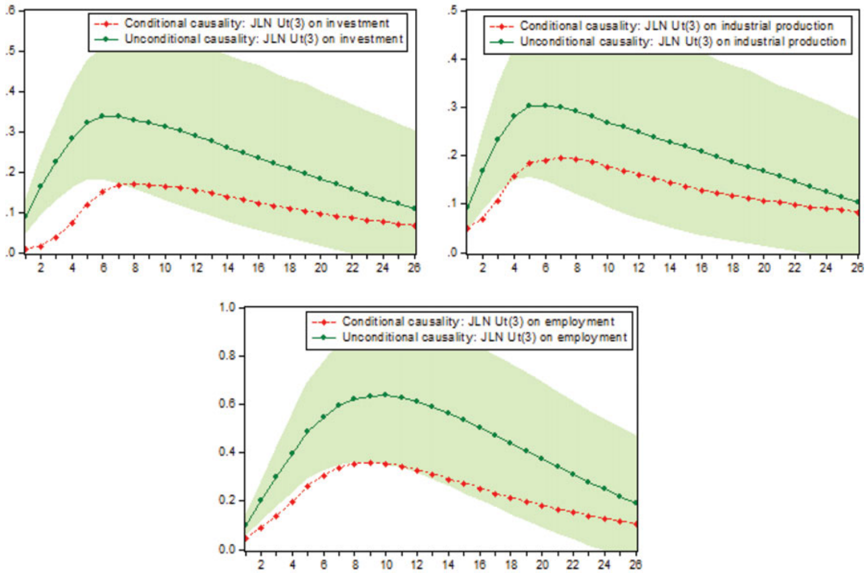

FIGURE 3. Unconditional (bivariate) and conditional (baseline) causality measures up to 26 months for JLN Ut(3) macrouncertainty. In total, 90% bootstrap percentile confidence intervals (shaded areas) correspond to the unconditional measures.

included (along with the other three VAR variables), which are found to transmit dynamic indirect effects, the $U_t(3)$ effects are much lower than the bivariate model suggests. Additional examples in Figure 3 include the unconditional cases for industrial production and employment, which also show higher predictability by $U_t(3)$ macrouncertainty in the bivariate model. Unconditional results with downside and upside uncertainty are similar.

We have also computed unconditional CM by excluding one variable at a time. For the case of $U_t(3)$, only when we exclude consumption or the S&P 500 we get CM that differ from our baseline results and are closer to those of the bivariate model. This is highly suggestive for the presence of indirect links with respect to those two variables that would otherwise remain undetected.

Focusing on the opposite direction (and feedback effects), the macroeconomic variables do not significantly anticipate JLN uncertainty. The CM magnitude is neither sizeable nor statistically significant across any horizon (in agreement with DPR results).[33] On the other hand, investment is found to induce some short-run effects to RS downside uncertainty while for employment the measure is only marginally statistically significant. Investment anticipates downside uncertainty and the forecast improvement is sizeable and statistically significant the first 4 quarters. This result is not observed with upside uncertainty, while, further, it is not observed in the DPR results. Zhang et al. (2016) also find some cases in which dynamic noncausality is not rejected, but the CM is statistically significant, and

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consider this as evidence indicating that CM might be a more powerful way to examine Granger noncausality. Finally, the feedback effect from employment to EPU as estimated by the CM is sizeable and statistically significant across horizons 1–12.[34] Hence, the measures suggest that employment is a variable or an economic indicator that anticipates EPU, and the strength of the forecast improvement is quite important.

5. DISCUSSION

Estimated CM and their confidence intervals are generally in agreement to the dynamic causality results. The magnitude of the forecast improvement is generally high at horizons in which the dynamic causality method rejects the null hypothesis of noncausality from economic uncertainty to each of the macroeconomic activity variables. In addition, evidence of the indirect transmission channels observed in DPR is reinforced; CM confidence interval bands do not exclude zero for horizons at which the dynamic causality results do not reject direct noncausality, while they are statistically significant at higher horizons found to represent indirect links in DPR results.

Combining the DPR and CM results, we see that the more informative uncertainty proxies, in terms of predictability, about future economic activity are the JLN and RS macrouncertainty indices. Macroeconomic uncertainty, as measured by JLN and RS, can help in forecasting key macroeconomic aggregates across multiple horizons, and this predictive power or forecast improvement is economically and statistically significant. Interestingly, the RS downside uncertainty that is based on a single series considered to represent the overall state of the business cycle is of similar informational value about economic activity as the JLN index that is constructed using a large number of macroeconomic and financial indicators. On the other hand, the predictive or informational content of the EPU index for macroeconomic activity is weaker. EPU does not appear to include much unique information about future activity.

By construction, EPU includes subjective elements, e.g., subjective conditional expectations about policy uncertainty on behalf of the agents involved in newspaper articles and might reflect underlying sentiment levels. For example, a notable difference in the behavior of EPU and $U_t(h)$ measures can be found in the persistent level break that EPU exhibits in the postfinancial crisis period. It is only after 2013 that the normalized levels of EPU and JLN measures converge. This persistent level break of EPU might in fact reflect agents' concerns about global uncertainty (e.g., European uncertainty as well) and agents' concerns about slow recovery. BBD attribute this behavior to the long-run character of EPU as opposed to short-run uncertainty movements. Gregory and Rangel (2012) back this view, since they found that implied volatility levels show strong positive correlation to policy uncertainty that increases with maturity (reaching 0.86 after 2 years of maturity).

We further notice that reduced form errors from the EPU and log(S&P 500) VAR equations are contemporaneously correlated (estimated correlation is −0.26), which is not the case for the $\mathrm{U}_t(h)$ and RS measures and S&P 500.[35] The significant contemporaneous correlation between EPU and S&P 500 reduced form errors (implying that EPU and S&P 500 respond to the same or very similar shocks), along with the fact that both variables are "sensitive" to news-based information might be an explanation about the weak predictive content of EPU for the macroaggregates conditional on S&P 500. Overall, EPU increases might capture bad news about the economic environment, which yet are already captured by other VAR variables (the stock price variable).

One recent study in which EPU is also not found to produce significant macroeconomic effects is Meinen and Röhe (2017). The authors find that the magnitude and statistical significance of the estimated impulse response functions are not important across several European countries (Germany, France, Italy, Spain) when uncertainty is measured by EPU. On the other hand, JLN and RS uncertainty measures constructed for the four European countries are found to produce significant negative investment responses that are consistent across countries and robust under several model specifications.

Overall, our empirical results support the view that macroeconomic uncertainty plays an important role in macroeconomic activity. One important issue when studying predictability of aggregate macroeconomic variables and analyzing economic events is whether the latest vintage or real-time data are used [Swanson (1996), Croushore and Stark (2003)]. In most empirical studies, including our own work, researchers use the most recent vintage of historical data, where the latter are revised data provided by statistical authorities today and are the most easily to obtain. However, real-time data might be more appropriate in studying predictability, because they are the data available to economic agents when making forecasts at any given point in time. Real-time data, on the other hand, are not easy to collect or to obtain. The extent to which different data vintages (if available) might affect empirical results regarding the role of macroeconomic uncertainty in macroeconomic aggregates is an interesting topic for future research.

6. ROBUSTNESS CHECKS

We perform a number of robustness checks to ensure our main findings are supported under several alternative model specifications. We first consider different VAR lag lengths, and we set the number of lags to 12 (1 year) for the monthly VAR with JLN $U_t(3)$, 4 lags for the quarterly VAR with RS U^-_{t+4} and U^+_{t+4}, and 6 lags for the monthly VAR with BBD EPU.[36] The obtained dynamic causality results are very similar to the baseline cases (Table A2.1, Appendix). The JLN $U_t(3)$ and RS U^+_{t+4} direct effects (consumption, industrial production) and indirect effects (employment, investment) are still observed. RS U^-_{t+4} again produces direct effects to consumption and GDP. The effects to employment now appear to be direct (at the 10% level), and the effects to investment are indirect with a 1-month delay. In some cases, the causal channels are less clear to be established. For example, the causal channel from $U_t(3)$ to investment still includes consumption, yet the direct effects of consumption to investment are now marginally statistically significant at the 10% level (p-value is 0.10).

The results obtained from CM are also very similar to the baseline cases (Figure A2.1, Appendix). More precisely, the magnitude (i.e., the strength of the observed relations) is similar across all uncertainty measures, whereas statistical significance of the CM confirms the direct and indirect effects previously observed. One difference is that the CM from JLN $U_t(3)$ to employment and investment now imply the absence of a causal delay to the effects of macroeconomic uncertainty, yet the measures are only marginally statistically significant during the first 1–3 horizons, and evidence in favor of indirect effects (as implied by the dynamic causality results) cannot be precluded.[37] Another difference pertains to the CM with RS U^{-}_{t+4}, which are now statistically significant for a shorter time period compared to the baseline case. Notice, however, that their magnitude and their direct and indirect nature does not substantially change. Overall, the classification into direct and indirect effects of economic uncertainty to macroeconomic activity, as well as the magnitude of the CM, appear to be robust with respect to the VAR lag order.

We also consider the possible effects of omitted variables and the zero-lower bound (ZLB). More precisely, (i) we include as an additional variable the consumer sentiment index (constructed by the University of Michigan using the Michigan Surveys of Consumers), which reflects consumers' expectations about the future evolution of the business cycle/economic system. This variable is related to uncertainty to some extent and uncertainty shocks may confound or proxy confidence shocks rather than representing exogenous uncertainty variations, and (ii) we take into account the fact that the short-term interest rate reached the ZLB (in December 2008), which some studies suggest that it might induce a stronger impact of uncertainty shocks.[38] We consider two cases: include the longer term 2-year treasury constant maturity rate as an alternative indicator of monetary policy instead of the federal funds rate, which did not reach the ZLB, and consider the prezero lower bound sample, i.e., restrict our sample until 2008m09 (or 2008q3 for quarterly data).

Figure 4 shows that JLN and RS CM results are quantitatively similar when including (i) the consumer sentiment index as an additional variable or (ii) the 2-year maturity rate instead of the effective federal funds rate (graphs present the cases for investment and industrial production). When we restrict our sample up to December 2008, the magnitude of the JLN measures is larger than in the baseline case, yet the measures reach zero earlier. On the other hand, the magnitude of the CM based on the RS indices is smaller, yet it is still sizeable from an economic viewpoint across several horizons. Based on our results, there is no definitive picture regarding the role of the ZLB in the impact of uncertainty shocks.

7. CONCLUSIONS

In this paper, we investigate the macroeconomic impact of uncertainty by using three recently constructed US economic uncertainty indices/proxies. These proxies

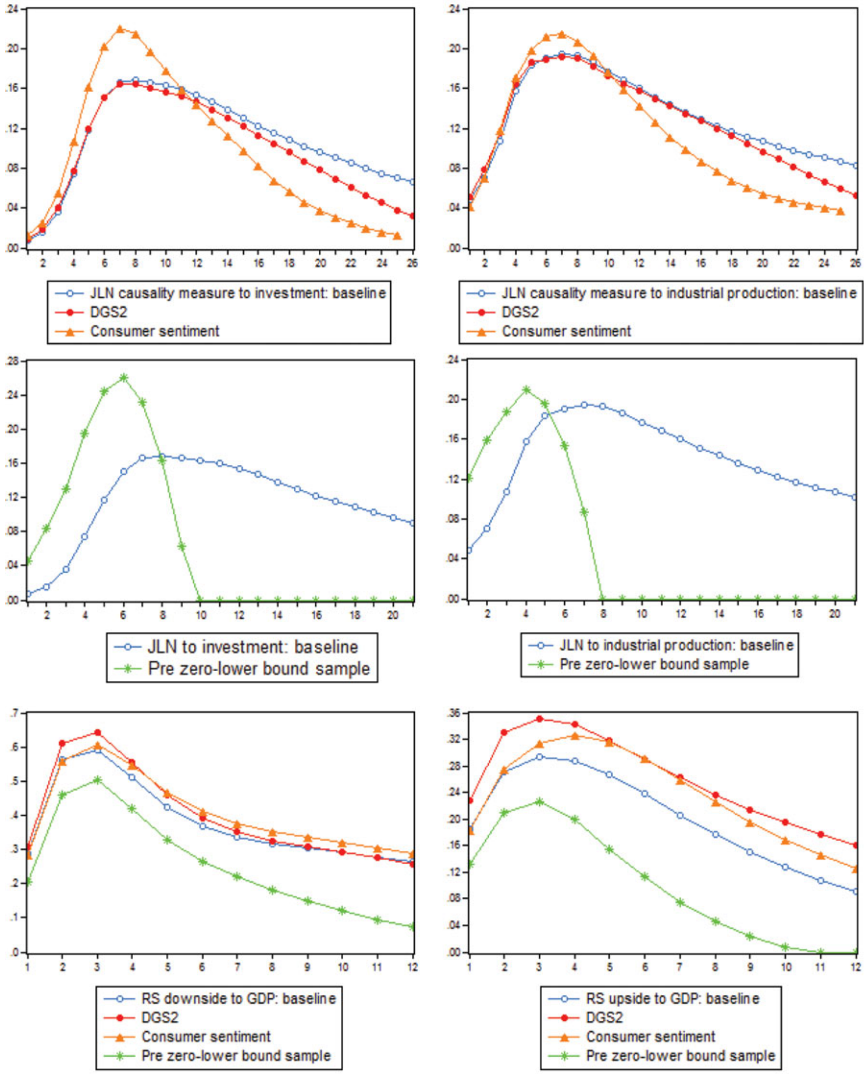

FIGURE 4. Causality measures of JLN and RS uncertainty proxies: Baseline VAR, DGS2 instead of the federal funds rate, Consumer sentiment index as an additional variable, Pre zero-lower bound sample.

are built using different methodological or conceptual approaches and different sets of economic variables, and reflect several aspects of economic policy or macroeconomic uncertainty. One of the indices further reflects asymmetry in uncertainty, by distinguishing between downside (negative) or upside (positive) uncertainty.

We first employ a dynamic causality method that provides evidence on the presence of direct and/or indirect Granger-causal structures at different horizons (examining the informational value of uncertainty proxies and their ability to better predict economic activity). Then, we estimate multihorizon CM to assess the magnitude of the forecast improvement induced by economic uncertainty and quantify the strength of the observed dynamic relations.

Our first finding is that macroeconomic uncertainty plays an important role in macroeconomic activity, and can help in forecasting key macroeconomic aggregates across multiple horizons. The JLN and RS macroeconomic uncertainty indices help to anticipate all macroaggregates, namely industrial production, consumption, investment, and employment, both at short-run and long-run horizons. Uncertainty anticipation effects on industrial production and consumption are direct and last for several months ahead. The effects on investment and employment are indirect, occurring with a time-delay. For example, in the case of the JLN $U_t(3)$ macrouncertainty index, significant anticipation effects on investment and employment occur with a 3-month and 6-month delay, respectively.

Second, dynamic causality reveals that the transmission chains of macroeconomic uncertainty for investment include consumption and the stock market as intermediate variables, while for employment include consumption and investment. These results reflect the major transmission channels of uncertainty effects on economic activity emphasized by the theoretical literature. We do not find substantial evidence of feedback effects from real activity to economic uncertainty.

Our third finding is that the impact, in terms of predictability, of macrouncertainty on economic activity is strong; the CM suggest that the predictive power or the magnitude of the forecast improvement induced by macroeconomic uncertainty is economically and statistically significant. Evidence of indirect transmission channels is further supported by the CM; the measures are not statistically significant at horizon one, in cases where direct noncausality is not rejected.

Fourth, asymmetry in macroeconomic uncertainty is important, when it is taken into account in the methodological approach, as implied by the dynamic causality results and CM. Upside and downside uncertainty produce significant macroeconomic effects, yet downside uncertainty produces the strongest impact.

Our last finding is that the information content of the mainly "news-based" EPU index is weaker. Dynamic causality and CM are generally not statistically significant and/or sizeable from an economic point of view. We attribute this result to the agents' concerns about long-run movements in the real economy (e.g., global uncertainty concerns and/or concerns about the slow recovery), as well as on the observed significant contemporaneous correlation between EPU and S&P 500 shocks, which implies that EPU does not include much unique information about economic activity compared to the stock price index.

SUPPLEMENTARY MATERIAL

To view supplementary material for this article, please visit https://doi.org/10.1017/S1365100518000081.

NOTES

1. For further discussion on uncertainty driving the slow recovery, see Baker, Bloom, Davis (2012), Bloom, Floetotto, Jaimovich, Saporta-Eksten, Terry (2014), and particularly on the slow recovery of the labor market, see Leduc and Liu (2013).
2. For further discussion, see e.g., Meinen and Röhe (2017).
3. Multiple-horizon or indirect causality might occur between two variables of direct interest of the high-dimensional VAR at higher forecast horizons, revealing nuanced details which would be collapsed out when employing standard Granger causality test procedures. See also Hill (2007).
4. Alexopoulos and Cohen (2009) further use a news-based uncertainty indicator and reach similar conclusions. Their analysis is further extended in Alexopoulos and Cohen (2015).
5. The authors consider this assumption as being consistent with the "wait-and-see" effect discussed in Bloom (2009). The "wait-and-see" effect suggests that firms stop investing and hiring if they suddenly find themselves in a more uncertain environment.
6. A similar approach is also used in Nodari (2014).
7. Henzel and Rengel (2016) also estimate non-linear VAR models and find that uncertainty induces larger effects when increases in uncertainty are big.
8. In their recent study, Rossi and Sekhposyan (2016) construct the Rossi and Sekhposyan (2015) macroeconomic uncertainty measures for individual European countries and the Euro Area.
9. Forecast errors are obtained from the Survey of Professional Forecasters' (SPF) forecasts.
10. The inclusion of the S&P 500 index to the VAR is important. Jurado, Ludvigson and Ng (2015) point that this index and economic uncertainty are expected to be dynamically related.
11. Similar VARs have been employed in Baker, Bloom, Davis (2013), Jurado, Ludvigson, Ng (2015), and Rossi and Sekhposyan (2015). These studies, however, focus on the effects of uncertainty on output and employment, while they are based on impulse responses. Further macroeconomic aggregates and their relation to uncertainty shocks are not examined or discussed in detail. Two other studies that have included consumption and investment in the VAR model are Alexopoulos and Cohen (2009) and Beetsma and Giuliodori (2012), yet these studies, among other differences, include different measures of uncertainty such as the stock market volatility index.
12. The results are not presented in order to conserve space. They are available upon request.
13. The DPR method is not applicable on vector error correction models (VECM). We could pretest for cointegration but such pretesting procedures have several limitations as well (Lütkepohl 2011) and accurate results are difficult to obtain for models that include a large number of variables.
14. A detailed calculation procedure is given in Dufour et al. (2006, p. 344 - 346).
15. The procedure based on nonstationary VAR models is described in detail in DPR (2006, p. 347-349), where the readers are referred for further details. A recent application of the Dufour et al. (2006) procedure based on nonstationary series may be found in Salamaliki et al. (2013).
16. Dufour et al. (2006, p.351).
17. These coefficient matrices correspond to the VMA(∞) coefficient matrices if Y_t is stationary
18. The percentile bootstrap intervals are improved by applying a bias correction to the VAR autoregressive coefficients described at the end of Section 8 in DT (we use 2000 replications). In practice, due to bootstrap samples, the estimated causality measures could become negative. In this case a non-negativity truncation is imposed.
19. Results with $\mathrm{U}_t(1)$ and $\mathrm{U}_t(12)$ are very similar and are presented in the online Appendix B.
20. The lag order for the VAR with EPU is 4, for the VAR with each of the $\mathrm{U}_t(1)$, $\mathrm{U}_t(3)$, $\mathrm{U}_t(12)$ is 5, and for the VAR with U^{-}_{t+4}, U^{+}_{t+4} and $\mathrm{U}^{\mathrm{overall}}_{t+4}$ is 2.
21. Based on a number of unit root tests not presented in the paper in order to conserve space.

22. The software used in our empirical analysis to estimate the (p, h)-autoregressions and perform the dynamic causality tests, as well as to estimate the causality measures is gretl (Gnu Regression, Econometrics and Time-series library), `http://gretl.sourceforge.net/`

23. Some effects of macro uncertainty to PCE are also observed at higher horizons. Also, in the case of industrial production when macro uncertainty $\mathrm{U}_t(12)$ is used, the effect appears to be indirect with an 1-month delay.

24. Substantial evidence on the financial frictions mechanism and it's role in the uncertainty - investment relation can be found in Gilchrist, Sim and Zakrajšek (2014) who include credit spreads in their VAR, an indicator commonly used to represent the degree of financial frictions.

25. This chain is stronger in the $\mathrm{U}_t(1)$ case.

26. Evidence on the chains for employment are stronger with the Rossi and Sekhposyan indices.

27. Details are available from the authors upon request.

28. The effects to investment now appear to be direct. Notice, however, than an observed delay when using monthly data might appear as direct (no delay) at the quarterly level. For example, up to 3-months delays might appear as direct (one-quarter ahead) with quarterly data.

29. Details are available from the authors upon request.

30. With respect to industrial production, the DPR test does not reject the null hypothesis of no-causality at any horizon although we do find causal effects from EPU on investment and from investment on industrial production. This might be a case of causal neutralization (Hill 2007).

31. Details are available from the authors upon request.

32. As in Zhang et al. (2016), the lag order is the same for conditional and unconditional VARs and causality measures, for reasons of comparison.

33. Details are available from the authors upon request.

34. The DPR method rejects non-causality from employment to EPU at $h = 4, 7 - 10$, suggesting indirect effects from employment to EPU. However, a causal chain cannot be established based on the bootstrapped p-values.

35. Correlation is estimated to be $-0.075, -0.058, 0.014$, and $0.074, -0.041$ for $U_t(1)$, $U_t(3)$, $U_t(12)$, and U^-_{t+4}, U^+_{t+4}, respectively.

36. Twelve lags (1 year) are included in the baseline VAR model employed in Jurado, Ludvigson and Ng (2015). The baseline lag order in Baker, Bloom, Davis (2013) is three, while six lags are also considered in their robustness checks. The VAR lag order in Rossi and Sekhposyan (2015) is one.

37. A possible explanation may be that when enlarging the VAR lag order, indirect effects may become direct if the original VAR order is too small. We would like to thank a referee for pointing this out. The lag choice effects from a theoretical (simulation-based) perspective will be pursued in future research.

38. For discussion on the inclusion of the consumer sentiment index, and the presence of the zero-lower bound, see also Caggiano et al. (2014) and Leduc and Liu (2015).

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