DOI: 10.1111/jmcb.12727

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News and Uncertainty Shocks

We provide novel evidence that technological news and uncertainty shocks, identified one at a time using vector autoregressive (VAR) models as in the literature, are correlated; that is, they are not truly structural . We then proceed by proposing an identification scheme to disentangle the effects of news and financial uncertainty shocks. We find that by removing financial uncertainty effects from news shocks, the positive responses of economic activity to news shocks are strengthened in the short term; and that the negative responses of activity to financial uncertainty shocks are deepened in the medium term as "good uncertainty" effects on technology are purged.

E32, E44
Keywords: forecasting error variance, structural VAR, news shocks, uncertainty shocks

NEWS SHOCKS ARE ANTICIPATED SHOCKS that affect the economy in the current period, even though it may take some time until they materialize. Jaimovich and Rebelo (2009) explain how news about future total factor productivity affects current output, consumption, and investment, and Beaudry and Portier (2006) and Barsky and Sims (2011) provide empirical evidence of the effects of technology news shocks on macroeconomic variables using vector autoregressive models. In contrast, Schmitt-Grohe and Uribe (2012) argue that anticipated productivity shocks

We would like to acknowledge the comments and suggestions by Anthony Garratt, Carlo Favero, Franck Portier, Gary Koop, Giovanni Ricco, James Mitchell, Luca Sala, Massimiliano Marcellino, Michael Moore, Haroon Mumtaz, Michael Owyang, Roberto Pancrazi, Ivan Petrella, and Marija Vukotić, the participants of the conferences SNDE, RES, IAAE, EEA, LuBraMacro, and CFE, and in particular by two referees of this journal. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the view of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

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Received January 26, 2017; and accepted in revised form January 15, 2020.

Journal of Money, Credit and Banking, Vol. 00, No. 0 (xxxx 2020)

are not as important for explaining business cycle fluctuations as alternative shocks,[1] and Christiano, Motto, and Rostagno (2014) find that anticipated risk shocks play a key role.

Uncertainty shocks are an alternative source of belief-driven business cycle fluctuations (Bloom 2009). The empirical evidence on the short-run negative effects of uncertainty shocks on economic activity using vector autoregressive models is extensive (Bachmann, Elstner, and Sims 2013, Jurado, Ludvigson, and Ng 2015, Baker, Bloom, and Davis 2016, Caldara et al. 2016, Rossi, Sekhposyan, and Soupre 2016, Shin and Zhong 2020).

In this paper, we provide novel empirical evidence linking anticipated technology and financial uncertainty shocks. Technological news and uncertainty shocks are identified by maximizing the respective forecasting error variances of productivity and observed uncertainty using the same reduced-form vector autoregressive model. This identification strategy was first proposed for anticipated technological shocks by Barsky and Sims (2011) as a variance decomposition extension of the penalty function approach by Faust (1998) and Uhlig (2005), which was applied by Caldara et al. (2016) to identify uncertainty shocks. As in Barsky and Sims (2011), news shocks are identified as the linear combination of reduced-form innovations that maximizes the productivity forecasting variance in the long run (over 10 years), and it is orthogonal to a surprise technological shock. Uncertainty shocks, instead, are identified as the linear combination that maximizes the observed uncertainty short-run forecasting variance (over two quarters, as in Caldara et al. 2016). If news and uncertainty shocks are structural from an economic perspective, they should be orthogonal even when separately identified. For example, Forni, Gambetti, and Sala (2017) evaluate whether the variables in the vector autoregressive model are informative about technological news shocks but otherwise assume that news shocks, identified as in Beaudry and Portier (2006) and Barsky and Sims (2011), are truly structural. However, we find that news and financial uncertainty shocks are positively correlated, indicating that technological news shocks, identified as in Barsky and Sims (2011), are not truly structural.

Supported by these empirical results, we propose a new identification strategy to disentangle the importance of news and financial uncertainty shocks in explaining business cycle variation. The strategy requires the identification of "truly news" shocks, uncorrelated with unexpected changes in financial uncertainty, and of "truly uncertainty" shocks, uncorrelated with anticipated changes in technology. As a by-product of our identification strategy, we are able to evaluate the impact of "good uncertainty" effects, that is, unexpected increases in financial uncertainty that have a medium-term (2–3 years) positive effect on productivity by increasing the likelihood of technological news shocks.

We analyze the correlation between news and the estimates of uncertainty shocks computed for 11 different proxies for observed uncertainty. The uncertainty proxies

1. Görtz and Tsoukalas (2017) challenge these results by incorporating a linkage between financial markets and real activity, amplifying the effects of technological news shocks.

are divided into two groups, as in Ludvigson, Ma, and Ng (Forthcoming): financial and macroeconomic. The group of macroeconomic uncertainty measures includes professional forecasters' disagreement, which is associated with ambiguity changes as in Ilut and Schneider (2014). Financial uncertainty measures are related to quantifiable risk as in Christiano, Motto, and Rostagno (2014). We find robust evidence of a positive correlation between news shocks and financial uncertainty shocks and some evidence of negative correlation with macroeconomic uncertainty shocks. Because macroeconomic uncertainty shocks have no significant dynamic effects on productivity, as is the case with financial uncertainty shocks, our identification strategy considers disentangling the effects of news and financial uncertainty shocks while keeping an observed measure of macroeconomic uncertainty in the model's information set. If we apply similar strategy to macroeconomic uncertainty shocks instead, we find smaller quantitative effects because the link between macroeconomic uncertainty and news shocks is weak.

Our paper contributes to the literature on measuring the relevance of technology news and uncertainty shocks as a source of business cycle variation. Barsky and Sims (2011) report that news shocks explain approximately 40% of the variation in output over long horizons (10 years), while Bachmann, Elstner, and Sims (2013) provide evidence that 12% of the long-run variation in manufacturing products is explained by shocks to stock market volatility—a popular measure of financial uncertainty. In contrast to the long-run effects of news shocks, the impact of uncertainty shocks typically peaks after 1 year (Jurado, Ludvigson, and Ng 2015, Baker, Bloom, and Davis 2016). Bachmann, Elstner, and Sims (2013) report an exception, showing that shocks to a measure of business forecaster dispersion have a persistent impact on manufacturing output, explaining up to 39% of the variation after 5 years. In general, uncertainty shocks explain 10% of the long-run variation in economic activity, as suggested by Jurado, Ludvigson, and Ng (2015) and Caldara et al. (2016). When considering macroeconomic and financial uncertainty shocks separately, Carriero, Clark, and Marcellino (2018) suggest that macroeconomic uncertainty explains approximately 20% of the variation in economic activity variables, while financial uncertainty explains approximately 10%. The identification scheme in Ludvigson, Ma, and Ng (Forthcoming) reverts these results in favor of financial uncertainty shocks.

Our identification strategy provides evidence of positive and significant responses of output, consumption, investment, and hours to technology news shocks, even at short horizons. A recent survey by Beaudry and Portier (2014) indicates that by applying the Barsky and Sims (2011) identification scheme, the response of hours to news shocks is normally positive, but it is not statistically different from zero over short horizons. By removing the correlation between news and financial uncertainty shocks, we remove the attenuation bias due to financial uncertainty effects and find a positive and significant effect in hours. In addition, "truly news" shocks are able to explain 61% of the variation of consumption and 44% of the variation of output at long horizons, but we find only 39% and 28%, respectively, if we use the Barsky and Sims (2011) identification scheme.

Our identification strategy also provides evidence that responses to uncertainty shocks are not all the same since their effects may depend on the observed proxy for uncertainty. Ludvigson, Ma, and Ng (Forthcoming) and Carriero, Clark, and Marcellino (2018) provide strategies to disentangle the impact of different uncertainty shocks in the macroeconomy. By working with the correlation between financial uncertainty and news shocks, we are able to measure the impact of "good uncertainty" effects, that is, the fact that an increase in financial uncertainty may be associated with an increase in the likelihood of technology news shocks. As we apply the "truly uncertainty" identification scheme that removes "good uncertainty" effects from financial uncertainty shocks, we find that "truly" financial uncertainty shocks explain a sizable share (22%) of the variation in output over medium-run horizons (2 years). If instead we apply the "truly news" scheme, where the financial uncertainty shock resembles the one obtained when shocks are separately identified, we find that financial uncertainty shocks play a smaller role explaining only 6% of the variation and peaking at horizons up to 1 year, in agreement with Jurado, Ludvigson, and Ng (2015) and Baker, Bloom, and Davis (2016). The differences between these explained variation shares, about 15% at a 2-year horizon, are then attributed to "good uncertainty" effects, since financial uncertainty shocks under the "truly uncertainty" scheme have a larger and stronger negative effect on all economic activity variables.

Our results support a variety of theories that consider the role of uncertainty as a business cycle driver, including "wait-and-see" effects (Bachmann, Elstner, and Sims 2013), confidence effects (Ilut and Schneider 2014), growth options effects (as suggested in Bloom 2014), and the possibility of uncertainty traps (Fajgelbaum, Schaal, and Taschereau-Dumouchel 2017).

We present empirical evidence on the correlation between technological news and uncertainty shocks in Section 1, where we also provide the details of the reduced-form Vector Autoregressive (VAR) model and analysis of the responses to news and uncertainty shocks. Section 2 describes the identification strategy used to disentangle both sources of business cycle variation and an analysis of "good uncertainty" effects. Section 2 also presents the empirical results obtained with our identification strategy and discusses implications for the literature on understanding the effects of uncertainty on the macroeconomy.

1. NEWS, UNCERTAINTY SHOCKS, AND THE MACROECONOMY

In this section, we apply an identification strategy based on maximizing the forecast error variance decomposition of a target variable over a defined number of horizons, as has been previously proposed in the literature, to estimate technology news and uncertainty shocks using a VAR model. When the target variable is observed uncertainty, we consider a set of proxies, following the literature. We then examine the correlations between different estimates of uncertainty shocks and the news shock estimate. Finally, we analyze the responses of key macroeconomic and financial variables to the shocks of interest to shed light on the evidence of correlation between news and uncertainty shocks.

1.1 Identification of News and Uncertainty Shocks in a VAR Model

We employ the same reduced-form VAR to identify news and uncertainty shocks. However, we compute the matrices required for identification of these shocks separately as if we were only interested in either news (Barsky and Sims 2011) or uncertainty shocks (Rossi, Sekhposyan, and Soupre 2016) to mimic the way authors usually treat these.

A set of 11 endogenous variables is considered in the reduced-form VAR model, which is estimated with quarterly data from 1975Q1 to 2017Q4. They include the variables listed in the first panel of Table 1 and also one proxy for uncertainty from the ones described in Table 1. Following the literature (Beaudry and Portier 2006, Barsky and Sims 2011), technology-induced productivity changes are measured using the utilization-adjusted total factor productivity (TFP) computed by Fernald (2014). The measures of economic activity in the VAR are consumption, output, investment, and hours. Relevant forward-looking variables are included among the endogenous variables, such as stock prices, since these are required for the identification of a news shock (Beaudry and Portier 2006). Additional endogenous variables are measures of aggregate prices, the policy rate, and the slope of the yield curve. The VAR model also includes a measure of credit conditions—the excess bond premium (EBP), as computed by Gilchrist and Zakrajšek (2012).

In the literature, we are able to find many different proxies for uncertainty, which is the 11th variable in the VAR. Macroeconomic uncertainty measures are typically related to the forecasting uncertainty of macroeconomic variables, such as real GDP and the aggregate price level. Financial uncertainty variables are measures of equity markets volatility, that is, of quantified risk. Bloom (2014) considers professional forecasters' dispersion as a measure of uncertainty, but Ilut and Schneider (2014) employ forecasters' dispersion as a measure of ambiguity. Table 1 describes the measures of uncertainty considered and divides them into two groups: financial and macroeconomic uncertainty. Policy uncertainty and business uncertainty, listed in the bottom panel, are not typical macroeconomic uncertainty measures, since they are not computed with respect to variables such as GDP and inflation, but they are illustrative of the macroeconomy beyond financial markets. We consider one of these uncertainty proxies one at a time in the VAR model.

The VAR variables are in log levels as in Barsky and Sims (2011), allowing for the possibility of cointegration among the variables. Because of the large number of coefficients to estimate as we set the VAR autoregressive order to 5 in a model with 11 endogenous variables, we employ Bayesian methods to estimate the VAR. Specifically, we take advantage of Minnesota priors (Litterman 1986, Bańbura, Giannone, and Reichlin 2010) and the "dummy observation prior," and prior hyperparameters are selected as in Carriero, Clark, and Marcellino (2015).[2] Confidence bands for the impulse response graphs are computed using 1,000 draws from the posterior distribution.

2. We obtain the overall prior tightness of 0.2 by maximizing the log-likelihood over a discrete grid, as in Carriero, Clark, and Marcellino (2015).

TABLE 1

Description Of Variables

	Name	Description	Source
1	Utilization-adjusted TFP	Utilization-adjusted TFP in log levels. Computed by Fernald (2014).	Fernald's website (Aug./2018)
2	Consumption	Real per capita consumption in log levels. Computed using PCE (nondurable goods + services), price deflator, and population.	Fred
3	Investment	Real per capita investment in log levels. Computed using PCE durable goods + gross private domestic investment, price deflator, and population.	Fred
4	Output	Real per capita GDP in log levels. Computed using the real GDP (business, nonfarm) and population.	Fred
5	Hours	Per capita hours in log levels. Computed with total hours in nonfarm business sector and population values.	Fred
6	Prices	Price deflator, computed with the implicit price deflator for nonfarm business sector.	Fred
7	SP500	SP500 stock index in logs levels.	Fred
8	EBP	Excess bond premium as computed by Gilchrist and Zakrajšek (2012).	Gilchrist's website (Aug/2018)
9	FFR	Fed funds rate + Wu–Xia Shadow Rate.	Fred, Atlanta Fed
10	Spread	Difference between the 10-year Treasury rate and the FFR.	Fred
	Financial Uncertainty Measures		
1	Realized volatility	Realized volatility computed using daily returns using the robust estimator by Rousseeuw and Croux (1993).	CRSP/WRDS
2	VXO	Option-implied volatility of the SP100 future index. Available from 1986Q1.	CBOE
3 4 5	LMN-fin-1 LMM-fin-3 LMN-fin-12	Financial forecasting uncertainty computed by Ludvigson, Ma, and Ng (Forthcoming). −1 is 1-month-ahead, −3 is 3-month and −12 is 1-year ahead.	Ludvigson's website (Aug/2018)
	Macro-economic uncertainty measures		
1	Policy uncertainty	Economic Policy Uncertainty Index in logs computed by Baker, Bloom, and Davis (2016). Available from 1985Q1.	Bloom's website (Aug/2018)
2	Business uncertainty	Business forecasters' dispersion computed by Bachmann, Elstner, and Sims (2013). Available up to 2011Q4.	AER website
3	SPF disagreement	SPF forecasters dispersion on one-quarter-ahead Q/Q real GDP forecasts computed using the interdecile range.	Philadelphia Fed
4 5 6	LMN-macro-1 LMN-macro-3 LMN-macro-12	Macro forecasting uncertainty computed by Ludvigson, Ma, and Ng (Forthcoming). −1 is 1-month-ahead, −3 is 3-months and −12 is 1-year ahead.	Ludvigson's website (Aug/2018)

Note: All for the 1975Q1–2017Q4 period except when noted. Monthly series converted to quarterly by averaging over the quarter. Realized volatility calculated by the authors based on data from the Center for Research in Security Prices (CRSP), accessed through the Wharton Research Data Services (WRDS).

The news shock is identified following the procedure proposed by Barsky and Sims (2011), and it is closely related to Francis et al. (2014) and Uhlig (2005)'s maximum forecast error variance approach. The full description of the identification scheme is in Appendix A. The news shock s_t^{news} is identified as the shock that best explains future unpredictable movements of utilization-adjusted TFP, which is a proxy for technology. This result is equivalent to finding the linear combination of the reduced-form VAR innovations u_t that maximizes the forecasting variance of productivity over a predefined period. Moreover, the parameters of the linear combination γ_2^{news} are obtained under the restriction that the news shock s_t^{news} will be uncorrelated (or orthogonal) to the TFP's own innovation, which is the unexpected TFP shock, s_t^{unexp}. This last restriction guarantees that the utilization-adjusted TFP response to a news shock is zero at impact. Following Barsky and Sims (2011) and Kurmann and Otrok (2013), the horizon to maximize the forecasting variance of productivity is set to 10 years ($H = 40$). Because of the large information set included in the VAR model described, we are confident that fundamentalness is not an issue affecting these empirical results, as suggested by Forni, Gambetti, and Sala (2014).

The uncertainty shock is the one that best explains future unpredictable movements of an observable proxy for uncertainty. As in the case of news shocks, s_t^{unc} is obtained by maximizing the forecast error variance decomposition of uncertainty over a specific horizon. In contrast with news shocks, no additional restriction is imposed and the horizon for forecast variance maximization is of two quarters (as in Caldara et al. 2016), that is, uncertainty shocks are the linear combination γ_3^{unc} of the reduced-form innovations u_t that maximizes the short-term unexpected variation of uncertainty.[3] In practice, the responses obtained with this approach are not very different from the application of short-run restrictions as in the case of a recursive approach, but this approach has the advantage of clearly stating that uncertainty shocks have short-run effects in contrast with the long-run effects of technology news shocks.

1.2 Correlation between News and Uncertainty Shocks

This section investigates the correlation between news and uncertainty shocks. We compute the news and uncertainty shocks using a reduced-form VAR with 11 variables estimated for the 1975–2017 period with estimation and identification procedures as explained in Section 1.1. Recall that news s_t^{news} and uncertainty s_t^{unc} shocks are identified one at a time as is normally done in the literature.

We consider different observed measures of uncertainty in the reduced-form VAR to obtain different measures of $s_{t,i}^{unc}$. We use one of the 11 uncertainty measures ($i = 1, \ldots, 11$) in the bottom panel of Table 1 at a time. We then calculate the correlations between news s_t^{news} and each uncertainty shock measure $s_{t,i}^{unc}$. These values

3. As the VAR parameters change, the signs of the identified shocks might flip because the identification is based on the forecast error variance. To ensure a positive news shock, we check whether the response of total factor productivity is positive after 40 quarters. If the response is negative, all computed responses are multiplied by (-1). In the case of uncertainty shocks, we simply check whether the shock has a positive impact on the uncertainty measure and multiply the responses by (-1) if they are negative.

TABLE 2

Correlation Between News And Uncertainty Shocks For Different Uncertainty Measures

	Correlation	
Financial uncertainty		
Realized volatility	0.45	[0.000]
LMN-fin-1	0.37	[0.000]
LMN-fin-3	0.36	[0.000]
LMN-fin-12	0.34	[0.000]
VXO	0.54	[0.000]
Macro uncertainty		
Policy uncertainty	−0.39	[0.000]
Business uncertainty	−0.02	[0.829]
SPF disagreement	0.07	[0.425]
LMN-macro-1	−0.34	[0.000]
LMN-macro-3	−0.30	[0.000]
LMN-macro-12	−0.18	[0.028]

Note: Values in brackets are *p*-values for the test of zero correlation under the null hypothesis, and are computed by taking into account the false discovery rate of positively dependent tests, following the methodology by Benjamini and Hochberg (1995). These results are computed for a reduced-form VAR model with the 10 variables in the first panel of Table 1 + one measure of uncertainty at time, as indicated. Identification schemes computed one at a time are described in Section 2.1. See data description in Table 1. The sample period is 1975Q1–2017Q4, but due to data availability it is shorter in the following cases: from 1986Q1 with VXO, from 1985Q1 with policy uncertainty, and up to 2011Q4 with business uncertainty.

TABLE 3

Correlation between News and Uncertainty Shocks for Different Uncertainty Measures with Data up to 2007Q4

	Correlation	
Financial uncertainty		
Realized volatility	0.47	[0.000]
LMN-fin-1	0.43	[0.000]
LMN-fin-3	0.44	[0.000]
LMN-fin-12	0.43	[0.000]
VXO	0.56	[0.000]
Macro uncertainty		
Policy uncertainty	0.08	[0.483]
Business uncertainty	−0.13	[0.196]
SPF disagreement	0.06	[0.492]
LMN-macro-1	−0.42	[0.000]
LMN-macro-3	−0.33	[0.000]
LMN-macro-12	−0.16	[0.109]

Note: See notes to Table 2. Sample period: 1975Q1 to 2007Q4, but due to data availability it is shorter in the following cases: from 1986Q1 with VXO and from 1985Q1 with policy uncertainty.

are presented in Table 2 and include the *p*-values of a test for the null hypothesis that the correlation is equal to zero, which takes into account the issue of multiple testing using the method in Benjamini and Hochberg (1995). In Table 3, we compute correlation using data only up to 2007Q4 by reestimating the shocks with this shorter period.

The main result from Table 2 is that there is a positive and significant correlation between news and all measures of financial uncertainty shocks. This finding indicates that these are not truly structural shocks, implying that if we use them separately to estimate their contribution to business cycle variation, such as the one done by Barsky and Sims (2011), Gilchrist and Zakrajšek (2012), Jurado, Ludvigson, and Ng (2015), Caldara et al. (2016), we may obtain biased estimates. The correlation is stronger if financial uncertainty is proxied by the VXO (0.54), although this might be the effect of the shorter period for which this series is available (since 1986). For the uncertainty measures proposed by Ludvigson, Ma, and Ng (Forthcoming), the correlation decreases with the forecasting horizon (1, 3, or 12 months ahead). If we use data up to 2007, these correlations are even higher, as presented in Table 3, indicating that these positive correlations among "structural shocks" are not a consequence of the great recession or the zero-lower bound period. Note that for the full sample estimates we use the Wu–Xia (Wu and Xia 2016) shadow rate instead of the Fed funds rate during the zero lower bound period (see Table 1). As indicated in Table C.1 in the Online Appendix, the correlations between news and uncertainty shocks decline if we increase the maximization horizon of the news shock from 10 years (as in Tables 2 and 3) to 20, 30, and 50 years. The correlation is still positive and significant for some financial uncertainty measures if news shocks are identified using either a 20- or 30-year horizon instead of the 10-year horizon.

In contrast, the correlations between news and macroeconomic uncertainty shocks are either statistically zero or are not robust to the sample period (as the case of policy uncertainty when we compare the results in Tables 2 and 3). An exception is the correlation with the short-term macroeconomic forecasting uncertainty measures, LMN-macro-1 and LMN-macro-3 computed by Ludvigson, Ma, and Ng (Forthcoming), as we find a significant negative correlation, which is robust over periods.

We investigate in detail the implications of these correlations for the estimated responses of economic variables to news, financial, and macroeconomic uncertainty shocks in the remainder of this section.

1.3 Responses to News Shocks

We previously found that news shocks are positively correlated with all five financial uncertainty shocks considered but negatively correlated with some specific measures of macroeconomic uncertainty shocks. We now enlarge the reduced-form VAR model to include 12 variables, that is, the 10 variables in the top panel of Table 1, plus two measures of uncertainty. The first one is the realized volatility[4] (a popular measure of financial uncertainty), and the second one is the 1-month macroeconomic forecasting uncertainty (LMN-macro-1). We use the 12-variable VAR model and the identification strategy described in detail in Appendix A to present the effects of news shocks on eight endogenous variables of interest. We are aware that these are not truly structural shocks, but an analysis of responses to these may improve our understanding of effects of the estimated empirical correlations.

4. Realized volatility calculated by the authors based on data from the Center for Research in Security Prices (CRSP), accessed through the Wharton Research Data Services (WRDS).

Figure 1 shows the responses of economic activity variables (output, consumption, investment, and hours), productivity (utilization-adjusted TFP), stock prices, financial uncertainty, as measured by the realized volatility, and macroeconomic uncertainty, as measured by LMN-macro-1, to news shocks. These results follow the previous literature surveyed in Beaudry and Portier (2014). News shocks have a positive impact effect on output, consumption, and investment, as in Beaudry and Portier (2006) and Barsky and Sims (2011), but the impact effects do not differ significantly from zero, as indicated by the 68% confidence bands. In the long run, technology news shocks explain 39% of the consumption variation, 28% of the output variation, and 20% of the investment variation as indicated by the baseline results in Table 4.

A novel and interesting result arises from observing the effect of news shocks on financial uncertainty. News shocks drive a significant increase in uncertainty of approximately 1.7 percentage points, albeit a short-lived effect that is near zero after 1 year. Although the positive effect of news shocks on uncertainty is evidence that we have not seen anywhere else in this aggregate context, these results are not surprising, since Bloom (2009) finds a positive correlation between stock market volatility and cross-sectional standard deviation of industry TFP growth. Matsumoto et al. (2011) show that news shocks are positively related to equity prices and equity volatility. Indeed, our evidence in Figure 1 is that both financial uncertainty and stock prices increase in the short term as a response to news shocks. Matsumoto et al. (2011) argue that an increase in stock market volatility arises from the delayed adjustment of prices by firms following a news shock, but this effect tends to vanish over time; thus, the effects are short-lived.

In contrast to the large positive effects on financial uncertainty, macroeconomic uncertainty declines as a response to positive technology news shocks. Note, however, that the estimated responses are uncertain since the 68% bands cover zero at all horizons.

Görtz, Tsoukalas, and Zanetti (2016) show that news shocks have negative effects on the EBP. The baseline VAR specification includes EBP as an endogenous variable and confirms their results. In this paper, we treat EBP as a variable that should be kept in the information set, but the main aim is to make an inference on how uncertainty responds to news shocks.

1.4 Responses to Uncertainty Shocks

The results in Tables 2 and 3 suggest that uncertainty shocks computed with financial and macroeconomic proxies are substantially different. As done previously, we consider responses computed using a 12-variable VAR model and present the results for eight variables as in Figure 1. We separately identify financial and macroeconomic uncertainty shocks using the maximization of the forecast error variance decomposition of uncertainty over two quarters as described in Section 1.1; thus, these shocks may not be truly structural, but as it will be made clear below, this empirical exercise motivates our identification strategy in Section 2. The responses to the financial uncertainty shock are presented in Figure 2 by employing the

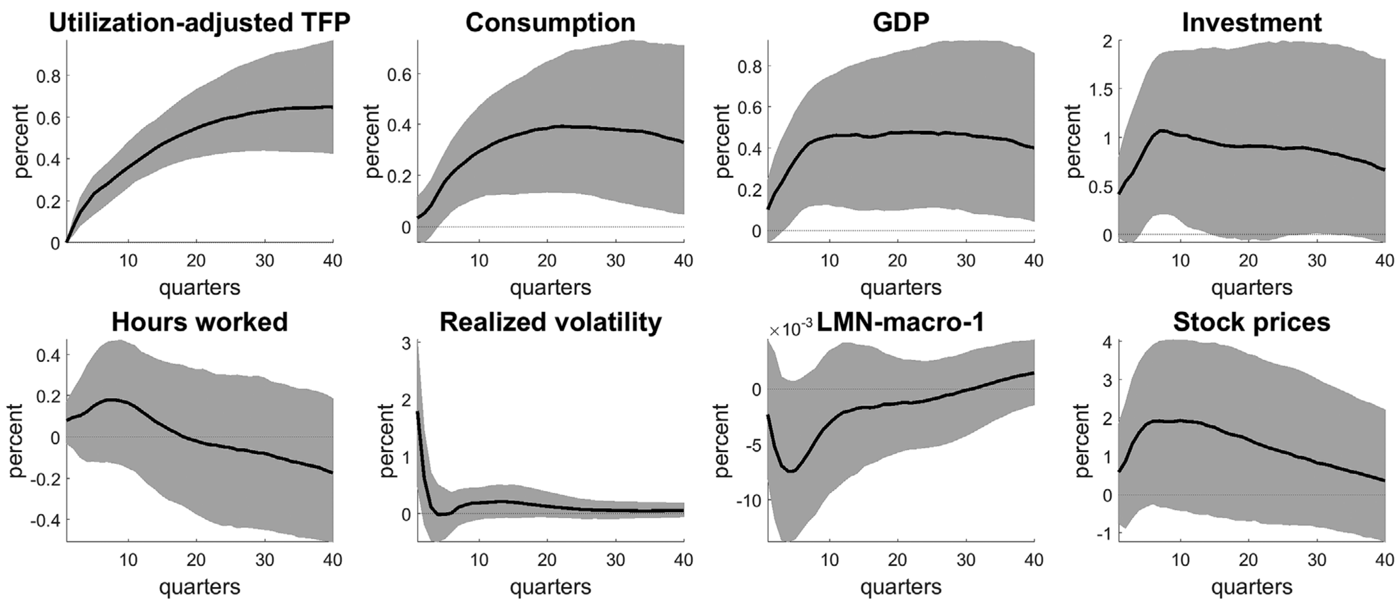


Fig 1. Responses to News Shocks.

NOTE: Shaded areas describe 68% confidence bands computed with 1,000 posterior draws. The baseline identification scheme for news shocks is described in Section 1.1, and Appendix A. The reduced-form VAR model includes all variables in the first panel of Table 1 + a proxy for financial uncertainty (realized volatility) + a proxy for macroeconomic uncertainty (LMN-macro-1). Sample period: 1975Q1–2017Q4.

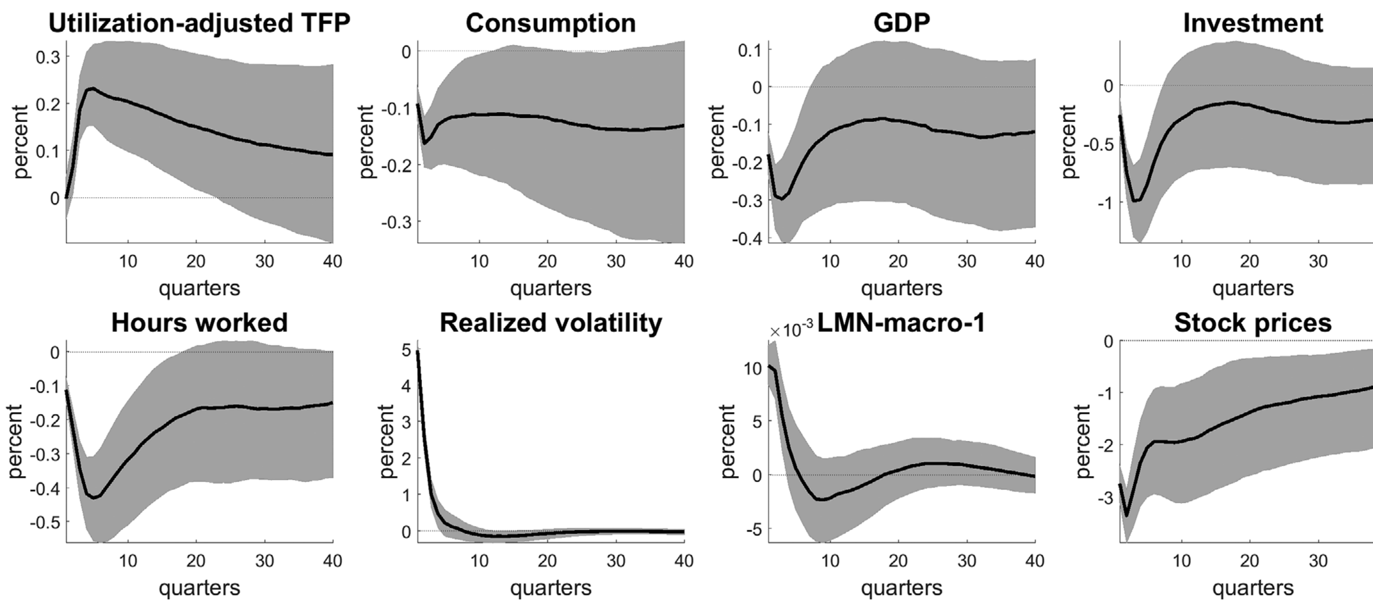


Fig 2. Responses to Financial Uncertainty (Realized Volatility) Shocks.

NOTE: Shaded areas describe 68% confidence bands computed with 1,000 posterior draws. The baseline identification scheme for uncertainty shocks is described in Section 1.1. The reduced-form VAR model includes all variables in the first panel of Table 1 + a proxy for financial uncertainty (realized volatility) + a proxy for macroeconomic uncertainty (LMN-macro-1). Sample period: 1975Q1–2017Q4.

TABLE 4

Variance Decomposition of Output, Consumption, Investment, and Hours to News and Financial Uncertainty Shocks

(a) Output

	News shock			Fin. uncertainty shock			
h	Baseline	Truly news	Truly unc.	Baseline	Truly news	Truly unc.	Good uncertainty
0	4.1	11.8	4.1	6.0	6.0	13.7	7.7
8	17.5	32.9	17.5	6.2	6.2	21.6	15.4
16	23.1	37.1	23.1	3.5	3.5	17.5	14.0
40	28.5	43.8	28.5	2.6	2.5	17.9	15.3

(b) Consumption

	News shock			Fin. uncertainty shock			
h	Base-line	Truly News	Truly Unc.	Base-line	Truly News	Truly Unc.	Good uncertainty
0	1.2	5.5	1.2	5.3	5.3	9.6	4.3
8	16.4	30.2	16.4	5.7	5.7	19.5	13.8
16	30.0	48.2	30.0	4.0	4.0	22.2	18.2
40	38.6	61.1	38.6	3.9	3.9	26.4	22.5

(c) Investment

	News shock			Fin. uncertainty shock			
h	Baseline	Truly news	Truly unc.	Baseline	Truly news	Truly unc.	Good uncertainty
0	9.2	16.2	9.2	1.8	1.8	8.8	7.0
8	16.8	33.4	16.8	7.5	7.5	24.2	16.7
16	18.2	31.0	18.2	4.2	4.2	17.0	12.8
40	19.6	32.1	19.6	3.1	3.1	15.7	12.6

(d) Hours

	News shock			Fin. uncertainty shock			
h	Baseline	Truly news	Truly unc.	Baseline	Truly news	Truly unc.	Good uncertainty
0	4.7	12.7	4.7	5.5	5.6	13.5	8.0
8	6.6	23.7	6.6	17.9	17.9	35.1	17.2
16	6.0	19.4	6.0	12.6	12.7	26.1	13.5
40	3.1	10.0	3.1	8.5	8.5	15.5	7.0

Note: The baseline identification scheme is described in Section 1.1, and the "truly news" and "truly uncertainty" schemes in Section 2.1. In all cases, the reduced-form VAR model includes all 10 variables in the first panel of Table 1 + a proxy for financial uncertainty (realized volatility) + a proxy for macroeconomic uncertainty (LMN-macro-1). Sample period: 1975Q1–2017Q4.

realized volatility to measure financial uncertainty. Figure 3 presents the responses to the macroeconomic uncertainty shock using the Ludvigson, Ma, and Ng (Forthcoming) 1-month-ahead macroeconomic forecasting uncertainty.

As in Bachmann, Elstner, and Sims (2013), Jurado, Ludvigson, and Ng (2015), Baker, Bloom, and Davis (2016), and Caldara et al. (2016), uncertainty shocks have significant negative effects on economic activity variables. The responses to macroeconomic uncertainty shocks (Figure 3) are stronger and more persistent than the re-

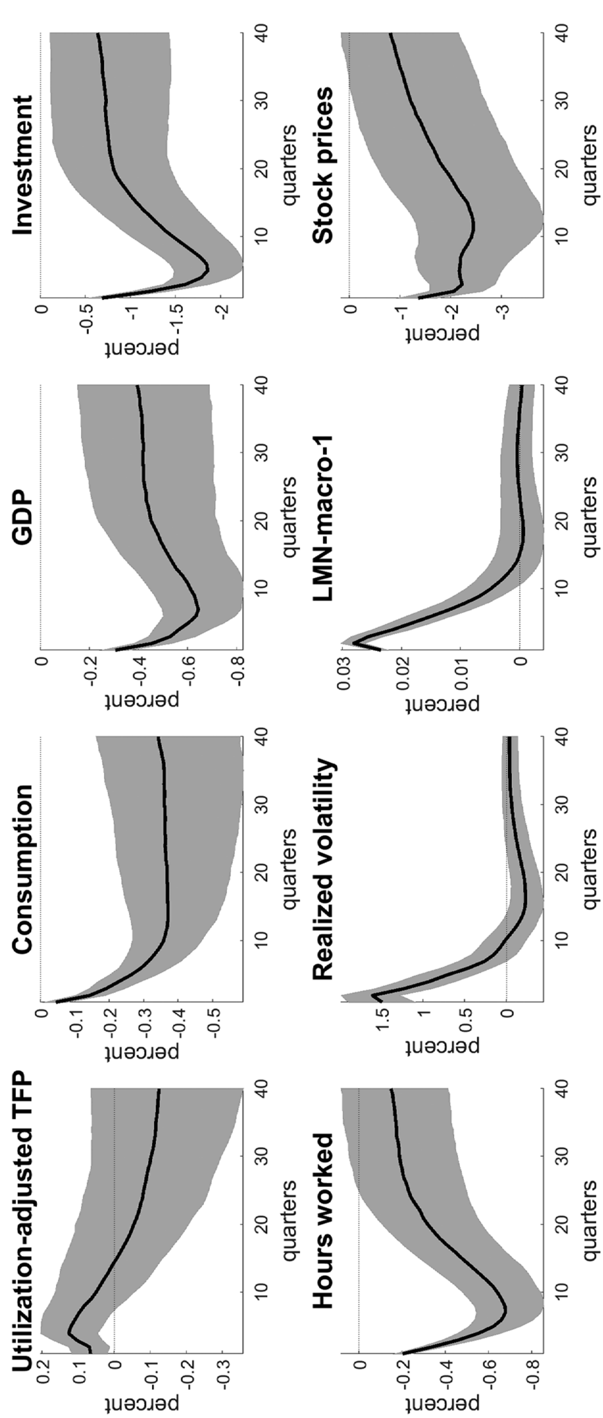


Fig 3. Responses to Macro-Economic Uncertainty (LMN-macro-1) Shocks.

NOTE: See notes of Figure 2.

sponses to financial uncertainty shocks (Figure 2). Surprisingly, financial uncertainty shocks have positive effects on technology (utilization-adjusted TFP), while macroeconomic uncertainty shocks have no significant effects on technology changes. The effect of financial uncertainty on technology peaks at five quarters, but it is persistent, dying out only over the long run.

These differences in the effects of macroeconomic and financial uncertainty on technology hold even if the proxy for financial and macroeconomic uncertainty is changed. Figure 4 presents the effect of a financial uncertainty shock on utilization-adjusted TFP for all the five measures of financial uncertainty employed here, and Figure 5 considers the six measures of macroeconomic uncertainty.[5] These results indicate that the positive effect of financial uncertainty shocks on productivity (as in Figures 2 and 4) may attenuate the negative effects of uncertainty on economic activity.

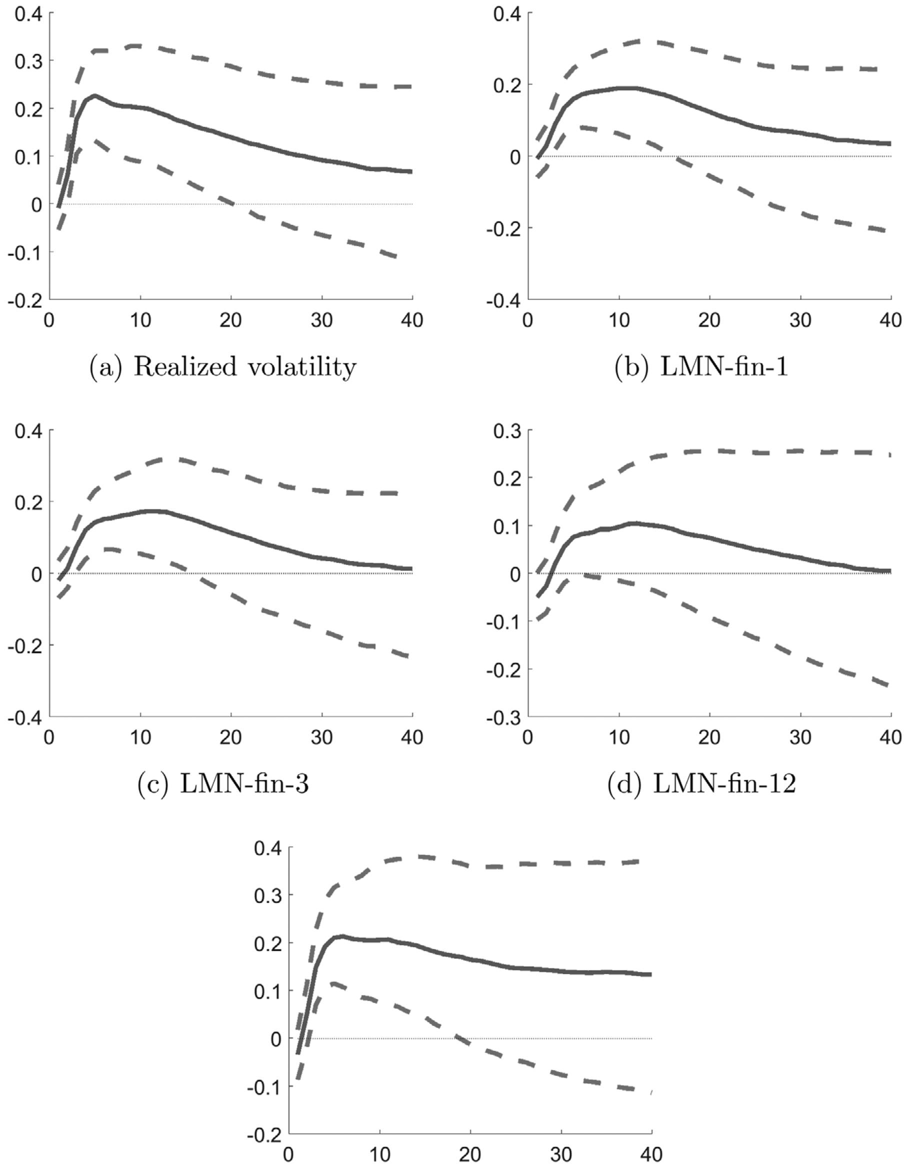
The persistent positive effect of financial uncertainty shocks on technology might be seen as counterintuitive. Bloom et al. (2018) and Bloom (2014) note that uncertainty makes productive firms less aggressive in expanding and unproductive firms less aggressive in contracting. This reallocation of production factors after an uncertainty shock should reduce total productivity.

We shed light on this puzzle by examining the responses of nonadjusted TFP to uncertainty shocks. They allow for us to evaluate the impact of utilization adjustment, that is, the removal of productivity changes due to factor utilization, on these results. Figure 6 provides the impulse responses of TFP to financial uncertainty shocks, and Figure 7 shows similar results for macroeconomic uncertainty shocks. The results are now consistent with Bloom et al. (2018) and Bloom (2014), since both types of uncertainty shocks have short-lived negative effects on productivity. This finding implies that the responses of productivity to uncertainty shocks reflect a combination of two effects: a short-lived negative effect driven by a reduction of factor utilization and a positive medium-horizon effect generated by technology improvements.

1.5 Summary

In this section, we provided the results for news and uncertainty shocks identified and estimated one at a time by maximizing the forecast error variance decomposition of an adequate proxy variable. The maximization is over the long term (10 years) in the case of news shocks and over the short term (2 quarters) in the case of uncertainty shocks. Our results show that (i) uncertainty and news shocks are correlated (thus not truly structural); (ii) financial uncertainty shocks have positive medium-term effects on productivity and economic activity; (iii) news shocks have short-term positive effects on financial uncertainty; and (iv) macroeconomic uncertainty shocks have deeper effects on economic activity than financial uncertainty shocks, but they

5. These responses were computed using the 11-variable VAR (top 10 variables in Table 1 + 1 uncertainty proxy) as in Table 2.



(a) Realized volatility

(b) LMN-fin-1

(c) LMN-fin-3

(d) LMN-fin-12

(e) VXO

Fig 4. Responses of Utilization-Adjusted TFP to Different Measures of Financial Uncertainty Shocks.

NOTE: See Table 1 for description of uncertainty measures. Dotted lines are 68% confidence bands computed with 1,000 posterior draws. The sample period is 1975Q1–2017Q4, but due to data availability it is shorter in the following cases: from 1986Q1 with VXO, from 1985Q1 with policy uncertainty, and up to 2011Q4 with business uncertainty. These responses are computed for one financial uncertainty proxy at a time in the reduced-form VAR that includes the 10 variables in the top panel of Table 1 + 1 proxy for financial uncertainty. Identification scheme as described in Section 1.1.

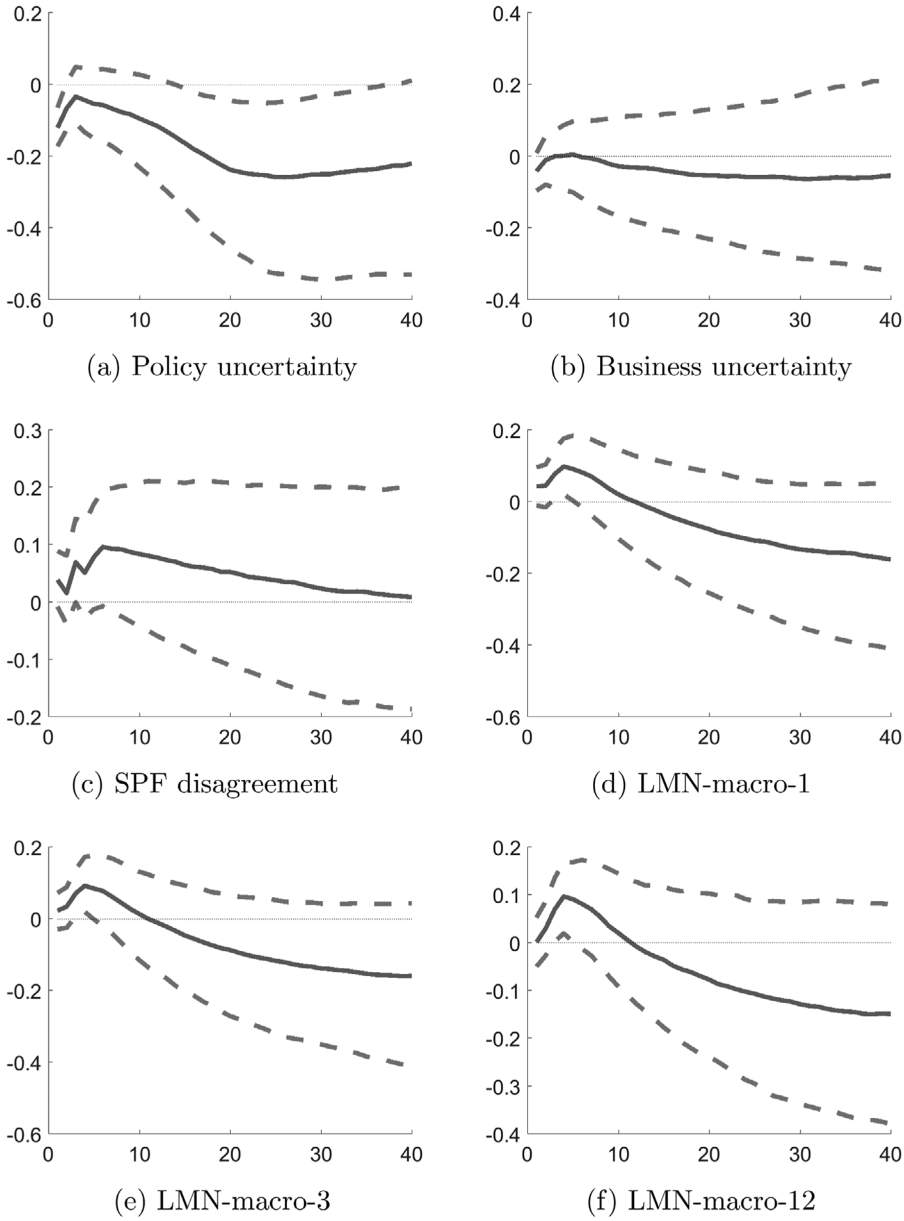
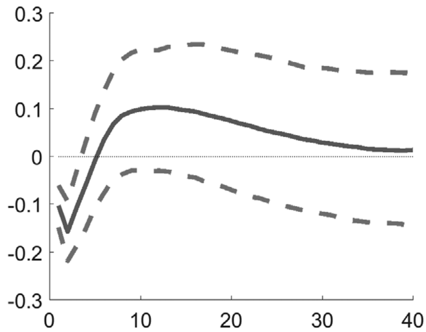
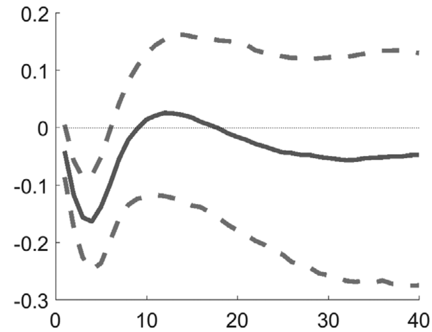


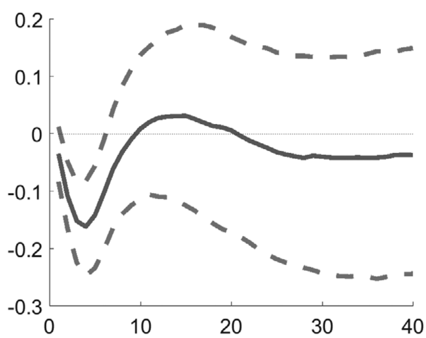
Fig 5. Responses of Utilization-Adjusted TFP to Different Measures of Macroeconomic Uncertainty Shocks.
NOTE: See notes to Figure 4. These responses are computed for one macroeconomic uncertainty proxy at a time in the reduced-form VAR that includes the 10 variables in the top panel of Table 1 + 1 proxy for macroeconomic uncertainty. Identification scheme as described in Section 1.1.



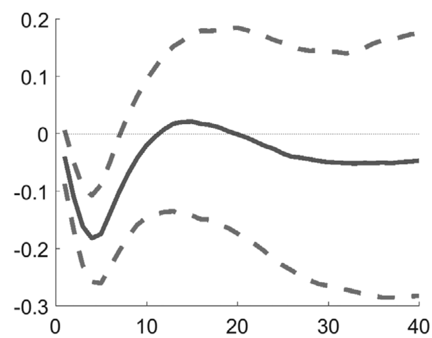
(a) Realized volatility



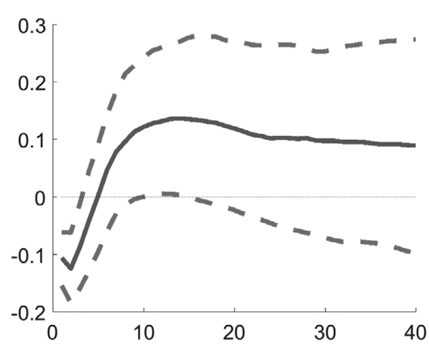
(b) LMN-fin-1



(c) LMN-fin-3



(d) LMN-fin-12



(e) VXO

Fig 6. Responses of Nonadjusted TFP to Different Measures ofFinancial Uncertainty Shocks in the Baseline Model.

NOTE: See notes to Figure 4. These responses are computed for one financial uncertainty variable at a time in a VAR that also includes the 10 variables in the top panel of Table 1. The difference between these results and Figure 4 is that here TFP is not adjusted for utilization. Identification scheme as described in Section 1.1.

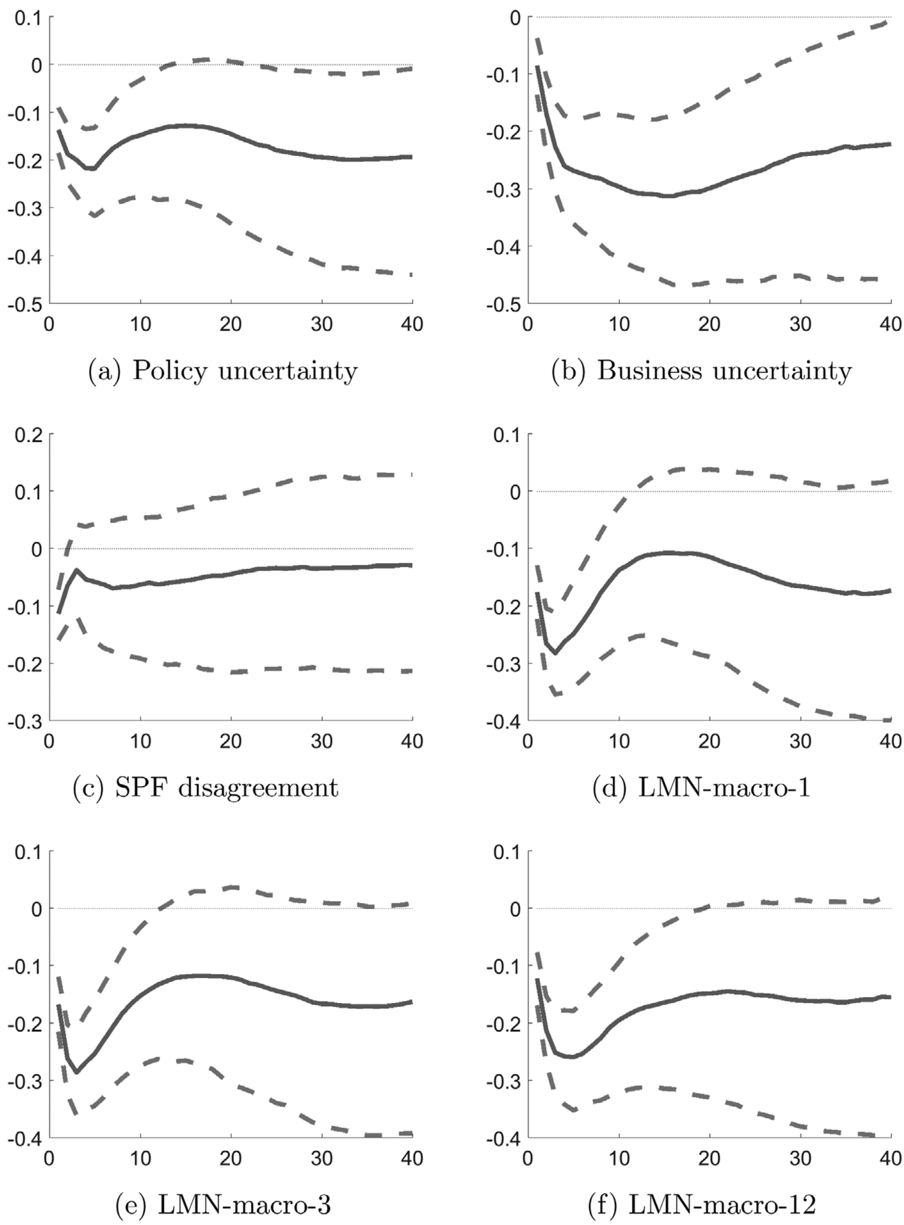


Fig 7. Responses of Nonadjusted TFP to Different Measures of Macro-Economic Uncertainty Shocks in the Baseline Model.

NOTE: See notes to Figure 4. These responses are computed for one macro-economic uncertainty variable at a time in a VAR that also includes the 10 variables in the top panel of Table 1. The difference between these results and Figure 5 is that here TFP is not adjusted for utilization. Identification scheme as described in Section 1.1.

have no effect on productivity. We see these novel interesting empirical results as motivation for our new identification scheme discussed in the next section.

2. DISENTANGLING UNCERTAINTY AND NEWS SHOCKS

Our previous results suggest that if identified separately, news and uncertainty shocks are correlated. In this section, we build identification strategies to obtain truly structural news and financial uncertainty shocks to be able to measure the relevance of each shock in explaining business cycle variation.

2.1 Identification of "Truly" News and Financial Uncertainty Shocks

In the previous section, we found that news shocks are positively correlated with financial uncertainty shocks and that this evidence is robust to different periods and proxies for financial uncertainties. We also found that uncertainty shocks computed for short-term measures of macroeconomic forecasting uncertainty (as in Ludvigson, Ma, and Ng Forthcoming) are negatively correlated with news shocks. We show that productivity increases in the medium term as a response to financial uncertainty shocks but not as response to macroecononomic uncertainty shocks. In addition, financial uncertainty strongly increases as a response to news shocks, but the response of macroeconomic uncertainty is negative and weaker, as the responses of squared news to news shocks in Forni, Gambetti, and Sala (2017).

We examine identification strategies for the "truly news" and the "truly financial uncertainty" shocks in this section. The main advantage of considering two identification schemes is that together they allow for the measurement of "good uncertainty" effects, as described in detail in Section 2.3.

The reduced-form VAR, as in Sections 1.3 and 1.4, includes the 10 variables in the top panel of Table 1 plus measures of financial uncertainty (realized volatility) and macroeconomic uncertainty (LMN-macro-1). Because the links between financial uncertainty and news shocks seemed stronger and more interesting than those between macroeconomic uncertainty and news shocks, we prefer to consider identification strategies for "truly financial uncertainty" shocks only while keeping a measure of macro-economic uncertainty in the VAR information set. We assess how our results might change if we use instead macroeconomic uncertainty in Section 2.5.

Using the Barsky and Sims (2011) approach to identify technology news and unexpected technology shocks, we obtain s_t^{unexp} and s_t^{news} as described in Appendix A using the 12-variable VAR described in Section 1.3. Then using also the 12-variable VAR, we obtain s_t^{finunc} by maximizing the forecast error variance decomposition of a measure of financial uncertainty (realized volatility) over two quarters. The evidence in Section 1.2 is that s_t^{finunc} and s_t^{news} are correlated and not truly structural. Our proposed identification strategy employs the vector $s_t = (s_t^{unexp}, s_t^{finunc}, s_t^{news})'$ to obtain truly structural shocks $\tilde{s}_t = (\tilde{s}_t^{unexp}, \tilde{s}_t^{finunc}, \tilde{s}_t^{news})'$, that is, $\tilde{s}_t = \boldsymbol{C} s_t$. Because unexpected technological shocks are by construction orthogonalized to news shocks, we have initially:

$$\begin{bmatrix} \tilde{s}_t^{unexp} \\ \tilde{s}_t^{finunc} \\ \tilde{s}_t^{news} \end{bmatrix} = \begin{bmatrix} 1 & c_{12} & 0 \\ c_{21} & 1 & c_{23} \\ 0 & c_{32} & 1 \end{bmatrix} \begin{bmatrix} s_t^{unexp} \\ s_t^{finunc} \\ s_t^{news} \end{bmatrix}. \tag{1}$$

We need to impose additional restrictions to be able to identify all shocks in $\tilde{s}_t$. We consider two strategies: the "truly news" strategy sets $c_{23} = 0$, that is, news shocks have zero effects on financial uncertainty shocks implying that $\tilde{s}_t^{news}$ is orthogonalized with respect to s_t^{finunc}. The second strategy is called "truly uncertainty," and imposes $c_{32} = 0$, that is, financial uncertainty shocks have zero effects on news shocks leading to the orthogonalization of $\tilde{s}_t^{finunc}$ with respect to s_t^{news}.

We estimate the vectors required for the identification of $\tilde{s}_t$ by applying the restrictions described above using a QR decomposition over the three γ vectors that have originally defined s_t (as, for example, equation (A10)). The new $\tilde{\gamma}$ vectors are obtained from the orthonormal "Q part" of the decomposition.[6] Because the structural shocks $\tilde{s}_t$ are a linear combination s_t, which are themselves a linear combination of the reduced-form shocks $\boldsymbol{u_t}$, the impact effect of these shocks on the endogenous variables in the VAR are not constraint to zero with the exception of the zero-effect restriction of s_t^{news} on TFP.

The estimation of the "truly news" identifying vectors is based on a four-step procedure. In the first step, the procedure for the identification of the unexpected TFP and news shocks, described in Appendix A, is applied to obtain γ_2^{news} (and γ_1^{unexp}). Then, the financial uncertainty identification vector γ_3^{finunc} is obtained by maximizing the variance decomposition of financial uncertainty up to horizon 2. The third step imposes the orthogonality between the financial uncertainty and the unexpected shock using QR decomposition to obtain $\tilde{\gamma}_3^{finunc}$. The fourth step uses $\tilde{\gamma}_3^{finunc}$ and a QR decomposition to obtain $\tilde{\gamma}_2^{news}$ such that we are able to obtain technology news shocks that are orthogonalized to financial uncertainty shocks. Additional details on how we obtain impulse responses are in Appendix B.

The "truly uncertainty" identification scheme implies a different ordering in the orthogonalization strategy. In the case of the "truly uncertainty" scheme, the technology-based shocks, news and unexpected, are ordered before the uncertainty shock in the orthogonalization structure; thus, the news shock under this scheme is as the baseline case in Section 1.1 ($\tilde{\gamma}_2^{news} = \gamma_2^{news}$) as the financial uncertainty shock is orthogonalized to the unexpected and news shocks.[7]

6. The QR decomposition is an application of the Gram–Schmidt orthonormalization procedure. In our application, the first vector (orthonormal by construction) remains unchanged. The second vector is computed by subtracting its projection over the first one. The third vector is obtained by subtracting its projection over the first two.

7. An alternative method to estimate the truly structural shocks is a sequence of regressions to obtain the nonrestricted coefficients in the matrix $\boldsymbol{C}$ in equation (1). In the case of the "truly news" scheme, c_{21} is estimated by a regression of s_t^{finunc} on s_t^{unexp}, and c_{32} by regressing $\tilde{s}_t^{finunc}$, obtained in the previous step,

2.2 *Responses with the "Truly News" and the "Truly Uncertainty" Schemes*

Figures 8 and 9 show the responses to news and financial uncertainty shocks, respectively. We present the results for both the "truly news" and "truly uncertainty" identification schemes, and 68% confidence bands are included. In Figure 8, the dashed responses are those for the "truly uncertainty" scheme, and in Figure 9, they are for the "truly news" scheme.

Figure 8 clearly shows that news shocks have greater effects on economic activity variables (consumption, investment, hours, and output) if we remove uncertainty effects from the news shock as in the case of the "truly news" identification scheme. Note that, by definition, the responses to news shocks under the "truly uncertainty" scheme are as the responses in Figure 1. Consequently, the difference between the black and the dashed lines in Figure 8 measures the attenuation effect of increasing financial uncertainty with the arrival of news about technological developments. This attenuation effect is also noted on the negative effect that news has on macroeconomic uncertainty and the positive effect on stock prices, which are deepened in the "truly news" scheme.[8]

Interestingly, the "truly news" identification scheme recovers responses that show that hours, consumption, and investment move together with output, including responses that differ significantly from zero (based on the 68% bands) at the time of the impact of the news shock. This comovement is suggested by Beaudry and Portier (2006), but it is normally not observed when news shocks are identified by maximizing the forecasting variance, as in Barsky and Sims (2011) and this paper.

Figure 9 indicates that financial uncertainty shocks have stronger negative effects on the economic activity variables under the "truly uncertainty" identification scheme. Note that the responses to financial uncertainty shocks under the "truly news" scheme are virtually the same as the ones in Figure 2 since the correlation between s_t^{finunc} and s_t^{unexp} is small. The differences between the dashed and black lines in Figure 9 are mainly due to the removal of news shock effects from the financial uncertainty shock.[9] These lines show a reduction in the medium-run (3–4 years) positive effects of financial uncertainty shocks on utilization-adjusted TFP changes. There are still some positive effects on productivity at short horizons, but they are small since financial uncertainty shocks explain only a modest fraction of TFP variation (approximately 5% at $h = 16$). We attribute this small positive effects to measurement errors in the utilization-adjusted total factor productivity series as also reported in Cascaldi-Garcia (2017), Kurmann and Sims (Forthcoming), and Bouakez and Kemoe (2017).

on s_t^{news}. In the case of the "truly uncertainty" scheme, c_{21} and c_{23} are jointly estimated in a regression of s_t^{finunc} on s_t^{unexp} and s_t^{news}. These coefficients are then employed to compute $\tilde{s}_t^{finunc}$ (while $\tilde{s}_t^{news} = s_t^{news}$). The QR decomposition is employed because it is more convenient in this context, as indicated in Appendix B.

8. If the VAR is estimated with data up to 2007, the attenuation effects on GDP, consumption, and investment are not as strong, but similar effects for hours and stock prices are found as indicated in Figure C.1 in the Online Appendix.

9. Similar effects are found when the VAR is estimated using data only up to 2007 as indicated in Figure C.2 in the Online Appendix.

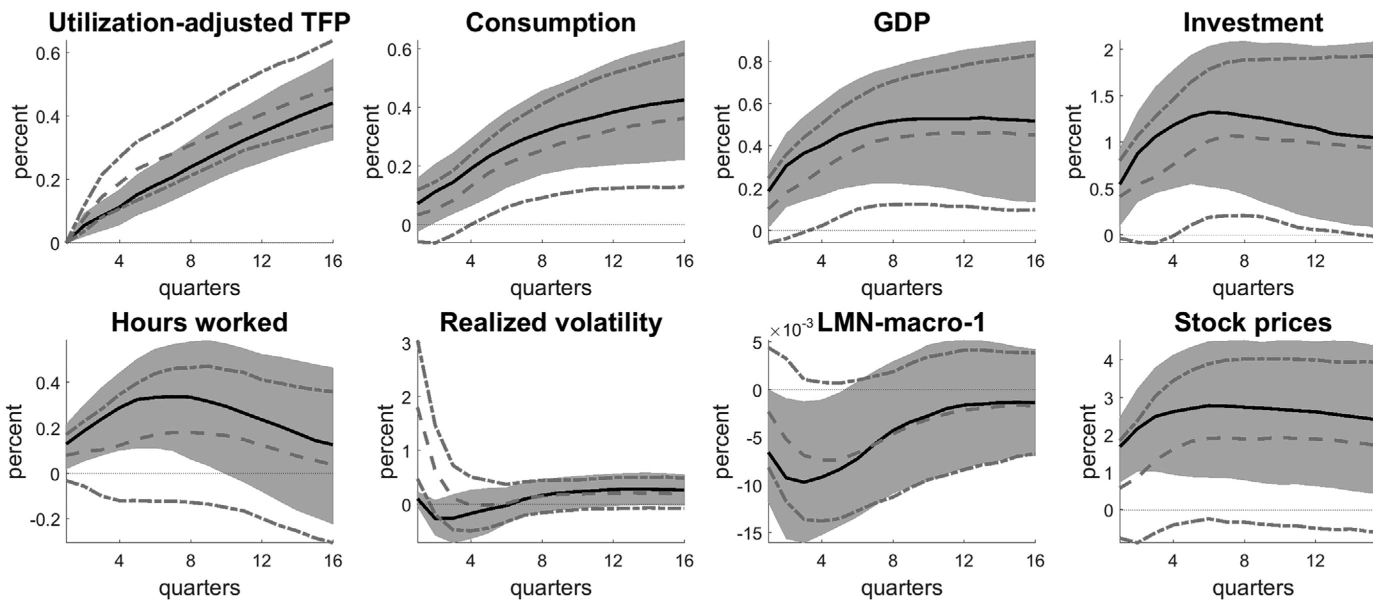


Fig 8. Responses to News Shocks with the "Truly News" (Solid Lines) and the "Truly Uncertainty" (Dashed Lines) Identification Schemes.

NOTE: Shaded and dashed areas are 68% confidence bands computed with 1,000 posterior draws. The "truly news" and "truly uncertainty" identification schemes are described in Section 2.1. The reduced-form VAR model includes all variables in the first panel of Table 1 + a proxy for financial uncertainty (realized volatility) + a proxy for macroeconomic uncertainty (LMN-macro-1). Sample period: 1975Q1–2017Q4.

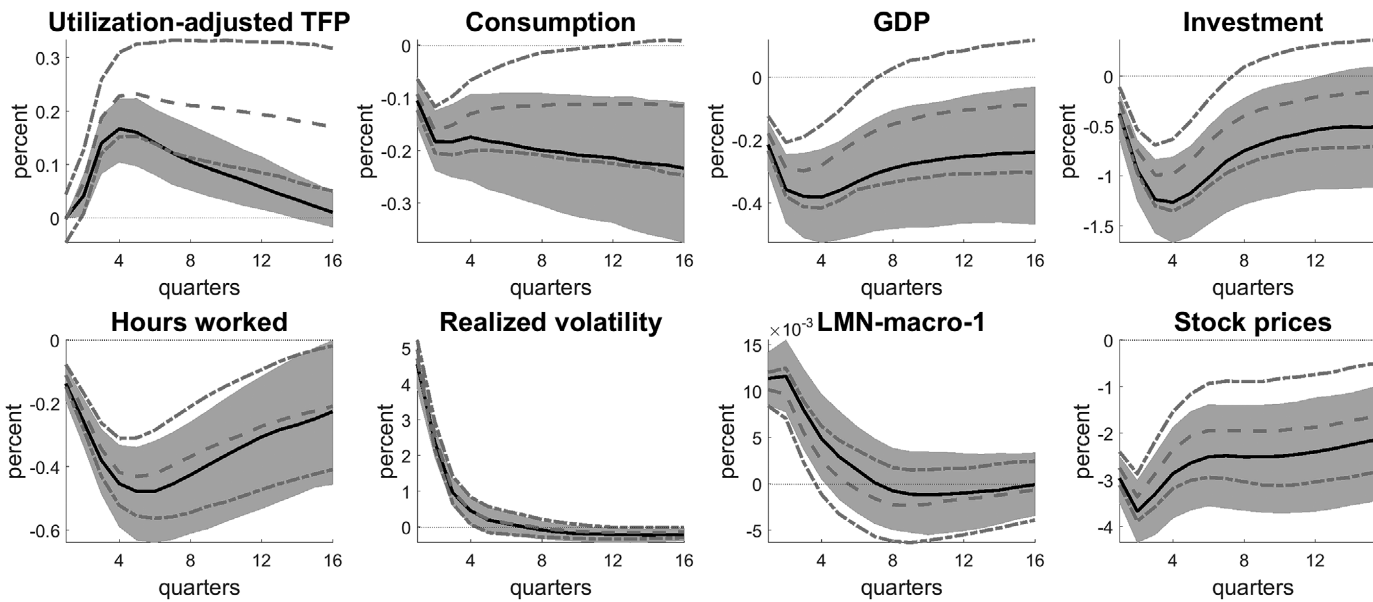


Fig 9. Responses to Financial Uncertainty Shocks with the “Truly News” (Dashed Lines) and the ‘Truly Uncertainty’ (Solid Lines) Identification Schemes.

NOTE: See notes to Figure 8.

One can say that the attenuation effects from using the “truly news” identification ($c_{23} = 0$ in equation (1)) instead of “truly uncertainty” ($c_{32} = 0$ in equation (1)) to compute the effects of financial uncertainty shocks are explained by “good uncertainty” effects, since they improve technology in the medium term. We elaborate on this point further in Section 2.4.

2.3 Explaining Business Cycle Variation

Table 4 presents the variance decomposition of economic activity variables (output, consumption, investment, and hours) explained by two shocks (news and financial uncertainty) based on three identification schemes (baseline, “truly news,” and “truly uncertainty”). In the baseline identification scheme (described in Section 1.1), the shocks are identified separately in the 12-variable reduced-form VAR. The values are computed at the posterior mean for horizons after zero quarters (at impact), eight quarters (2 years), 16 quarters (4 years), and 40 quarters (10 years).

The main result from Table 4 is that the relative importance of news and financial uncertainty shocks depends on whether we remove financial uncertainty effects from news shocks (c_{32} is nonzero but $c_{23} = 0$ in equation (1)). If that is the case, then “truly” technology news shocks explain a large share of the variance in the long run: 44% of the output variation, 61% of the consumption variation, 32% of the investment variation, and 10% of the hours variation. Uncertainty shocks under the “truly news” scheme play only a small role (up to 7% at the 2-year horizon in case of investment), similar to the baseline case.

If instead we remove technological effects from financial uncertainty shocks in the “truly uncertainty” scheme (c_{23} is nonzero but $c_{32} = 0$ in equation (1)), we find that the effects of news shocks are as in the baseline case such that the shares explained by news shocks at the 10-year horizon are as follows: 28% for output, 39% for consumption, 20% for investment, and 3% for hours. The effects of the financial uncertainty shocks are then boosted. “Truly financial uncertainty” shocks explain 17% of the output variation, 22% of the consumption variation, 17% of the investment variation, and 26% of hours variation after 4 years. In contrast, the variation of technology explained by financial uncertainty shocks declines in the “truly uncertainty” scheme, explaining only 5% of the medium-horizon variation ($h = 16$) in comparison to 10% in the baseline identification.

2.4 Good Uncertainty Effects

We call “good uncertainty” effects the unexpected changes in financial uncertainty that are correlated with news shocks. These are “good uncertainty” effects because they typically improve technology in the medium run as indicated by Figures 2 and 9.

This novel medium-run positive effect from financial uncertainty shocks to technological changes might be the result of firms’ reaction to the new economic environment. After the initial negative effect, firms seek to become more productive to reduce the impact of possible similar future shocks. The notion of an adaptation period recalls Comin (2000), who focus on the impact of uncertainty on the productivity of specialized capital. The initial negative impact of uncertainty shocks induces firms to substitute old technologies (inflexible and obsolete in an uncertain business environment) for more flexible ones, generating a positive shift in TFP. Bloom et al. (2018) also provide support for these "good uncertainty" medium-run effects. Uncertainty delays firms' investment projects, affecting expansion decisions and the hiring of new employees. However, when uncertainty recedes, firms reevaluate their suspended investment plans in order to attend the constrained demand. Bloom et al. (2018) argue that after the uncertainty period vanishes, firms increase hiring and investment, which can lead to increasing productivity.

"Good uncertainty" effects are computed using the differences between the "truly uncertainty" and the "truly news" identification schemes on the responses to financial uncertainty shocks. Using Figure 9, the differences between the "truly news" (dashed line) and the "truly uncertainty" (solid line) responses are "good uncertainty" effects. In the case of output and investment, the mean response is of -0.2% and -0.5%, respectively, after 4 years, but they do not rule out a zero effect if we allow for good uncertainty.

In Table 4, the differences between both identification schemes are labeled as "good uncertainty" in the last column. These results suggest that if we allow for "good uncertainty" effects, financial uncertainty shocks contribute little to explain business cycle variation, in line with the muted effects of financial uncertainty shocks in Carriero, Clark, and Marcellino (2018). However, if we consider only "bad uncertainty," as in the case of the "truly financial uncertainty" shock, we find large effects. The difference between both identification schemes is sizable if compared with alternative sources of business cycle variation in particular at medium horizons (2 years), where "good uncertainty" effects are associated with about 15% of the unexpected variation in output, consumption, investment, and hours.

As a consequence, not all financial uncertainty shocks are equal. An increase in equity market volatility may improve technology and productivity after 1 year if it is followed by a higher likelihood of technology news shocks. These beneficial effects of uncertainty shocks have a strong attenuation effect on the negative responses of economic activity to an exogenous increase in uncertainty. Indeed, the variation explained by "truly financial uncertainty" shocks in the economic activity variables is four times larger than the one computed in the baseline case.

2.5 Macroeconomic Uncertainty and Good Uncertainty Effects

In this section, we evaluate whether the evidence of "good uncertainty" effects can be extended to macroeconomic uncertainty shocks.

Table 5 replicates the results of Table 4 by applying the "truly news" and "truly uncertainty" identification scheme using $s_t^{macrounc}$ instead of s_t^{finunc} in equation (1), where $s_t^{macrounc}$ is obtained by finding the linear combination of the reduced-form shocks from the 12-variable VAR that maximizes the forecast error variance of the

TABLE 5

Variance Decomposition of Output, Consumption, Investment, and Hours to News and Macroeconomic Uncertainty Shocks

(a) Output

	News shock			Macro uncertainty shock			
h	Baseline	Truly news	Truly unc.	Baseline	Truly news	Truly unc.	Good uncertainty
0	4.1	1.1	4.1	17.9	20.6	17.6	3.0
8	17.5	8.5	17.5	35.7	37.5	28.5	9.0
16	23.1	12.8	23.1	34.4	35.8	25.6	10.2
40	28.5	18.2	28.5	28.5	29.7	19.4	10.3

(b) Consumption

	News shock			Macro uncertainty shock			
h	Baseline	Truly news	Truly unc.	Baseline	Truly news	Truly unc.	Good uncertainty
0	1.2	0.7	1.2	1.2	1.4	0.9	0.5
8	16.4	9.4	16.4	22.4	23.3	16.3	7.0
16	30.0	19.1	30.0	29.8	30.4	19.5	10.9
40	38.6	26.4	38.6	29.3	29.4	17.3	12.1

(c) Investment

	News shock			Macro uncertainty shock			
h	Baseline	Truly news	Truly unc.	Baseline	Truly news	Truly unc.	Good uncertainty
0	9.2	5.0	9.2	13.4	14.8	10.6	4.2
8	16.8	7.9	16.8	37.4	38.5	29.5	9.0
16	18.2	9.7	18.2	30.7	31.5	23.1	8.4
40	19.6	12.2	19.6	22.4	23.2	15.8	7.4

(d) Hours

	News Shock			Macro uncertainty shock			
h	Baseline	Truly news	Truly unc.	Baseline	Truly news	Truly unc.	Good uncertainty
0	4.7	1.7	4.7	18.7	16.0	13.0	3.0
8	6.6	1.4	6.6	43.0	40.2	35.0	5.2
16	6.0	1.3	6.0	39.5	36.7	32.1	4.6
40	3.1	1.0	3.1	23.4	21.5	19.4	2.1

Note: The baseline identification scheme is described in Section 1.1, and the "truly news" and "truly uncertainty" schemes in Section 2.1. In all cases, the reduced-form VAR model includes all 10 variables in the first panel of Table 1 + a proxy for financial uncertainty (realized volatility) + a proxy for macroeconomic uncertainty (LMN-macro-1). Sample period: 1975Q1–2017Q4.

macroeconomic (LMN-macro-1) uncertainty over two quarters. An inspection of Table 5 suggests that the percentage of the variation explained by news shocks under the "truly news" identification scheme and by the macroeoconomic uncertainty shocks under the "truly uncertainty" identification scheme is smaller than in the baseline case. The negative correlation between news and macroeconomic uncertainty shocks in Table 2 implies that the positive effects on output, consumption, investment, and hours from news shocks are enhanced in the short run if we employ s_t^{news} instead of

$\tilde{s}_t^{news}$. The main reason, as observed in Figure 1, is that technological news shocks as in s_t^{news} (correlated with macroeconomic uncertainty shocks) have short-term negative effects on macroeconomic uncertainty, which enhances the effects on the macroeconomic variables. Similar results are observed when evaluating the transmission of macroeconomic uncertainty shocks. Negative effects on macroeconomic variables are enhanced if we allow uncertainty shocks to be correlated with news shocks as indicated in Figure 3. Figures C.3 and C.4 in the Online Appendix provide supportive evidence of how identification affects the responses to news and macroeconomic uncertainty shocks.

We compute "good uncertainty" effects in Table 5 as how the proportion explained by macroeconomic uncertainty shocks varies between the "truly news" and the "truly uncertainty" schemes. If we compare with Table 4, the estimated values for "good uncertainty" are now smaller for all variables and horizons. Although we find some evidence of "good uncertainty" effects using macroeconomic instead of financial uncertainty shocks, the quantitative effects are larger and economically more interesting when we employ financial uncertainty shocks.

2.6 Discussion

We are able to provide evidence that not all uncertainty shocks are equal in their impact on the macroeconomy. The consensus is that we normally expect negative short-run effects from uncertainty shocks (Leduc and Liu 2016), but we are able to find positive effects on productivity from financial uncertainty shocks that attenuate the usual negative effects on economic activity. In contrast, similar effects are not detected when uncertainty shocks are computed using measures of macroeconomic forecasting uncertainty as in Ludvigson, Ma, and Ng (Forthcoming). Bloom (2014) argues, however, that many mechanisms might explain the impact of uncertainty shocks in the economy; thus, our novel evidence that different uncertainty measures deliver shocks with different effects on the economy is consistent with this view.

Typical uncertainty-driven business cycle theories (Bloom et al. 2018) are based on the idea that uncertainty reduces investment because when uncertainty is high, the price of the wait-and-see option is higher. Business-cycle theories that focus on risk as a cause of business cycles (Christiano, Motto, and Rostagno 2014) employ financial constraints to explain how uncertainty affects growth. In both cases, we expect short-run negative effects from increased uncertainty, which is compatible with our results for financial uncertainty shocks.

The evidence that uncertainty may have a positive effect on productivity is related to the idea that uncertainty increases the size of the potential return on an investment; that is, uncertainty increases the range of growth options. Segal, Shaliastovich, and Yaron (2015) employ a long-run risk consumption-based asset pricing model to disentangle the impact of good and bad uncertainty from that of positive and negative innovations on consumption growth. Although both measures of uncertainty have an impact on asset pricing within their model, they do not attempt to measure the relative impact of good and bad uncertainty on business cycle variation. Our results suggest that good uncertainty is more important at medium-term horizons (2 years) and that bad financial uncertainty is typically a short-run phenomenon.

3. CONCLUSION

Financial uncertainty and news shocks are correlated when standard identification assumptions are employed separately. It follows that the standard procedures fail to truly identify the structural shocks.

The implication is that responses of economic activity to news and financial uncertainty shocks include attenuation bias. In the case of news shocks, attenuation bias plays a role in the short run and implies that positive effects are lower than they would be if news shocks were assumed to be orthogonal to financial uncertainty shocks. For financial uncertainty shocks, attenuation bias plays a role in the medium run, and it is characterized by an increase in utilization-adjusted total factor productivity. The bias implies that the negative effects of uncertainty shocks are not as deep or persistent as they could have been. We measured the impact of these "good uncertainty" effects to find that they explain about 15% of the business cycle variation of economic variables, such as output, consumption, investment, and hours, at medium horizons (2 years).

In general, our novel empirical evidence supports the development of theories that focus on a set of anticipated shocks (Jaimovich and Rebelo 2009) and on uncertainty shocks (Fajgelbaum, Schaal, and Taschereau-Dumouchel 2017, Bloom et al. 2018) as sources of business cycles.

APPENDIX A: IDENTIFICATION OF NEWS SHOCKS

For an $n \times 1$ vector endogenous variables $\mathbf{y}_t$, the moving-average representation (in levels) is written as

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t. \tag{A1}$$

Assume that the first endogenous variable in the vector $\mathbf{y}_t$ is total factor productivity.

If there is a linear mapping of the innovations ($\mathbf{u}_t$) and the structural shocks ($\mathbf{s}_t$), this moving-average representation can be rewritten as

$$\mathbf{u}_t = \mathbf{A}_0\mathbf{s}_t \tag{A2}$$

and

$$\mathbf{y}_t = \mathbf{\Phi}(\mathbf{L})\mathbf{s}_t, \tag{A3}$$

where $\mathbf{\Phi}(\mathbf{L}) = \mathbf{B}(\mathbf{L})\mathbf{A}_0$, $\mathbf{s}_t = \mathbf{A}_0^{-1}\mathbf{u}_t$, and $\mathbf{A}_0$ is the impact matrix that makes $\mathbf{A}_0\mathbf{A}_0^{'} = \mathbf{\Sigma}$ (variance–covariance matrix of innovations). It is possible to rewrite $\mathbf{A}_0$ as $\tilde{\mathbf{A}}_0\mathbf{D}$, where $\tilde{\mathbf{A}}_0$ is the lower triangular Cholesky factor of the covariance matrix of reduced-form innovations (or any other orthogonalization), and $\mathbf{D}$ is any $k \times k$ matrix that satisfies $\mathbf{D}\mathbf{D}^{'} = \mathbf{I}$.

Considering that $\Omega_{i,j}(h)$ is the share of the forecast error variance of variable i of the structural shock j at horizon h, it follows that

$$\Omega_{1,1}(h)_{surprise} + \Omega_{1,2}(h)_{news} = 1 \forall h, \tag{A4}$$

where $i = 1$ refers to utilization-adjusted TFP, $j = 1$ is the unexpected TFP shock, and $j = 2$ is the news shock. The share of the forecast error variance of the news shock is defined as

$$\Omega_{1,2}(h)_{news} = \frac{\mathbf{e}_1^{'}\left(\sum_{\tau=0}^{h} \mathbf{B}_\tau \tilde{\mathbf{A}}_0 \mathbf{D} \mathbf{e}_2 \mathbf{e}_2^{'} \mathbf{D}^{'} \tilde{\mathbf{A}}_0^{'} \mathbf{B}_\tau^{'}\right)\mathbf{e}_1}{\mathbf{e}_1^{'}\left(\sum_{\tau=0}^{h} \mathbf{B}_\tau \boldsymbol{\Sigma} \mathbf{B}_\tau^{'}\right)\mathbf{e}_1} = \frac{\sum_{\tau=0}^{h} \mathbf{B}_{1,\tau} \tilde{\mathbf{A}}_0\, \gamma\gamma^{'} \tilde{\mathbf{A}}_0^{'} \mathbf{B}_{1,\tau}^{'}}{\sum_{\tau=0}^{h} \mathbf{B}_{1,\tau} \boldsymbol{\Sigma} \mathbf{B}_{1,\tau}^{'}}, \tag{A5}$$

where $\mathbf{e}_1$ is a selection vector with 1 in the position $i = 1$ and zeros elsewhere, $\mathbf{e}_2$ is a selection vector with 1 in the position $i = 2$ and zeros elsewhere, and $\mathbf{B}_\tau$ is the matrix of moving-average coefficients measured at each period until τ. The combination of selection vectors with the proper column of $\mathbf{D}$ can be written as γ, which is an orthonormal vector that makes $\tilde{\mathbf{A}}_0\gamma$ the impact of a news shock over the variables.

The news shock is identified by solving the optimization problem

$$\gamma_2^{news} = \text{argmax} \sum_{h=0}^{H} \Omega_{1,2}(h)_{news}, \tag{A6}$$

s.t.

$$\tilde{A}_0(1, j) = 0, \forall j > 1, \tag{A7}$$

$$\gamma_2(1, 1) = 0, \tag{A8}$$

$$\gamma_2^{'}\gamma_2 = 1, \tag{A9}$$

where H is the truncation period, and the restrictions impose that the news shock does not have an effect on impact ($t = 0$) on TFP and that the γ vector is orthonormal.

Based on the γ_2^{news} vector, the structural unexpected TFP (s_t^{unexp}) and the news shock (s_t^{news}) are

$$\begin{bmatrix} s_t^{unexp} \\ s_t^{news} \\ \cdots \end{bmatrix} = \tilde{\mathbf{A}}_0^{-1} \begin{bmatrix} \gamma_1^{unexp} & \gamma_2^{news} & \ldots \end{bmatrix}^{-1} \mathbf{u}_t^{\prime}, \tag{A10}$$

assuming that

$$\gamma_1^{unexp} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \ldots \end{bmatrix}. \tag{A11}$$

APPENDIX B: IDENTIFICATION OF TRULY STRUCTURAL SHOCKS

As described in Section 2.1, we compute the $n \times 1$ vectors $\tilde{\gamma}_2^{news}$ and $\tilde{\gamma}_3^{finunc}$ using QR decompositions to impose the orthogonality restrictions required by either the "truly news" or the "truly uncertainty" schemes on the original vectors γ_2^{news} and γ_3^{finunc}, computed as described either in the Appendix A (news, unexpected) or Section 1.1 (uncertainty).

The truly structural shocks are then obtained as:

$$\tilde{\mathbf{s}}_t = \begin{bmatrix} \tilde{s}_t^{unexp} \\ \tilde{s}_t^{news} \\ \tilde{s}_t^{finunc} \\ \ldots \end{bmatrix} = \tilde{\mathbf{A}}_0^{-1} \begin{bmatrix} \gamma_1^{unexp} & \tilde{\gamma}_2^{news} & \tilde{\gamma}_3^{finunc} & \ldots \end{bmatrix}^{-1} \mathbf{u}_t'. \tag{B1}$$

The impulse responses to the truly structural shocks are then computed as before employing the MA representation in equation (A3) using instead $\tilde{\mathbf{s}}_t$.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.