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Nonlinear Transmission of Financial Shocks: Some New Evidence

Financial shocks generate a protracted and quantitatively important effect on real economic activity and financial markets only if the shocks are both negative and large. Otherwise, their role is quite modest. Financial shocks have become more important for economic fluctuations after 2000 and have contributed substantially to deepening the recessions of 2001 and 2008. The evidence is obtained using a new econometric procedure based on a Vector Moving Average representation that includes a nonlinear function of the financial shock. This method is a contribution of the present work.

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THE 2008 RECESSION HAS SPARKED a renewed interest in understanding how financial crises propagate to the real economy. There is a long-standing literature on the interactions and linkages between the two sectors. Early works include Bernanke and Gertler (1989), Carlstrom and Fuerst (1997), Bernanke, Gertler, and Gilchrist (1999), and Kiyotaki and Moore (1997). More recent contributions focusing on the role of the financial sector in economic fluctuations include Christiano, Motto, and Rostagno (2003), ,2007), Curdia and Woodford (2010), Gertler and Karadi (2011), and Gertler and Kiyotaki (2011). Most of these papers rely on log-linear approximations that imply a linear propagation of economic shocks, including the financial shock.

Nevertheless, a few recent contributions have emphasized the importance of the nonlinear amplification of financial shocks on the real economy, see Mendoza (2010), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014) and the survey in Brunnermeier, Eisenbach, and Sannikov (2013). In the seminal paper by Brunnermeier and Sannikov (2014), BS henceforth, there are three kinds of nonlinearity at work. First, while small shocks tend to be easily absorbed without important consequences, large shocks may bring the economy far from the steady state, in regions where the amplification mechanisms are much stronger and the consequences for real economic activity much more severe. We refer to this kind of nonlinearity as the "size effect": large shocks may lead to disproportionally large outcomes. Second, there is a sign asymmetry: financial disruptions tend to have larger real effects than financial expansions. We refer to this kind of nonlinearity as the "sign effect." Third, when the economy moves away from the steady state, for instance in a downturn, even small shocks can have large effects. This kind of nonlinearity is a sort of state dependence: the effects are greater in bad times.[1]

On the empirical side, most of existing studies use linear models. In the seminal contribution of Gilchrist and Zakrajšek (2012), GZ from now on, the financial shock is identified in a VAR under a recursive ordering as the shock to the excess bond premium (EBP). This credit spread shock is found to have significant effects on macro-economic indicators. Similar findings are obtained in other works using various identification schemes (see, among others, Gilchrist, Yankov, and Zakrajšek 2009, Peersman 2011, Meeks 2012, Peersman and Wagner 2015, Caldara et al. 2016, Gambetti and Musso 2017, Furlanetto, Ravazzolo, and Sarferaz 2019, Boivin, Giannoni, and Stevanovic 2020, Brianti 2021).

The literature studying nonlinear effects of financial shocks is relatively scant. Balke (2000), Hubrich and Tetlow (2015), and Chatterjee et al. (2022), using various types of regime-switching VARs, find that the effects of financial shocks are

1. Several studies have pointed out that business cycle fluctuations tend to be asymmetric since recessionary episodes have larger effects on growth than booms, see, for instance, Neftci (1984), Sichel (1993), and Morley and Piger (2012).

magnified under conditions of credit-rationing or financial stress.[2] This evidence is broadly consistent with the third kind of nonlinearity in BS. Balke (2000) and Barnichon, Matthes, and Ziegenbein (2022) provide evidence supporting the existence of a sign asymmetry in the transmission of financial shocks: bad shocks have larger effects than good shocks on economic activity, in line with the sign effect pointed out in BS.[3] As far as we know, there are currently no papers attempting at verifying the first kind of nonlinearity highlighted in BS, that is, the size effect.

This paper contributes empirically to shed new light on the nonlinearity of the transmission mechanisms of financial shocks, identified as credit spread shocks. We extend the identification of GZ to a novel nonlinear setting where the economy has a Vector Moving Average (VMA) representation augmented with a nonlinear function of the financial shock. The effects of the financial shock on economic variables are a combination of the coefficients associated with the shock and its nonlinear function. This makes the impulse response functions potentially nonlinear and asymmetric. The identification and estimation procedure consists of two steps within a single model. In the first step, we identify the financial shocks as in GZ. In the second step, we use the shock and its nonlinear function to estimate the nonlinear transmission mechanisms. In the baseline model, we use the square of the shock as the nonlinear function. This specification enables us to verify whether there is evidence of the sign and size effect hypothesized in BS. In an extended version, we also allow for state-dependent effects.[4]

Our evidence confirms the existence of significant nonlinearities in the transmission mechanisms of financial shocks. The main results are as follows:

(i) The effects of big shocks, two standard deviations or more, are highly asymmetric: big financial disruptions generate a sizable and protracted downturn in real economic activity and the stock market, while big financial booms have modest effects. Big negative shocks also turn out to be a major driver of economic slowdowns in the last two decades. We find two such shocks in the sample considered, in early 2000 and in 2008, respectively. In both episodes, the nonlinear effects play a major role and contribute substantially to deepening the recessions that followed.

(ii) One-standard deviation shocks, or smaller, have symmetric effects, that is, similar in absolute value for positive and negative shocks. Although their

2. Atanasova (2003) and Saldias (2017) find similar results for monetary policy shocks.

3. There is evidence that financial shocks played an especially important role during (and perhaps after) the Great Recession: Alessandri and Mumtaz (2017) find that financial variables have an important predictive power on economic activity after 2008, but not before; similarly, Liu et al. (2019) find that the effects of yield spread shocks on unemployment and inflation increases substantially from early 2008 onward. This can be interpreted as state dependence but might in principle result also from the size effect.

4. The approach is similar in spirit to the local projection approach used, for instance, in Tenreyro and Thwaites (2016) and Alpanda, Granziera, and Zubairy (2021) to study the asymmetric and state-dependent effects of monetary policy shocks.

effects are significant, from a quantitative point of view their role for economic fluctuations is modest.
(iii) The effects of financial shocks are further amplified in periods of high uncertainty. No other state variables appear to matter for the transmission of financial shocks.
(iv) Overall, financial shocks have become much more important for economic fluctuations in the last two decades.

The above findings provide a confirmation for the type of asymmetries found in Barnichon, Matthes, and Ziegenbein (2022), but only for unusually large shocks, since for standard shocks, or smaller, the effects are essentially symmetric. This is because in our analysis the sign asymmetry interacts with a substantial size effect, which is ignored in their work. To corroborate our focus on quadratic effects, in the empirical section we compare our model with a model with sign asymmetry only and find evidence in favor of the former.

All in all, our results lend empirical support to both the sign and size nonlinearities highlighted in the theoretical model of BS, where big negative shocks matter, while small shocks appear to be quickly and easily absorbed without important real consequences. Regarding state dependence, we do not find a significant magnification effect related to financial stress (as measured by the Chicago Fed's National Financial Conditions Index, NFCI) when controlling for quadratic effects.

From a methodological point of view, the novel approach proposed in the present paper represents an alternative to that of Barnichon and Matthes (2018), which consists of the estimation, via maximum likelihood, of a nonlinear VMA. Both methodologies are flexible enough to handle various types of nonlinearities but have different strengths. Our method does not require any assumption about the probability distribution of economic shocks. This is important, since, as we shall see, the distribution of the estimated shock has fat tails. Moreover, the linear VAR is nested in our model, so that we can test for the significance of various kinds of nonlinearities by using standard techniques. In this paper, we employ a Cholesky scheme; Debortoli et al. (2022) extend the method proposed here to the important case of proxy-SVAR identification.

The remainder of the paper is organized as follows. Section 1 discusses the econometric approach. Section 2 presents the results and some robustness checks. Section 3 concludes.

1. ECONOMETRIC APPROACH

In this section, we present our econometric approach and show how to estimate the nonlinear effects of financial shocks on macro-economic and financial variables.

1.1 The Nonlinear Model

We assume that the macro-economic and financial variables in the n-dimensional vector x_t have the following structural representation:

$$x_t = \nu + \beta(L)g(u_{ft}) + B(L)u_t, \tag{1}$$

where u_t is a serially independent n-dimensional vector of structural shocks with zero mean and covariance equal to the identity matrix, u_{ft} is the financial shock and is the fth element of the vector u_t, $g(u_{ft})$ is a contemporaneous nonlinear function of the financial shock, ν is a vector of constants, $B(L) = (I + B_1B_0^{-1}L + B_2B_0^{-1}L^2 + \cdots)B_0$ is an $n \times n$ matrix of impulse response functions and $\beta(L) = \beta_0 + \beta_1 L + \beta_2 L^2 + \cdots$ is an n-dimensional vector of impulse response functions. One can think of (1) as a generalization of the standard VMA representation underlying Structural VARs, which, as discussed below, gives origin to nonlinear dynamics for the shock u_{ft}. Model (1) can also be seen as a restricted version of the Volterra representation of x_t (see Priestley 1988). Of course, there could be other shocks having nonlinear dynamics but they are not modeled here. Nonetheless, in the simulation section, we assess the performance of our econometric procedure in a more general context where also other shocks have a nonlinear transmission.

We further develop the model and derive an equivalent representation, which is the one we will estimate. Assuming invertibility of the linear term $B(L)u_t$, we obtain the representation

$$D(L)x_t = \mu + D(L)\beta(L)g(u_{ft}) + B_0u_t, \tag{2}$$

where $D(L) = (I + B_1B_0^{-1}L + B_2B_0^{-1}L^2 + \cdots)^{-1} = I - \tilde{D}(L)$, and $\mu = D(1)\nu$. For simplicity, we also assume that no lags of $g(u_{ft})$ enter equation (2), that is, $D(L)\beta(L) = \beta_0$. We will relax this assumption as a robustness check. The model can therefore be rewritten as

$$\begin{aligned} x_t &= \mu + \tilde{D}(L)x_t + \beta_0 g(u_{ft}) + B_0u_t \\ &= \mu + \tilde{D}(L)x_t + \beta_0 g(u_{ft}) + \alpha_0 u_{ft} + B_{-f0}u_{-ft}, \end{aligned} \tag{3}$$

where α_0 is the column of B_0 corresponding to the financial shock, B_{-f0} is the matrix formed by the $n-1$ columns of B_0 excluding α_0, and u_{-ft} is the $(n-1)$-dimensional vector containing the remaining structural shocks other than u_{ft}. Notice that the linear SVAR is nested in our model, so that we can test for the significance of the nonlinear term by using standard methods.

From equations (2) and (3), it is seen that the impulse response functions to u_{ft} and $g(u_{ft})$ are $\alpha(L) = D(L)^{-1}\alpha_0$ and $\beta(L) = D(L)^{-1}\beta_0$, respectively. The total effect is nonlinear and can be found by combining the two terms as

$$\text{IRF}(u_{ft} = u^*) = \alpha(L)u^* + \beta(L)g(u^*). \tag{4}$$

So, if nonlinearity is unimportant, that is, $\beta(L) = 0$, then the impulse response functions will be identical to those of a linear SVAR. On the contrary, if nonlinearity is actually important, then the propagation mechanisms of the financial shock willdiffer.

Now, suppose $g(u_{ft}) = u_{ft}^2$, which, as discussed below, is our baseline specification. The effect of the financial shock will then be

$$\mathrm{IRF}(u_{ft} = u^*) = \alpha(L)u^* + \beta(L)(u^*)^2. \tag{5}$$

A few remarks are in order. First, in equation (5), the coefficients $\beta(L)$ generate an asymmetry between positive and negative shocks. In particular, when $u^* = 1$, the effect is $\alpha(L) + \beta(L)$. When $u^* = -1$, the effect is $-\alpha(L) + \beta(L)$.

Second, a nonlinearity in terms of magnitude also arises. For $u^* = 1$, the effect is $\alpha(L) + \beta(L)$; for $u^* = 2$, the effect is $\alpha(L)2 + \beta(L)4$. Hence, a shock of double magnitude will not have twice the effects.

Notice that other types of nonlinearity can be considered. For instance, one can consider state dependence. Suppose we are interested in understanding whether the financial shock has different effects in different regimes. Let d_t be the state variable of interest, and let $d_t = 1$ if regime one is in place and $d_t = 0$ if regime two is. Defining $g(u_{ft}) = d_t u_{ft}$, the impulse response functions are

$$\mathrm{IRF}(u_{ft} = u^*) = \alpha(L)u^* + \beta(L)d_t u^*, \tag{6}$$

so that $\alpha(L)u^* + \beta(L)u^*$ is the response in regime one and $\alpha(L)u^*$ is the response in regime two.

The framework can also be extended to consider more than one nonlinear function. For instance, one can include both state dependence and the square term

$$\mathrm{IRF}(u_{ft} = u^*) = \alpha(L)u^* + \beta(L)(u^*)^2 + \gamma(L)d_t u^*, \tag{7}$$

where $\gamma(L)$ is another column vector of impulse response functions. In this specification, the nonlinearity depends on the sign and the size of the shock as well as the regime in place. We explore this extension in the empirical section.

1.2 Identification and Estimation

The estimation of the effects of the financial shock is based on a two-step procedure. In the first step, an estimate of the financial shock is obtained. In the second step, the nonlinear effects of the shock are obtained using the estimated shock and its nonlinear function as regressors in equation (3).

Step 1

The financial shock is estimated using GZ's strategy.[5] Let us briefly recall their approach. They estimate a VAR with a set of slow-moving variables ordered before the EBP, and a set of fast-moving variables ordered after. They then impose a Cholesky scheme where the financial shock is the fth element of the Cholesky representation, where f corresponds to the position of the EBP in the vector x_t. The shock is then normalized to have unit variance.

We adapt their identification strategy to our framework by imposing:

(A) B_0 is lower triangular, as in GZ. This entails that the financial shock has no contemporaneous effect on the slow-moving variables through the linear term, that is, $\alpha_{0,j} = 0$, $j = 1, \ldots, f-1$;
(B) the financial shock does not affect the slow-moving variables on impact through the nonlinear term, that is, $\beta_{0,j} = 0$, $j = 1, \ldots, f-1$, consistently with assumption (A);
(C) the financial shock does not affect the EBP on impact through the nonlinear term, that is, $\beta_{0,f} = 0$.[6]

Under restrictions A, B, and C, it is seen that the financial shock is identified and estimated consistently as in GZ, simply by imposing a Cholesky scheme in a standard linear VAR, despite the fact that the standard VAR is misspecified if the true model is the VARX in equation (3). This is shown in the Appendix. The intuition of this result is that restrictions A, B, and C imply that the nonlinear term enters only the equations of the fast-moving variables. Therefore, the first f shocks, including the financial shock, are simply combinations of the current and past values of the variables as in the linear VAR.

Note that while assumption A is necessary to identify the shock, assumptions B and C could be already satisfied in the data and therefore not imposed *ex ante*. Indeed, in the robustness section we estimate the model without imposing restrictions B and C and find almost identical results, suggesting that they hold in the data. This shows that the truly important assumption is A, which in turn implies that identification in the nonlinear model is, *de facto*, the same as in the linear model.

Step 2

We use the estimates of the shock and its nonlinear functions, $\hat{u}_{ft}$ and $g(\hat{u}_{ft})$, as regressors in model (3). We estimate (3) equation by equation with OLS imposing B and C, obtaining an estimate of $\alpha_0, \beta_0, \tilde{D}(L)$ and $D(L) = I - \tilde{D}(L)$. An estimate of the impulse response functions is obtained as $\hat{\alpha}(L) = \hat{D}(L)^{-1}\hat{\alpha}_0$ and $\hat{\beta}(L) = \hat{D}(L)^{-1}\hat{\beta}_0$, and the total effects are obtained from equation (4).

5. Note that more recently other identification procedures have been proposed. For instance, Caldara et al. (2016) employ a penalty function approach. While acknowledging that other schemes can be successful in identifying financial shocks, we believe the seminal GZ procedure is the best starting point for our analysis.

6. Note that the model even under A, B, and C is still more general than a linear SVAR under A, that is, the linear SVAR is nested in our model. The reason is that there is the nonlinear term which enters the equations of the fast-moving variables.

It should be noted that, unlike other approaches in the literature, ours does not require any distributional assumptions on the shocks, in addition to serial independence and orthogonality of structural shocks.

Note also that, having a narrative measure of the financial shocks, one could skip step 1 and go directly to estimation of the VARX in (3), without imposing identification restrictions. However, if the narrative measure is affected by an error, direct estimation of the VARX would produce biased estimates. An adaptation of the model proposed here to allow for proxy SVAR identification is presented in Debortoli et al. (2022).

In Barnichon, Matthes, and Ziegenbein (2022), local projections (LP henceforth) are used as a preliminary analysis to show that positive and negative shocks have different effects. The approach is in two steps. The first step is the same as ours: a standard linear VAR is used to identify and estimate the financial shock as in GZ. In the second step, LPs are used to assess the effects of positive and negative shocks. From an empirical point of view, this procedure resembles ours, the difference being the use of LP in place of a VARX in the second step.[7] From a theoretical point of view, however, the two steps are disconnected to each other, the former assuming a linear VAR model which is discarded in the latter. By contrast, in our setting the two steps have a unified theoretical basis, being part of a consistent estimation procedure for the same nonlinear VARX model. The essential element which makes the difference is the set of assumptions ensuring that the linear VAR produces consistent estimates of the shock in the first step, despite being misspecified.[8]

1.3 Variance Decomposition and Inference

Let us now consider variance decomposition. Standard formulas are not appropriate in the present context, since $\hat{u}_{ft}$ and $g(\hat{u}_{ft})$ are not orthogonal in general. A simple way to overcome this problem is to compute, for each horizon, the prediction error due to u_{ft}, including the nonlinear term, and divide its sample variance by the sample variance of the total prediction error. Precisely, the h-step-ahead prediction error implied by equation (1) is

$$e_{t+h} = \sum_{k=0}^{h-1} \beta_k g(u_{ft}) + \sum_{k=0}^{h-1} B_k u_{t+h-k}$$

7. See Plagborg-Møller and Wolf (2021) for the asymptotic equivalence of the two methods and Plagborg-Møller and Wolf (2022) for an extensive small-sample comparison.

8. Of course, in our setting using a VARX in second step is more appropriate. However, we use LP as a robustness check in the Online Appendix and show that the results are very similar to our baseline specification.

and, according to equation (4), the component of the prediction error driven by the financial shock is given by

$$e_{f,t+h} = \sum_{k=0}^{h-1} \alpha_k u_{ft} + \sum_{k=0}^{h-1} \beta_k g(u_{ft}).$$

We use the estimated coefficients and shocks to estimate $e_{f,t+h}$ and e_{t+h} according to the equations above. The variance contribution is then computed as the ratio of the sample variances.

Finally, the confidence bands of the impulse responses are constructed using a non-parametric bootstrap procedure which accounts for the generated regressors problem in the second step. The approach relies on the following steps: (i) we bootstrap the estimated shock u_{ft} obtained from step 1 and the estimated VARX residuals obtained by estimating (3); (ii) using the bootstrapped shock and residuals and the estimated coefficients of equation (3), we create a new sample; (iii) we reestimate the financial shock as in step 1 and model (3) as in step 2 with the new sample and compute the impulse response functions. We repeat steps (i)–(iii) 1,000 times to construct the confidence bands of the impulse responses.[9]

1.4 Simulations

We have shown in the previous section that the financial shock is identified and estimated consistently under assumptions A, B, and C. We now use a few Monte Carlo exercises to assess our econometric procedure in small samples.

We consider a three-variable VARX(1) where x_{1t} is the slow moving variable, x_{2t} is the EBP, and x_{3t} is the fast moving variable. The financial shock, u_{ft}, is the second shock in u_t. We assume $u_t \sim N(0, I)$ and $g(u_{ft}) = u_{ft}^2$. The shock u_{ft} has zero impact effects on x_{1t} and nonzero effects on x_{2t} and x_{3t}. The coefficients are

$$\tilde{D}_1 = \begin{pmatrix} 0.2 & 0.4 & 0.2 \\ 0.3 & 0.7 & -0.1 \\ 0.3 & -0.2 & 0.6 \end{pmatrix}$$

and the impact effects are

$$B_0 = \begin{pmatrix} 0.6 & 0 & 0 \\ -0.3 & 0.5 & 0 \\ -0.4 & -0.1 & 0.5 \end{pmatrix}.$$

Moreover, we assume that $\beta_0 = [0\ 0\ 0.5]'$ so that the restriction $\beta_{0,j} = 0,\ j = 1, 2,$ holds and $\mu = 0$. The parameterization is of course arbitrary. This however does not

9. This method is conceptually similar to a standard VAR bootstrap, the difference being that artificial data are generated according to the nonlinear model and are estimated according to our two-step procedure.

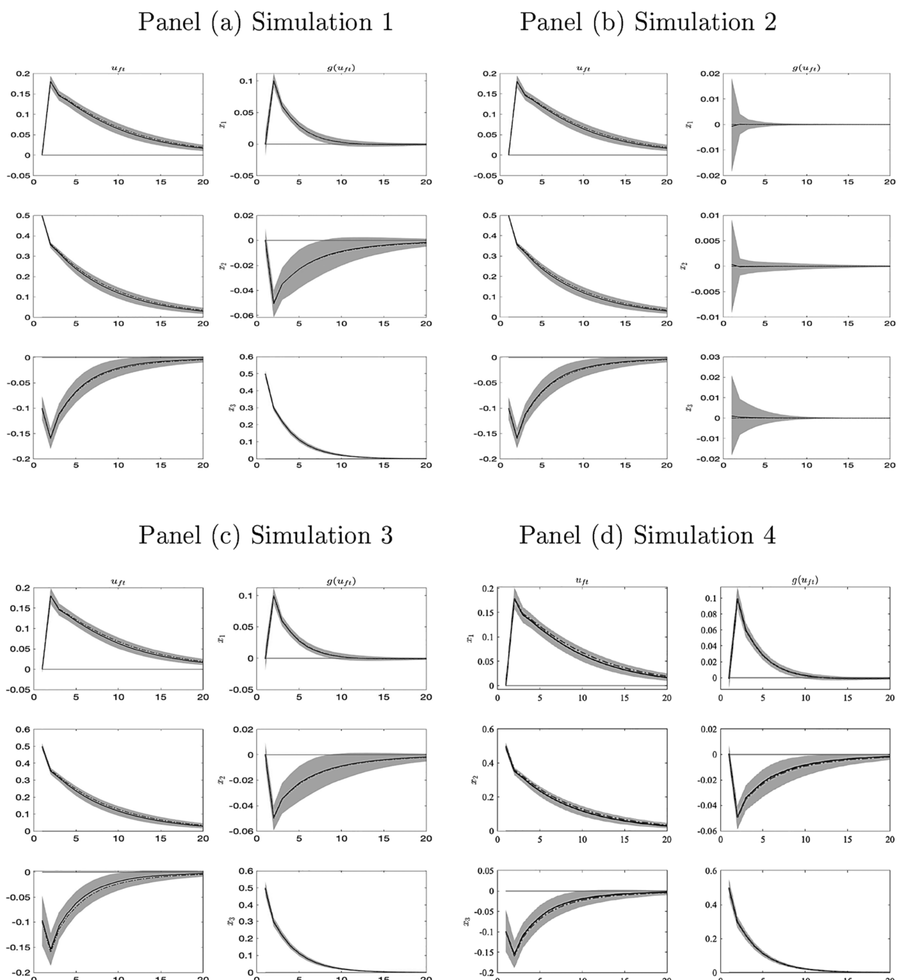

Fig 1. Monte Carlo Simulations.
NOTES: Solid lines are the average of the point estimates, the gray areas are the interval between the 16th and the 84th percentile and the 10th and 90th percentile, respectively, of the distribution of the point estimates. The dash-dotted lines are the theoretical responses.

affect the results as long as assumptions A, B, and C are satisfied. With other parameterizations, the same conclusions about the performance of our procedure are reached.

We generate $N = 1,000$ data sets of length $T = 564$ (as in the data set used in the empirical section). For each data set, we apply our two-step procedure and estimate $\alpha(L)$ and $\beta(L)$. Panel (a) of Figure 1 displays the results. The left column plots $\alpha(L)$, while the right column reports $\beta(L)$. The solid black lines are the mean (across data set) point estimates, the gray area is the region included in the 16th and 84th percentile of the point estimates distribution and the dash-dotted line is the theoretical response. The mean responses and the theoretical ones exactly overlap, suggesting that our procedure is successful in estimating the effects of the financial shock.

In a second simulation, we assume that the nonlinear function does not have any effects, that is, $\beta_0 = [0\ 0\ 0]'$. Panel (b) of Figure 1 displays the results. Our procedure is able to detect that the nonlinear term has no effect (second column).

In the third simulation, we assume a different distribution for u_{ft}, that is, a Pearson-type IV distribution with zero mean, standard deviation equal to 1, skewness equal to 0.5, and kurtosis equal to 4. Panel (c) reports the results of the simulation. As before, the procedure is able to estimate the true effects, since, as discussed earlier, it works independently of the distribution of the shock.

In the fourth simulation, we extend the model assuming that also u_{3t} has nonlinear effects. The model therefore becomes

$$x_t = \tilde{D}_1 x_{t-1} + \beta_0 u_{ft}^2 + \delta_0 u_{3t}^2 + B_0 u_t, \tag{8}$$

where $\delta_0 = [0\ 0\ -0.2]'$. Notice that the conditions for identification are satisfied. Panel (d) reports the results. Again, the estimated effects and the true effects overlap, suggesting that the procedure is robust even when other shocks have a nonlinear transmission.

Finally, we perform a simulation to assess the validity of our bootstrap procedure, reported in the Online Appendix, Section A.1. The overall result is that the bootstrap procedure has the correct coverage, properly capturing the uncertainty surrounding the estimated impulse responses.

2. RESULTS

In our empirical application, we use monthly U.S. data spanning the period 1973:M1–2019:M12. In our baseline specification, the vector x_t in equation (3) includes the following variables (in parenthesis, the abbreviation used throughout the paper), in the following order: the log of industrial production (INDPRO), CPI Inflation (CPI), the unemployment rate (UNRATE), the GZ excess bond premium index (EBP), the NFCI,[10] the log of the S&P500 Composite Stock Price Index (SP500),

10. The NFCI provides a weekly estimate on U.S. financial conditions in money markets, debt and equity markets, and the traditional and shadow banking systems. The index is a weighted average of 105 measures of financial activity. When the NFCI is positive, financial conditions are tighter than average. The methodology used to compute the NFCI is described in Brave and Butters (2012).

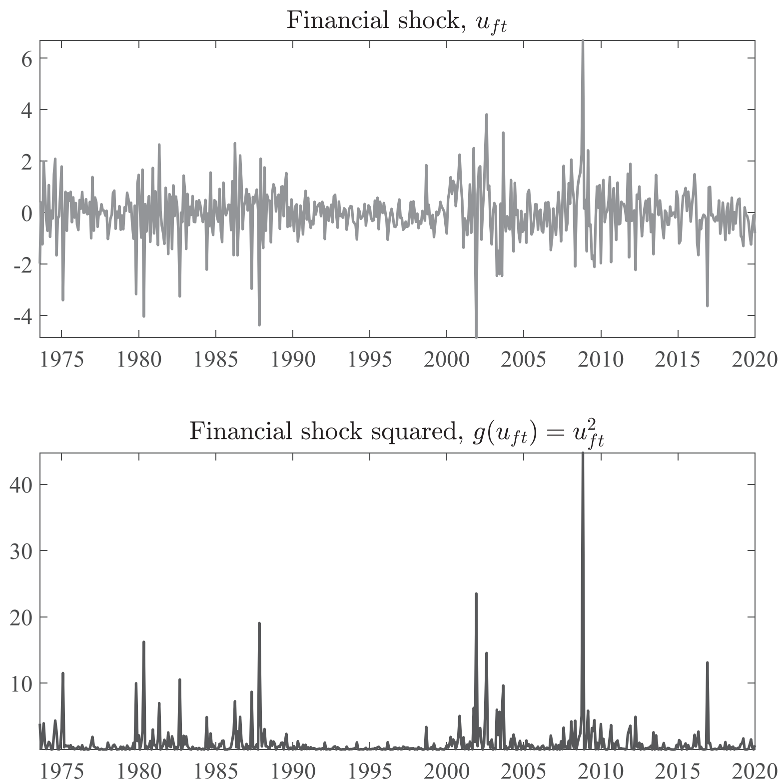

Fig 2. Financial Shock (Light Gray Line) and Its Square (Dark Gray Line) Obtained from the First Step.

and the federal funds rate (FFR).[11] We use five lags in $\tilde{D}(L)$. We set $g(u_{ft}) = u_{ft}^2$ as explained above.

2.1 *The Financial Shock*

Figure 2 plots the financial shock (top panel) estimated in the first step and its square (bottom panel). We observe two major positive spikes in August 2002 and November 2008, of about four and six standard deviations, respectively, which correspond to the stock market downturn of 2002 and the global financial crisis. We also

11. Data on industrial production, the CPI deflator, the unemployment rate, and the NFCI index is retrieved from the Federal Reserve Economic Data (FRED). The FFR is the effective federal funds rate until 2008:M8. From 2008:M9–2016:M8, it corresponds to the shadow rate of Wu and Xia (2016). The S&P500 Composite Stock Price Index is retrieved from Robert Shiller's webpage. All variables are specified in levels, with the exception of CPI Inflation which is computed as the log difference of the CPI deflator. We keep INDPRO and S&P500 in log levels to avoid possible cointegration problems between these two variables. In the Online Appendix, we check the robustness of our results to different data treatments.

observe two major negative spikes, of about five standard deviations, in November 1987 and December 2001, which reflect the rebound from the stock market crash of 1987 and 9/11, respectively. In general, we observe a number of large financial shocks in connection with three key events of turbulence in the history of U.S. financial markets: the stock market crash of 1987, the Dot-com bubble of the early 2000s, and the 2008 financial crisis. In contrast, the period between 1990 and 2000 is characterized by low volatility of the shock. The financial shock exhibits high kurtosis (equal to 9), meaning that the distribution of the shock is characterized by substantially fatter tails with respect to a Gaussian distribution. This finding highlights the importance of a procedure not requiring normality.

Overall, the shock seems to effectively capture key developments in U.S. financial markets. In the following subsections, we evaluate the effects of the financial shock and its square on macro-economic and financial variables.

2.2 *Is Nonlinearity Significant?*

Figure 3 reports the results of our two-step procedure using the squared shock. The black solid lines are the point estimates, while the gray areas are the 68% (dark gray) and 90% (light gray) confidence bands. The first column shows the linear response to the financial shock, that is, the estimate of $\alpha(L)$ appearing in equation (5), while the second column reports the responses of the square term estimated in the second step, that is, the estimate of $\beta(L)$ appearing in equation (5). The horizontal axis measures time in months from impact to 48 months after innovations have occurred.

The responses to the linear term (first column) are very much in line with previous findings in the literature (see GZ). The financial shock significantly reduces output and inflation and increases the unemployment rate, thus behaving like a typical demand shock. The effects on industrial production and unemployment are persistent and sizable. In addition, the shock leads to a short-run increase in the NFCI index, highlighting a worsening of overall financial conditions, and to a marked and persistent decline in stock prices. The FFR declines with a few months of delay, suggesting an endogenous monetary easing in response to the adverse economic developments.

Focusing on the responses to the nonlinear function of the financial shock (second column), the square has significant effects on real activity and financial variables. We observe a persistent decline in industrial production and a persistent increase in the unemployment rate. This result implies that the reduction in industrial production and the increase in unemployment following a bad financial shock are significantly amplified by the nonlinear term. Having a closer look at financial variables, the nonlinear effects are particularly relevant for stock prices, both in terms of magnitude and persistence. Overall, the results point toward significant nonlinear effects of financial shocks.

2.3 *Nonlinear Effects of Financial Shocks*

Let us now focus on the total effects of financial shocks by summing the two components whose separate effects have been discussed above.

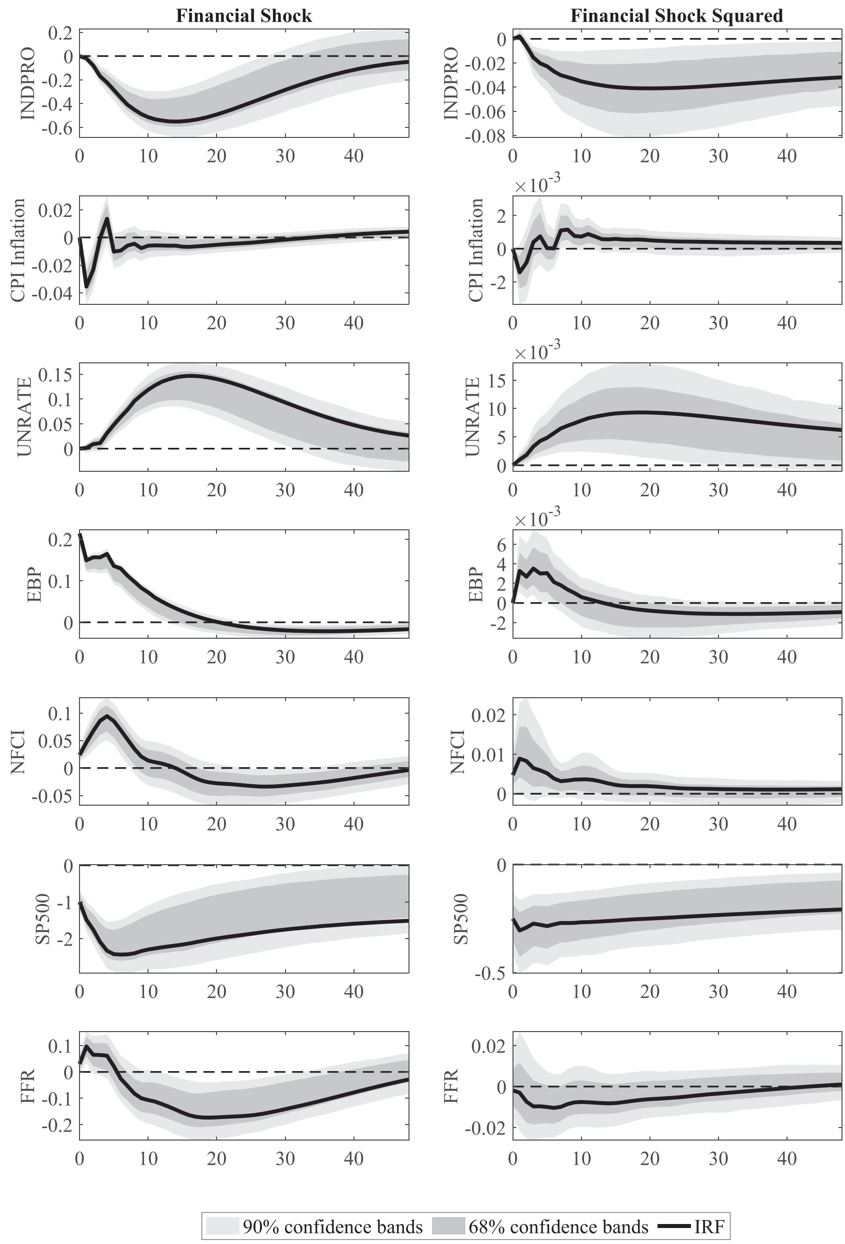

Fig 3. Impulse Response Functions of the VARX using $g(u_{ft}) = u_{ft}^2$.

NOTES: Black solid lines are the point estimates, the gray areas are the 68% and 90% confidence bands of the financial shock.

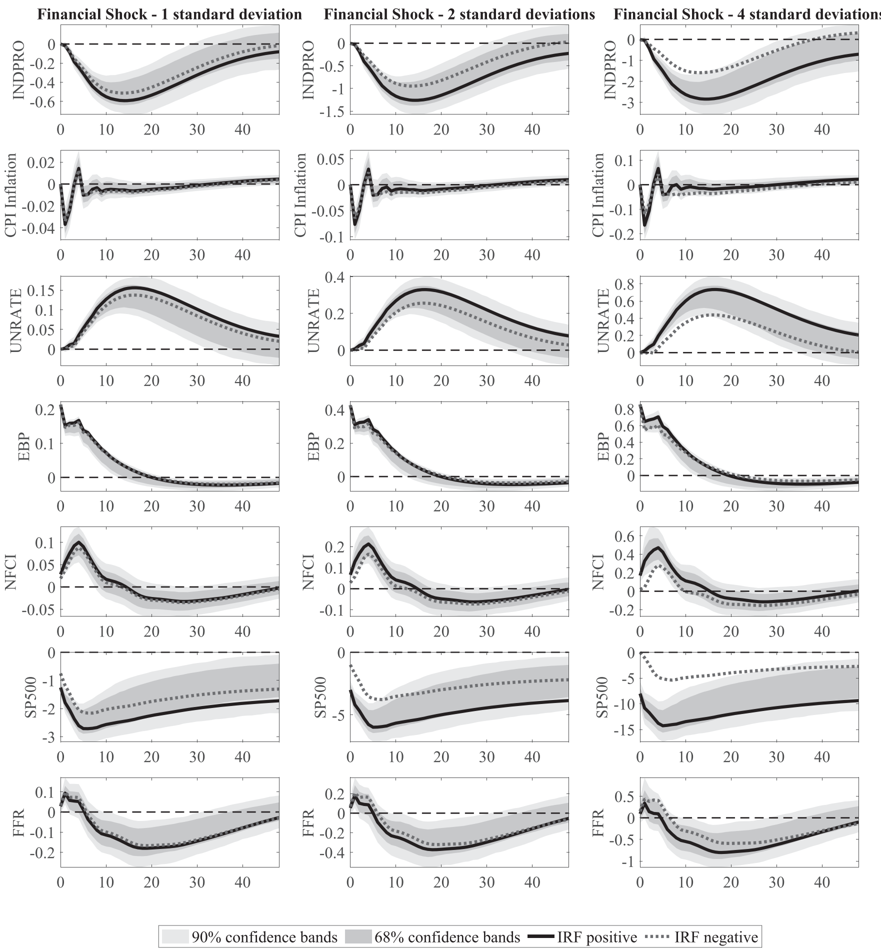

Fig 4. Impulse Response Functions of the VARX using $g(u_{ft}) = u_{ft}^2$.

Notes: Black solid lines are the point estimates, the gray areas are the 68% and 90% confidence bands of the bad financial shock. Dotted lines are the point estimates of the good financial shock.

The square term introduces two potential asymmetries, one in terms of the sign of the shock, and one in terms of the size of the shock. In the following, we assess their role for the overall response of macro-economic variables to financial shocks. Figure 4 shows the overall effects of positive (solid black line) and negative (dotted line) financial shocks for different magnitudes of the shock: one, two, and four standard deviations. Negative shocks are normalized to have the same sign as positive shocks, for the sake of comparison.

When considering a shock of one standard deviation, negative and positive shocks have very similar effects. The responses basically overlap for inflation, the EBP, the

NFCI index, and the FFR, while the effects on industrial production and the unemployment rate appear slightly larger for positive shocks. In this case, stock prices are the only variable displaying a significantly different response to positive and negative shocks.

The picture changes substantially when we consider shocks of larger magnitudes: bad credit shocks have markedly larger effects. The asymmetry between positive (i.e., a worsening of credit conditions) and negative shocks (an improvement of credit conditions) is clear in the case of a shock of two standard deviations and becomes very large in the case of a four standard deviations shock (third column). To give some figures, a four standard deviations positive shock leads to a decline in industrial production of about 2.8% after 1 year, while a negative shock of the same magnitude increases industrial production by 1.6%. For the unemployment rate, a negative shock produces a decrease of 0.3 percentage points, while a positive shock implies a rise of 0.7 percentage points. For stock prices, positive shocks have more than twice the effect of negative shocks.

The results seem to be very much in line with the theoretical predictions in BS. Relatively small shocks are easily absorbed by economic agents and the effects, although significant, are modest and symmetric. However, the size of the effects increases more than linearly with the size of the shock. Big financial disruptions have very large effects, while large financial expansions do not.

At this point, a natural question is how relevant financial shocks and their nonlinearities are in explaining fluctuations in the macro-economic and financial variables we include in the analysis. To address this question, we compute for each variable a historical decomposition, which allows us to evaluate the relative importance of the different disturbances at each point in time. Figure 5 reports the results. The black solid line represents, for each variable, the sum of the contributions of each shock in the system, that is, the variable in deviation from its deterministic components. The colored areas represent the contributions of the financial shock, its square and the remaining shocks in the system, which we label as "residual" for simplicity. The residual shocks include any macro-economic shock other than the financial one.

Until the late 1990s, fluctuations in industrial production, with the exception of a few years at the end of the 1980s, are essentially explained by the residual shocks. The role of financial shocks was very modest in the pre-2000 sample. However, after 2000, financial shocks become a major driver of fluctuations in industrial production. In particular, the shock substantially contributed to deepening the economic recessions of 2001 and 2008. Notably, the square of the financial shock plays a marked amplification role in both crises, magnifying the contribution of financial shocks to the decline in industrial production. In the aftermath of the Great Recession, the role of financial shocks essentially doubles due to the nonlinear component. A very similar pattern is present for stock prices and the unemployment rate. In linear SVAR models, the nonlinear component remains uncovered and this can explain why financial shocks have been found in previous contributions to account for a relatively small part of real economic activity fluctuations. When the nonlinear part is taken into account, the effects of financial shocks are substantially magnified, at least in the post-2000 period. The above findings are broadly in line with those of Liu et al.

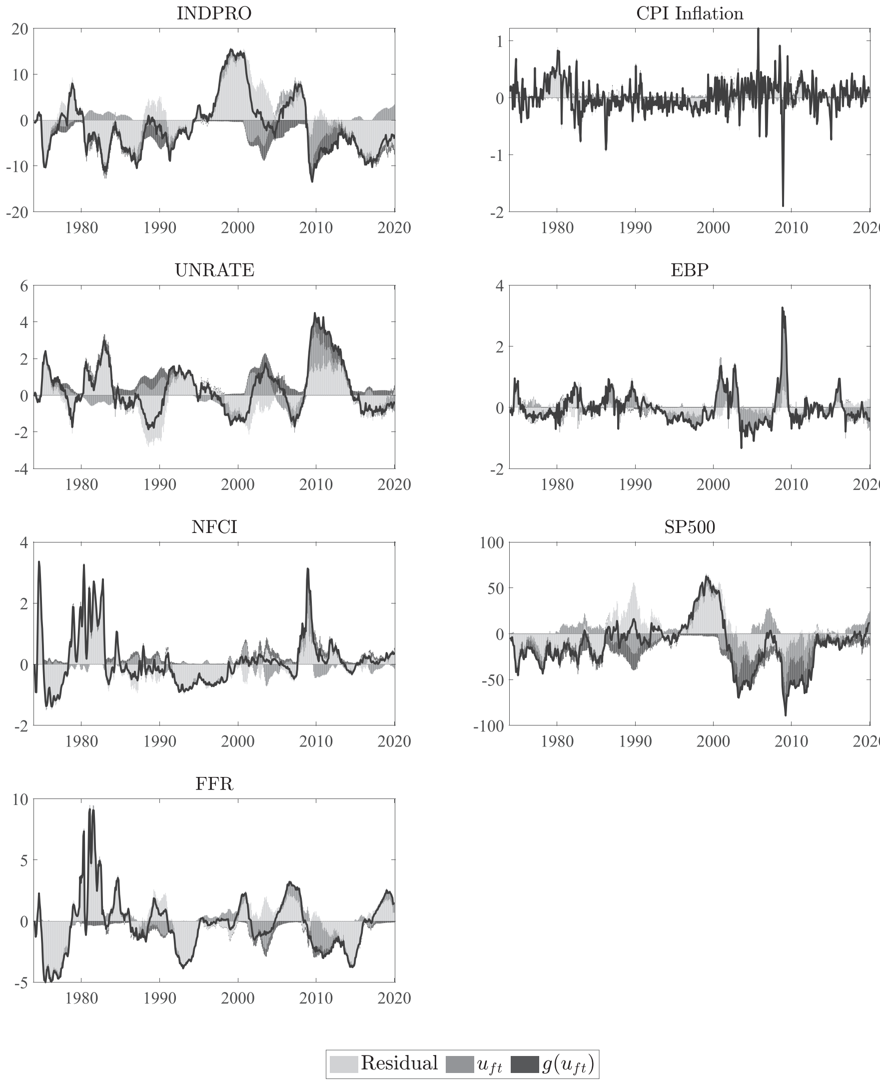

Fig 5. Historical Decomposition Using $g(u_{ft}) = u_{ft}^2$.

(2019) and Hubrich and Tetlow (2015), the difference being that we interpret the major role played by financial shocks in the Great Recession as resulting from quadratic effects rather than a regime change or a sort of state dependence.

By comparing the time series of the square of financial shocks (see Figure 2) with the historical decomposition, a clear-cut result emerges. When large shocks occur, the nonlinear term significantly amplifies the transmission of financial shocks

TABLE 1

VARIANCE DECOMPOSITION

	Linear				Total			
Nonlinear VARX	$h = 0$	$h = 12$	$h = 24$	$h = 48$	$h = 0$	$h = 12$	$h = 24$	$h = 48$
INDPRO	0.0	17.0	20.5	13.5	0.0	21.1	29.4	22.2
CPI	0.0	3.6	3.9	3.9	0.0	3.6	3.8	4.1
UNRATE	0.0	17.2	26.1	20.5	0.0	21.4	36.0	31.6
EBP	97.2	87.5	85.7	75.8	97.2	91.4	89.9	81.5
NFCI	3.9	8.0	7.8	8.4	5.2	10.8	9.6	9.2
SP500	9.3	24.9	22.9	20.9	14.3	40.2	44.3	43.3
FFR	0.5	2.6	7.4	10.6	0.5	3.3	9.9	14.2
Linear VAR					$h = 0$	$h = 12$	$h = 24$	$h = 48$
INDPRO					0.0	22.3	27.1	19.7
CPI					0.0	4.0	4.2	4.3
UNRATE					0.0	23.7	33.6	25.3
EBP					96.9	88.1	83.5	80.5
NSCI					3.3	6.8	6.0	7.3
SP500					9.7	31.4	32.5	31.0
FFR					0.2	3.1	10.6	14.4

NOTE: Upper panel: variance decomposition of our VARX, for the linear term (left side) and overall, variance computed as explained in Section 1.3 (right side). Lower panel: variance decomposition of the linear VAR.

to industrial production, unemployment, and stock prices, confirming that only big bad financial shocks generate quantitatively important effects on the real economy. Notice, however, that the square of the shock does not seem relevant in explaining fluctuations in inflation, the EBP and the FFR. This is not surprising, given that the relevance of the nonlinear term is small for those variables (see Figure 3).

Table 1, upper panel, reports the variance decomposition of our nonlinear model, obtained by considering only the component of the prediction error driven by the linear term (left side) and the overall explained variance, computed as explained in Section 1.3 (right side). At the 2-year horizon, the financial shock, including both the linear and the nonlinear term, explains around 29%, 36%, and 44% of the variance in industrial production, unemployment rate, and stock prices, respectively. For comparison, Table 1, lower panel, reports the variance decomposition of a linear VAR with the same variables. As expected, most of these numbers are in between the variance explained by our linear term, in the upper-left panel, and our overall explained variance, in the upper-right panel. All in all, results point to a more important role of the financial shock relative to that typically found in linear VARs at the 2- and 4-year horizons, particularly for stock prices.

2.4 *Adding State Dependence*

Another potential source of nonlinearity might be represented by the state of the economy. When the economy is going through a downturn, the effects of financial shocks are amplified with respect to periods of expansion. Here, we assess this prediction by estimating the model augmented with a term which captures the state of the economy (see equation (7)). The model is now

$$x_t = \nu + \beta(L)u_{ft}^2 + \gamma(L)d_t u_t + B(L)u_t, \tag{9}$$

where d_t is a dummy variable indicating which of the two possible states is in place. The VARX representation is

$$x_t = \mu + \tilde{D}(L)x_{t-1} + \beta_0 u_{ft}^2 + \gamma_0 d_t u_{ft} + \alpha_0 u_{ft} + B_{-f0}(L)u_{-ft}.$$

As before, we assume $\alpha_{0,i} = 0$ for $i = 1, 2, 3$, $\beta_{0,i} = 0$ for $i = 1, 2, 3, 4$. We also impose $\gamma_{0,i} = 0$ for $i = 1, 2, 3, 4$, so to make sure that the interaction term does not appear in the slow moving variables' equations. The impulse responses in this model are as in equation (7).

We consider several state variables: tightness of financial conditions, as reflected by the NFCI being above its average;[12] monetary policy tightening cycle, as reflected by the 10-year government bond being higher than its 5-year moving average as in Alpanda, Granziera, and Zubairy (2021); recessions and booms, as reflected by the unemployment rate being higher or lower than its average; high-low macro-economic uncertainty, as reflected by the Ludvigson, Sai, and Serena (2021) measure of uncertainty being higher or lower than its average. All indicators are dated $t - 1$ to avoid endogeneity.

For each of these variables, we estimate the model and compute the impulse response functions. The only state dependence that matters is the one associated to macro-economic uncertainty (see Figure 6). The first column reports $\alpha(L)$, the response to u_{ft}, the second column reports $\beta(L)$, the response to u_{ft}^2, while the third column shows $\gamma(L)$, the response to $d_t u_t$ (see equation (9)). The shock is assumed to be $u^* = 1$. In this case, the effects of financial shocks are significantly amplified in a regime of high uncertainty for all the variables but inflation and the FFR. The effects of the square term are quantitatively very similar to those obtained in the baseline model and significant. The same nonlinear amplification mechanisms obtained in the baseline model are at work even in this specification, but are enhanced in periods of high macro-economic uncertainty.

Figure A.3 in the Online Appendix reports $\gamma(L)$ for the other three state variables. In none of the three cases does state dependence generate significant effects on any of the variables, even though the point estimates have the correct sign. On the contrary, the square term remains significant at all times (not reported in the figures but available upon request).

12. This state variable is important not only in light of the regime-switching VAR literature quoted above, but also in light of the recent forecasting literature showing that adverse financial conditions can lead to sizable downside risk to economic activity (Adrian, Boyarchenko, and Giannone 2019, Caldara et al. 2020, Caldara, Scotti, and Zhong 2021).

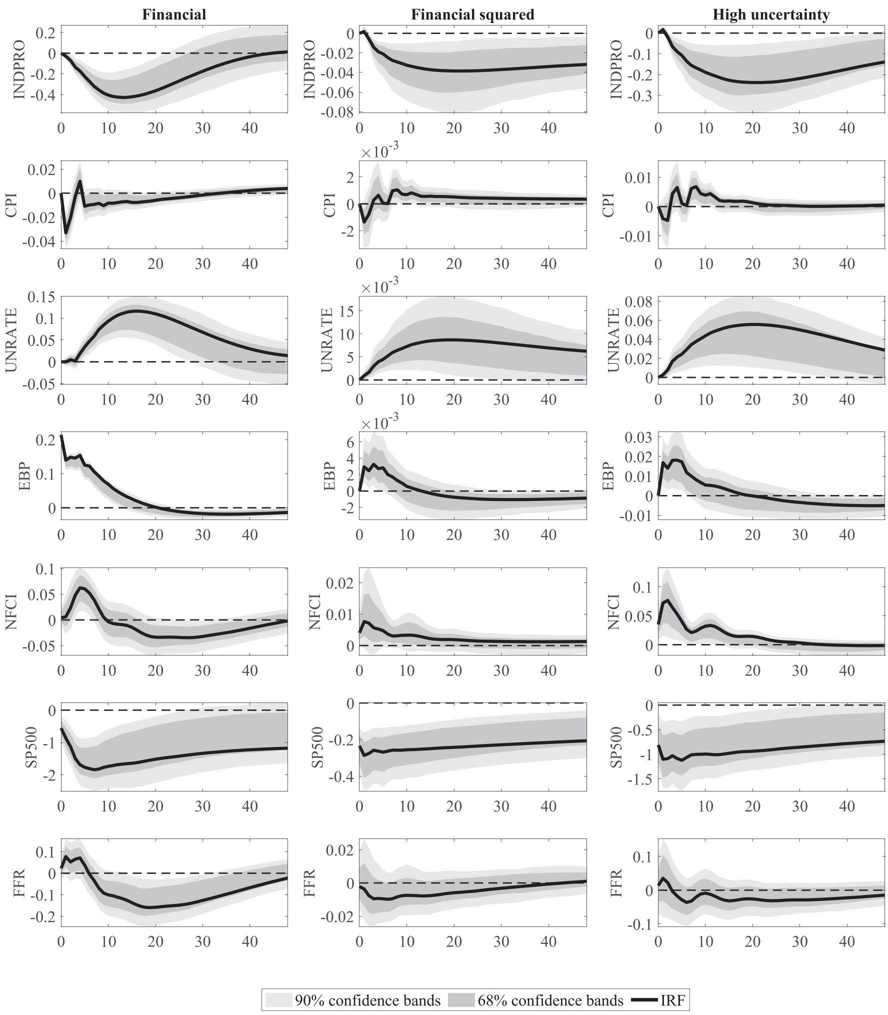

Fig 6. Impulse Response Functions of the VARX using $g(u_{ft}) = u_{ft}^2$ and $d_t = 1$ if macro-economic uncertainty is high.

Notes: Black solid lines are the point estimates, the gray areas are the 68% and 90% confidence bands of the financial shock.

2.5 *Which Kind of Nonlinearity?*

Here, we compare our baseline results with a version of the model which uses the absolute value of the shock, instead of the square. Using the shock along with its absolute value is of course equivalent to using positive and negative shocks separately as in Barnichon, Matthes, and Ziegenbein (2022). The impulse response functions are

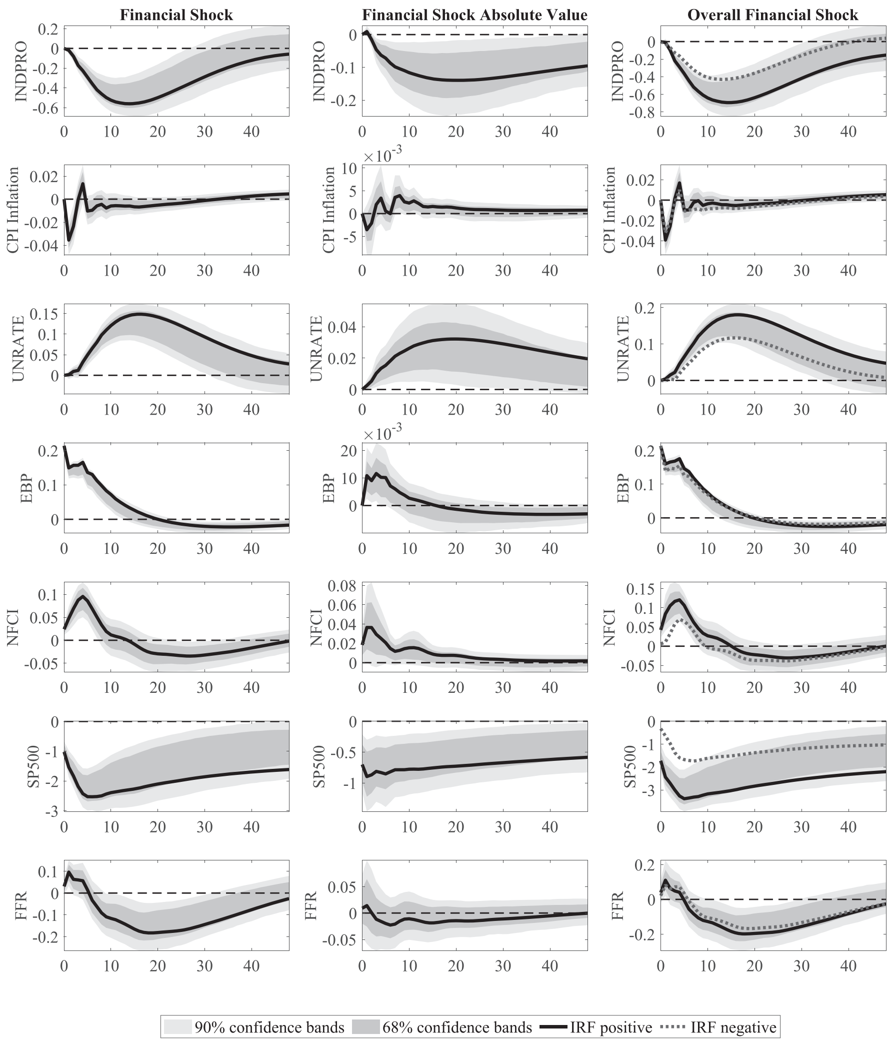

Fig 7. Impulse Response Functions of the VARX using $g(u_{ft}) = |u_{ft}|$.

NOTES: Black solid lines are the point estimates, the gray areas are the 68% and 90% confidence bands of the financial shock.

now

$$\mathrm{IRF}(|u_{ft}|, u_{ft} = u^*) = \alpha(L)u^* + \beta(L)|u^*|. \tag{10}$$

Figure 7 reports the results. The nonlinear term has significant effects on industrial production, unemployment, and stock prices. Again, for these three variables the signs are the same as those of the linear term: the nonlinear term reinforces the effects of an exogenous increase in the EBP. The third column shows the effects of positive (solid black line) and negative (dotted red line) financial shocks using the nonlinear function (10). As before, the negative financial shock is normalized to have the responses of the same sign of a positive shock. In line with the findings of Barnichon, Matthes, and Ziegenbein (2022), the evidence points to a significantly more important role of financial disruptions than expansions: the effects of an increase in the EBP are larger than the effects of a decrease, especially for industrial production, unemployment, and stock prices. Note that, with the absolute value, the size of the shock is no longer a source of nonlinearity. Thus, in the light of the empirical evidence discussed in the previous subsection, the asymmetry obtained here using the absolute value can be thought of as a sort of average of big shocks with large asymmetric effects and small shocks which are essentially symmetric.

At this point, a natural question is which nonlinear term, either the square or the absolute value, is more appropriate to capture the nonlinear transmission of the financial shock. To this end, we estimate a version of our model that includes both the square and the absolute value of the financial shock as sources of nonlinearity. We conduct, first, two simulation exercises to assess whether our model with both the square and the absolute value of the shock is able to properly recover the impulse responses if the true nonlinearity is either the square or the absolute value. The verification is successful. Details are reported in the Online Appendix, Section A.1.

Figure 8 shows the results when we estimate the model using actual data. The first column shows the effects of the linear term of the shock, while the second and third columns show, respectively, the absolute value and the square. A clear result emerges. Once both nonlinearities are considered, only the square of the financial shock matters, highlighting the importance of both size and sign asymmetries for the transmission of financial shocks.[13]

Table 2 presents the results of a likelihood ratio test where we compare the model estimated using both the square and the absolute value of the financial shock with the models that only use either the square or the absolute value. The first row presents the statistic and p-value of the test when the null is that the coefficients associated to the absolute value are all equal to zero. The second row presents the statistic and p-value of the test when the null is that the coefficients associated to the square are all equal to zero. We reject the null at the 5% confidence level only in the second case, suggesting the relevance of the square of the financial shock.

2.6 *Robustness*

In the Online Appendix, Section C, we perform several robustness checks.

13. In the Online Appendix, Section B.2, we try to disentangle the pure size effect from the sign effect, by replacing the squared shock with the function $u_{ft}^2 - |u_{ft}|$. The idea is that, by subtracting the absolute value of the shock, we clean the quadratic effects from the sign asymmetry, thus isolating a pure size effect. It turns out that the size effect is significant.

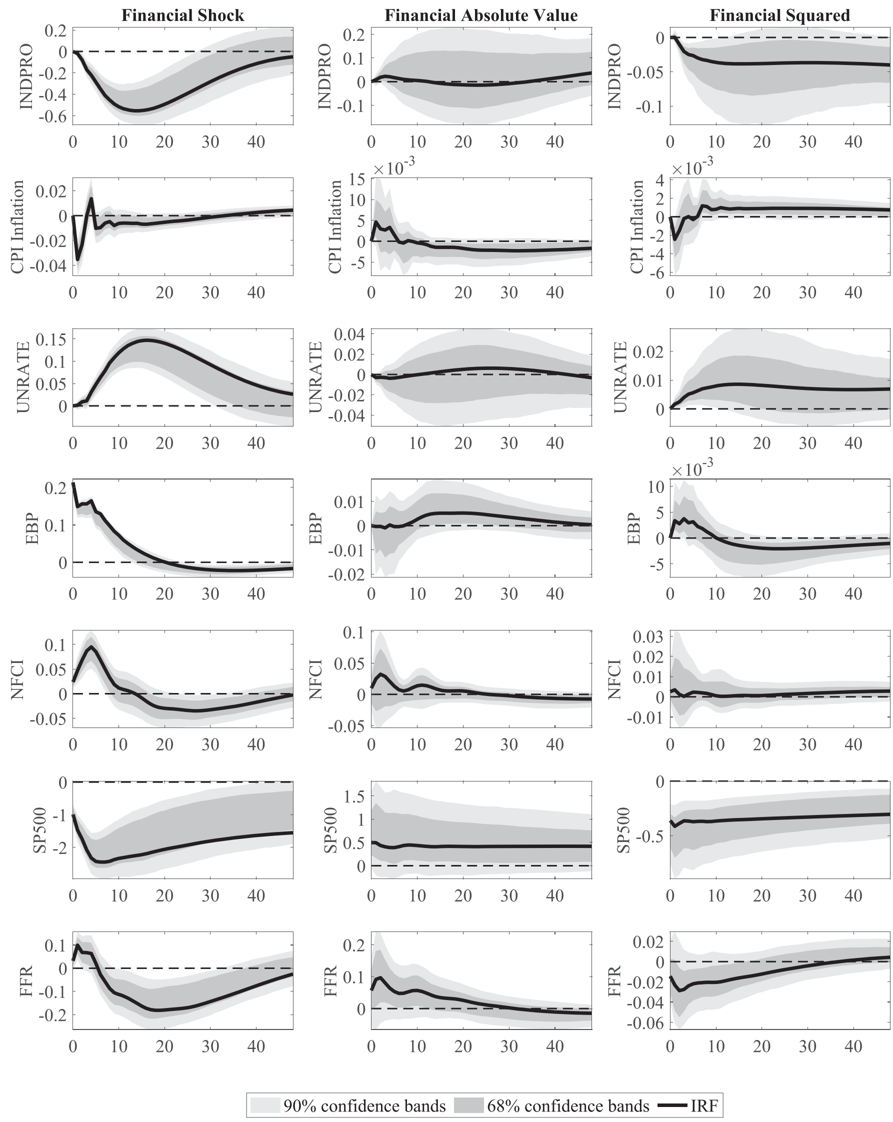

Fig 8. Impulse Response Functions of the VARX using $g(u_{ft}) = |u_{ft}|$ and $g(u_{ft}) = u_{ft}^2$.

NOTES: Black solid lines are the point estimates, the gray areas are the 68% and 90% confidence bands of the financial shock.

First, we relax, one at a time, assumptions B and C of Section 2.2, that is, the restriction $D(L)\beta(L) = \beta_0$ and the assumption that the nonlinear term has no contemporaneous impact on industrial production, inflation, the unemployment rate, and the EBP ($\beta_{0,j} = 0$). The main conclusions are essentially unchanged. These results validate the restrictions discussed in Section 2.2.

TABLE 2

Likelihood Ratio Test

Likelihood ratio test	Statistic	p-Value
Baseline model	3.83	0.80
Model with absolute value	14.68	0.04

Note: The model includes both $|u_t|$ and u_t^2. First row: the null is that the coefficients associated to the absolute value are all equal to zero, so that our baseline model holds. Second row: the null is that the coefficients associated to the square term are all equal to zero, so that the model with the absolute value holds.

Second, we estimate our model for different specification of the VAR variables. In particular, we show that our findings are robust to the exclusion of the NFCI index, to ordering the NFCI index before the EBP, and to the inclusion, in place of the stock market index, of the measure of excess stock market returns from CRSP and the 10-year bond yield, which are included in the GZ specification.

Third, we estimate the model for different data treatments, namely, including prices in log levels instead of log differences and differentiating all trending variables, as done in GZ. Results are almost identical to the baseline.

Fourth, we extend the baseline sample to 2021:M12, thus including the pandemic period, and the results are largely unaffected.

Finally, in the second step we use LPs in place of the VARX. The local projection includes a constant and one lag of the dependent variable as control. The results are very similar to the baseline specification.

To conclude this section, is worth noticing that our results are not robust to the use of the NFCI index in place of the EBP (Online Appendix, Section B.3): a shock to the financial stress index does not have the same effects as a shock to the credit spread. In particular, when using the NFCI index, the effects of the squared shock are not significant. Hence, using the identification scheme suggested in GZ, based on the EBP index, is crucial for our analysis.

3. CONCLUDING REMARKS

Financial shocks play an important role for the real economy and the financial markets only when they are negative and big (two standard deviations or more). One standard deviation (or smaller) shocks and large positive shocks play a modest role. Two large negative shocks are found in early 2000 and 2008, both contributing significantly to the economic downturn that followed.

This marked nonlinearity is obtained using a new econometric procedure based on the estimation of a VMA representation which includes a nonlinear function of the financial shock, with the financial shock identified along the lines of GZ.

Barnichon, Matthes, and Ziegenbein (2022) show that bad financial shocks have larger effects than good shocks. Here, complementing their analysis, we show that this sign asymmetry exclusively originates from big shocks, since small shocks (either positive or negative) are largely symmetric. Our findings are in line with the theoretical predictions in BS, where both sign and size effects in the amplification of financial shocks emerge.

APPENDIX A

In this Appendix, we show that if the true model is the VARX (3), with B_0 lower triangular and $\beta_{0j} = 0$ for $j = 1, \ldots, f$, then the financial shock u_{ft} is identical to the financial shock of a misspecified (linear) VAR model where we impose a Cholesky identification scheme. As a result, we can consistently estimate the financial shock following Gilchrist and Zakrajšek (2012) (GZ)'s strategy as explained in Section 1.2, Step 1.

Consider the misspecified VAR model

$$x_t = \alpha + C(L)x_{t-1} + \eta_t,$$

where η_t is orthogonal to x_{t-k}, $k > 0$. Under the recursive identification scheme, the VAR innovations are linked to the (misspecified) structural shocks $\tilde{u}_t$ by the relation $\Gamma\tilde{u}_t = \eta_t$, where Γ is the lower triangular matrix such that $\Gamma\Gamma' = E(\eta_t\eta_t')$.

Now, let A^f be the submatrix of A including only the first f rows of A. Then, by imposing our restrictions $\beta_{0j} = 0$, $j = 1, \ldots, f$, the first f equations in (3) can be written as

$$x_t^f = \mu^f + \frac{\tilde{D}(L)^f}{L} x_{t-1} + B_0^f u_t.$$

By comparing the VAR and the VARX (and observing that both η_t and u_t are orthogonal to past x's) it is seen that the first f equations are the same, so that

$$\mu^f = \alpha^f, \qquad \frac{\tilde{D}(L)^f}{L} = C(L)^f, \qquad B_0^f u_t = \eta_t^f = \Gamma^f \tilde{u}_t.$$

Since both B_0 and Γ are lower triangular, all entries of the last $n - f$ columns of both B_0^f and Γ^f are zero, so that, denoting by B_0^{ff} and Γ^{ff} the $f \times f$ matrices obtained by eliminating these columns from B_0^f and Γ^f, respectively, we get $B_0^{ff} u_t^f = \Gamma^{ff}\tilde{u}_t^f$. Since $E(u_t^f u_t^{f'}) = E(\tilde{u}_t^f \tilde{u}_t^{f'}) = I_f$ and both B_0^{ff} and Γ^{ff} are lower triangular, uniqueness of the Cholesky factorization implies $B_0^{ff} = \Gamma^{ff}$ and $u_t^f = \tilde{u}_t^f$.

In conclusion, under our assumptions, the first f equations of the VARX model are identical to the corresponding equations of the VAR model where the nonlinear term is omitted, and the first f Cholesky shocks are the same.[14] It follows that GZ's

14. It is well-known that the shocks obtained with the Cholesky identification scheme are equal, up to a normalization, to the residuals of a recursive VAR. By observing this, it is seen that these shocks can be obtained without resorting to the fast moving variables and the related equations.

financial shock is estimated consistently even if the VAR is misspecified. Of course, the remaining $n - f$ Cholesky shocks and all impulse response functions are not.

The above result is still valid under more general conditions. In particular, the assumption that the lags of the nonlinear term do not appear in equation (3), $D(L)\beta(L) = \beta_0$, can be relaxed and we can allow $g(u^f_{t-k})$, $k > 0$, to affect the slow-moving variables (but not the EBP).

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SUPPORTING INFORMATION

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

Figure A.1: Monte Carlo Simulations.
Figure A.2: Monte Carlo simulations.
Figure A.3: Impulse response functions of the VARX using $g(u_{ft}) = u_{ft}^2$ and $d_t = 1$ if financial conditions are tight (first column), interest rates are high (second column) or the economy is in a recession (third column).
Figure A.4: Impulse response functions of the VARX using $|u_{ft}|$ and $u_{ft}^2 - |u_{ft}|$ as nonlinear terms of the financial shock.
Figure A.5: Impulse response functions of the VARX using $g(u_{ft}) = u_{ft}^2$ and 5 lags of the nonlinear term.
Figure A.6: Impulse response functions of the VARX using $g(u_{ft}) = u_{ft}^2$ and 5 lags of the nonlinear term.
Figure A.7: Impulse response functions of the VARX using $g(u_{ft}) = u_{ft}^2$ and leaving the impact response of INDPRO, CPI, UNRATE and EBP to the nonlinear term unrestricted.

Figure A.8: Historical decomposition using $g(u_{ft}) = u^2_{ft}$ and leaving the impact response of INDPRO, CPI and UNRATE to the nonlinear term unrestricted.

Figure A.9: Impulse response functions of the VARX using $g(u_{ft}) = u^2_{ft}$, excluding the NFCI index.

Figure A.10: Impulse response functions of the VARX using $g(u_{ft}) = u^2_{ft}$, ordering the NFCI before EBP.

Figure A.11: Impulse response functions of the VARX using $g(u_{ft}) = u^2_{ft}$, excluding S&P500 and including excess stock market returns from CRSP and the 10-year Treasury yield.

Figure A.12: Impulse response functions of the VARX using $g(u_{ft}) = u^2_{ft}$ and the log of the CPI deflator in levels.

Figure A.13: Impulse response functions of the VARX using $g(u_{ft}) = u^2_{ft}$ and INDPRO and SP500 in first differences.

Figure A.14: Impulse response functions of the VARX using $g(u_{ft}) = u^2_{ft}$ and the sample extended to 2021:M12.

Figure A.15: Historical decomposition using $g(u_{ft}) = u^2_{ft}$ and the sample extended to 2021:M12.

Figure A.16: Local projections.