Are the Effects of Financial Market Disruptions Big or Small?*

Regis Barnichon,† Christian Matthes,‡ and Alexander Ziegenbein§

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Abstract

While episodes of financial distress are followed by large and persistent drops in economic activity, structural time series analyses point to relatively mild and transitory effects of financial market disruptions. We argue that these seemingly contradictory findings are due to the asymmetric effects of financial shocks, which have been predicted theoretically but not taken into account empirically. We estimate a model designed to identify the (possibly asymmetric) effects of financial market disruptions, and we find that a favorable financial shock —an easing of financial conditions— has little effect on output, but an adverse shock has large and persistent effects. In a counter-factual exercise, we find that over two thirds of the gap between current US GDP and its 2007 pre-crisis trend was caused by the 2007-2008 financial shocks.

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†Federal Reserve Bank of San Francisco, CEPR. E-mail: regis.barnichon@sf.frb.org

‡Indiana University and Federal Reserve Bank of Richmond. E-mail: christian.matthes@rich.frb.org

§University of Vienna. E-mail: alexander.ziegenbein@univie.ac.at

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1 Introduction

What are the effects of financial market disruptions on economic activity? The recent global financial crisis suggests that the effects are large and highly persistent: by 2017, 10 years after the beginning of the crisis, the US and UK GDPs remain far —10 percentage points (ppt) or more— from their pre-crisis trends (Figure 1). More systematic narrative studies of financial stress episodes point to similar conclusions. For instance, Christina D. Romer and David H. Romer (2017) study a panel of OECD countries and find that GDP is typically 9ppt lower five years after an extreme financial stress episode like the recent crisis.[1]

Surprisingly, however, these numbers stand in sharp contrast with the findings of another influential literature on the importance of financial markets for economic activity. Multivariate time series models (i.e., structural VARs) find relatively mild and short-lived effects of financial shocks —shocks to the effective “risk-bearing capacity” of the intermediary financial sector— . For instance, the results of Simon Gilchrist and Egon Zakrajšek (2012) imply that output should be only 1.3ppt lower 5 years after an adverse financial shock like the one experienced in the recent crisis.[2]

To make sense of this conundrum, we first point to separate shortcomings of the two aforementioned approaches —narrative accounts and structural VARs—. On the one hand, and unlike structural VARs, narrative accounts are not designed to identify the causal effect of financial strains on economic activity, only the existence of a correlation. On the other hand, structural VARs do not take into account that financial shocks are likely to have asymmetric effects on economic activity, as has been predicted theoretically (Enrique G. Mendoza, 2010; Zhiguo He and Arvind Krishnamurthy, 2013; Markus K Brunnermeier and Yuliy Sannikov, 2014). In contrast, narrative accounts implicitly allow for asymmetric effects

[1]See also Valerie Cerra and Sweta Chaman Saxena (2008), Òscar Jordà, Moritz Schularick and Alan M Taylor (2011), Michael D Bordo and Joseph G Haubrich (2017), Laurence M Ball (2014), Carmen M Reinhart and Kenneth S Rogoff (2014), Olivier Blanchard, Eugenio Cerutti and Lawrence Summers (2015), Arvind Krishnamurthy, Tyler Muir and S Yale (2015).

[2]See also Thomas Helbling, Raju Huidrom, M Ayhan Kose and Christopher Otrok (2011), Simon Gilchrist, Vladimir Yankov and Egon Zakrajšek (2009), Gilchrist and Zakrajsek (2011; 2012) and Jean Boivin, Marc P Giannoni and Dalibor Stevanović (2013).

because they only focus on adverse financial developments, i.e., negative "shocks".

We then consider an empirical model, a Vector Moving-Average (VMA) model, designed to address these separate limitations, i.e., to (i) identify the causal effects of financial shocks, and (ii) take into account the possible asymmetric effects of financial shocks. Like VARs, VMAs can incorporate structural identifying restrictions to tease out causal effects, but unlike VARs, VMAs can easily be generalized to allow for asymmetric effects of shocks.

Our baseline evidence is based on US data, and we establish the causal effect of financial shocks by using an identification strategy that builds on, but also expands, Gilchrist and Zakrajšek (2012, GZ). We isolate innovations to the Excess Bond Premium (EBP) —the component of credit spreads purged from the expected default risk of borrowers— that are contemporaneously orthogonal to macro variables, and we separate the EBP innovations into monetary shocks and financial shocks using a proxy variable approach based on Christina D. Romer and David H. Romer's (2004) narrative measure of exogenous monetary policy changes.

We find that a favorable financial shock —an easing of financial conditions— has little effect on economic activity, but an adverse financial shock has large and persistent effects on economic activity. These results help reconcile the seemingly contradictory findings between narrative accounts and structural time series analyses: structural VARs have found mild and transitory effects of financial shocks on GDP, because VARs are linear models, in which the large and persistent effects of adverse shocks are mixed with the (according to our results) small and transitory effects of favorable shocks, leading to mild *average* effects of financial shocks. In contrast, narrative studies focus solely on crisis episodes, i.e., adverse events, which have large and persistent effects on output. Our estimated effects of financial market disruptions are smaller than narrative studies like Romer and Romer (2017), however, consistent with the fact that some of the movements in financial distress identified by narrative studies are likely endogenous.

We then use our model to revisit the effects of the financial crisis on output, and in particular on the large gap that opened between output and its pre-crisis trend. To do so, we conduct a counterfactual model simulation based on parameters *estimated with pre-2007 data*, in which we turn off the financial shocks experienced over 2007-2008. We find that without the 2007-2008 financial shocks, the decline in output would have been a lot milder and only transitory. We conclude that a large fraction (over two thirds) of the gap between current GDP and its pre-crisis trend was caused by the financial crisis.

As additional evidence, we also consider the effects of financial shocks from UK data, and we obtain very similar conclusions. We follow the same identification strategy as in the US, using data on the excess bond premium from Michael Bleaney, Paul Mizen and Veronica Veleanu (2016) and the narrative measure of exogenous monetary policy changes from James Cloyne and Patrick Hürtgen (2016). As with the US, financial market disruptions have large and persistent effects on output, so that a large fraction of the gap between current UK output and its pre-crisis trend can be attributed to the financial crisis.

While VMAs are attractive because of their great flexibility (particularly to allow for non-linearities), they are also difficult to estimate because of their large parameter space. To estimate VMAs, we use a Functional Approximation of Impulse Responses (FAIR) method recently proposed in Regis Barnichon and Christian Matthes (2018). The method consists in approximating the impulse response functions (i.e., the VMA representation) with a (small) number of basis functions. The approximation considerably shrinks the dimensionality of the problem and makes the estimation of VMAs feasible using maximum likelihood or Bayesian methods. The parsimony of the approach, in turn, allows us to estimate more general non-linear models, in our case models with asymmetry.

The remainder of the paper is structured as follows. Section 2 provides some background and highlights the conflicting conclusions reached by the two leading strands of the literature on the effects of financial market disruptions; Section 3 presents a simple approach to assess whether asymmetric effects of financial shocks hold any promise to reconciling the literature; Section 4 introduces our empirical model, our method to approximate impulse responses using Gaussian basis functions and our strategy to identify financial shocks; Section 5 presents our baseline evidence from US data; Section 6 presents evidence on the asymmetric effects of financial shocks from UK data; Section 7 concludes and lays out possible paths for future research.

2 Background

In part motivated by the experience of the recent crisis, a large literature has aimed to better understand the effects of financial market disruptions on output. A first "narrative" strand studies the behavior of output around narratively identified financial crisis episodes, focusing on measuring the correlation between financial strain and economic activity. A second strand uses structural Vector AutoRegressions (VARs) to identify the causal effects of shocks originating in financial markets.

As we will see, these two strands reach strikingly different conclusions: While the narrative approach finds that financial distress is associated with large and persistent drops in output, the structural VAR literature finds relatively mild and short-lived effects of financial distress on output.

Narrative accounts of financial distress episodes

Narrative studies of financial crises go back to Valerie Cerra and Sweta Chaman Saxena (2005) and Carmen M. Reinhart and Kenneth S. Rogoff (2009), who estimate the average path of output following financial crisis episodes. While this approach did not initially take into account the severity of the crisis —only attributing a dummy value of one in case of a crisis—, Romer and Romer (2017, RR) recently refined the methodology by using narrative accounts from the OECD Economic Outlook on country conditions to capture the intensity of financial strains on a 0 (no financial distress) to 15 scale (extreme distress). Their series measures financial distress in 24 OECD countries at a semi-annual frequency for the period 1967-2012.

To estimate the impulse responses of output to an impulse to financial distress, RR use

Òscar Jordà (2005)'s local projection method. The particular specification they estimate is

$$y_{j,t+h} = \alpha_j^h + \gamma_t^h + \beta^h F_{j,t} + \sum_{l=1}^{4} \phi_l^h F_{t,t-l} + \sum_{l=1}^{4} \theta_l Y_{j,t-l} + u_t^h, \qquad h = 0, 1, ..., H \qquad (1)$$

where the j subscripts index countries, the t subscripts index time, and the h superscripts denote the horizon (in half-years after time t) being considered. $y_{j,t+h}$ is log real GDP for country j at time $t + h$. $F_{j,t}$ is the RR financial distress index for country j at time t. RR use four lags of log real GDP and financial distress as control variables. α_j^h are country fixed effects capturing that the normal behavior of output may differ across countries. γ_t^h are time fixed effects, included to control for economic development facing all countries in a given year.

While RR's main evidence is based on a panel of countries, we will show the results based only on US data (dropping the time fixed effects).[3] Using only US data has one important advantage; it will allow us to convert the movements in RR financial distress index (whose level is arbitrary) into an objective measure of financial strain —the US Excess Bond Premium (EBP)— and thereby relate the RR findings to the rest of the literature. The US EBP, constructed by Gilchrist and Zakrajšek (2012) and displayed in Figure 2, is the component of US corporate credit spreads purged from expected default risk, liquidity risk, and prepayment risk, and is meant to capture the effective risk-bearing capacity of the financial sector. An important advantage of the EBP compared to the RR index is that the EBP is an *objective quantitative* measure of financial strains. By studying the impulse response of the US Excess Bond Premium (EBP) to innovations to the RR index, we can quantify the magnitude of the financial strains implied by RR's narrative index.

Figure 3(a) plots the impulse responses of output and the EBP to an innovation to RR financial distress index. The size of the innovation is set so that the EBP rises by 1 ppt at its peak, which corresponds to a moderate financial crisis in RR scale (an RR financial distress level of close to +7). Confirming RR, a *transitory* increase in financial distress is

[3]In the appendix, we show that the results using US data only are very similar to RR's original results using a panel of 24 OECD countries.

associated with a *large* and *persistent* drop in output: while the EBP is back to its initial level 2 years after the shock, real GDP is still 4.5ppt lower 5 years after the shock, and the impulse response shows little sign of mean reversion.

Structural VARs

The second strand in the literature uses structural Vector AutoRegressions (VARs) to try to identify the causal effects of credit supply shocks originating in financial markets.[4] Specifically, the approach builds on Gilchrist and Zakrajšek's (2011, 2012, GZ) EBP measure to identify exogenous innovations to the risk-bearing capacity of the financial sector, i.e., shocks to credit supply. For simplicity, we will refer to these shocks as financial shocks.

GZ use the EBP in a quarterly-frequency VAR along with macroeconomic and financial variables.[5] To identify financial shocks, they use a recursive ordering, i.e., they postulate that macroeconomic variables react with a one-period lag to changes in the EBP, and that the EBP reacts with a lag to changes in monetary policy. Figure 3(b) replicates the results of GZ and plots the impulse responses to a financial shock that raises the EBP by 1ppt at its peak. For clarity of exposition, we only show impulse responses for real GDP and the excess bond premium. An exogenous increase in the EBP of 1ppt leads to a 2ppt drop in real GDP one year after the shock, followed by a recovery so that the effect is no longer significantly different from zero after 2 years. In fact, 5 years after the shock, output is only 0.6ppt lower.[6]

[4]See Helbling et al. (2011), Gilchrist, Yankov and Zakrajšek (2009), Gilchrist and Zakrajsek (2011; 2012) and Boivin, Giannoni and Stevanović (2013).

[5]The variables in the VAR are: (i) log-difference of real personal consumption expenditures; (ii) log-difference of real business fixed investment; (iii) log-difference of real GDP; (iv) log-difference of the GDP price deflator; (v) quarterly average of the EBP; (vi) quarterly (value-weighted) excess stock market return from CRSP; (vii) the ten-year (nominal) Treasury yield; (viii) the effective (nominal) federal funds rate. GZ estimate the VAR using two lags on all variables.

[6]Other VAR studies report similarly mild and transitory effects of financial shocks on US output, e.g., Boivin, Giannoni and Stevanović (2013) or Simon Gilchrist, Jae W. Sim and Egon Zakrajek (2014). Similar results hold for the major Euro area countries (Germany, France, Italy and Spain) with Simon Gilchrist and Benoit Mojon (2018) reporting mild and transitory effects of financial shocks on output. In fact, Gilchrist and Mojon (2018) find that economic activity is back to its unconditional mean 5 years after a financial shock.

Taking stock

To put the previous results into perspective, Figure 3(c) simultaneously reports the impulse responses obtained with the two different methods —narrative accounts and VARs—. While the impulse response of the EBP is very similar across methods, the behavior of output is very different: compared to the VAR estimates, the drop in output estimated with the RR narrative approach is (i) about 4 times larger and (ii) much more persistent.

Going back to the recent financial crisis, the two approaches lead to very different conclusions about the role of the 2007-2008 crisis in the persistent "output loss" displayed in Figure 1. The RR financial distress index reaches 14 —an *extreme crisis*— in the US in 2008. Thus, the RR estimates imply that the crisis should be followed by a roughly $2 * 4.5 = 9$ppt persistent drop in output, thereby attributing 90 percent of the "output loss" from Figure 1 to the financial crisis. In contrast, GZ VAR estimates imply that the 2007-2008 financial shocks —a 2ppt exogenous increase in the EBP— can *only* explain a $0.6 * 2.0 = 1.3$ppt drop in output five years after the shock, so only 13 percent of the 10ppt "ouput loss".[7]

3 The asymmetric effects of financial shocks: a first pass

To better understand the discrepancy between the results from VARs and narrative accounts, we note that the two approaches suffer from two separate shortcomings: (i) causality —unlike structural VARs, narrative accounts are not designed to identify the causal effect of financial strains on economic activity, only the existence of a correlation—, and (ii) asymmetry — while a number of papers have argued that financial shocks are likely to have asymmetric effects (Mendoza, 2010; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014), VARs impose symmetric effects of shocks. In contrast, narrative accounts implicitly allow for asymmetric effects because they only focus on adverse financial developments, i.e., negative

[7] The sum of shocks to the EBP identified from the GZ VAR in 2007-2008 is roughly 2ppt.

"shocks". Thus, the presence of asymmetry in the effects of financial shocks could help explain the seemingly conflicting results in the literature.

A simple way to quickly assess whether such asymmetric effects hold any promise to reconciling the literature is to use the VAR-identified shocks in a local projections setup similar to (1). The VAR-based financial *shocks* allow us to establish causality, while local projections allow us to estimate asymmetric impulse responses with a regression of the form

$$y_{t+h} = \alpha_h + \beta_h^+ \xi_t^+ + \beta_h^- \xi_t^- + \gamma' x_t + u_{t+h}, \qquad h = 0, 1, ..., H \tag{2}$$

where y_{t+h} is the variable of interest, x_t contains lags of y_t, and ξ_t is our VAR-based estimate of the financial shock at time t. The coefficient β_h^+ captures the impulse response to a positive financial shock ξ_t^+, and β_h^- captures the response to a negative financial shock ξ_t^- at horizon h.

We estimate equation (2) for the EBP and the log-difference of industrial production, and Figure 4 plots the corresponding impulse responses. Note the large asymmetric effect of a financial shock. An adverse financial shock causes a large decline in output, while a favorable shock generates little movements in output. In terms of magnitude, an increase of 1ppt in the EBP translates into a 5ppt persistent decline in IP after five years.

To put these estimates in the context of the 2007-2008 financial crisis, we can do a back-of-the-envelope calculation. The VAR-identified financial shocks over 2007-2008 correspond to an increase in the EBP of about 2ppt. According to our estimates, a 2ppt exogenous increase in the EBP implies a $2 * 5 = 10$ppt output loss, which is very close to the RR estimates of the output loss from the 2007-2008 financial crisis. In fact, this first-pass exercise attributes all of the "output loss" since 2007 (Figure 1) to the adverse financial shock.

While these results are alluring, this simple exercise is only suggestive of the presence of non-linear effects. Indeed, if the data are generated by a nonlinear process (as our results suggest), the linear VAR model is mis-specified, and the VAR-identified shocks will not be consistently estimated.[8] To do so, one should use an empirical model that explicitly accounts for the non-linearities in the data-generating process. This is the subject of the next section.

4 A model to estimate the asymmetric effects of financial shocks

In this section, we present an empirical model designed to (i) identify the causal effects of financial shocks, and (ii) take into account the possible asymmetric effects of financial shocks.

4.1 A structural Vector Moving-Average model (VMA)

Our empirical model is a nonlinear VMA, in which the behavior of a vector of macroeconomic variables is dictated by its response to past and present structural shocks.

Specifically, denoting $\boldsymbol{y_t}$ a vector of stationary macroeconomic variables, the economy is described by

$$\boldsymbol{y_t} = \sum_{k=0}^{K} \boldsymbol{\Psi}_k(\boldsymbol{\varepsilon}_{t-k})\boldsymbol{\varepsilon}_{t-k}, \tag{3}$$

where $\boldsymbol{\varepsilon}_t$ is a vector of structural shocks with $E(\boldsymbol{\varepsilon}_t) = 0$, $E(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}'_t) = \boldsymbol{I}$, K is the number of lags, which can be finite or infinite, and z_t is a stationary variable that can be a function of past values of $\boldsymbol{y_t}$ or of exogenous variables. $\boldsymbol{\Psi}_k$ is the matrix of lag coefficients, i.e., the impulse response functions to shocks.

Note that (3) is a nonlinear VMA, because the coefficients of $\boldsymbol{\Psi}_k$ can depend on the values of the structural innovations $\boldsymbol{\varepsilon_{t-k}}$, so that the impulse response functions to a given structural shock depend on the value of the shock at the time of shock, and a positive shock may trigger a different impulse response than a negative shock.

Importantly, our empirical model is *not* a structural Vector AutoRegression (VAR). While the use of a VAR is a common way to estimate a moving-average model, it relies on the

[8] In contrast, if the data were generated by a linear process, the exercise would be valid in that the local projections (2) will estimate the same impulse responses as the VAR (in population), see Mikkel Plagborg-Møller and Christian K Wolf (2019).

existence of a VAR representation. However, in a nonlinear world where $\boldsymbol{\Psi}_k$ depends on the sign of the shocks $\boldsymbol{\varepsilon}$ as in (3), the existence of a VAR is compromised, because inverting (3) is generally not possible (Barnichon and Matthes, 2018). Thus, in this paper, we work with an empirical method that side-steps the VAR and instead directly estimates the VMA model (3).

4.2 Functional Approximations of Impulse Responses (FAIR)

Estimating a moving-average model is difficult because the number of free parameters $\{\boldsymbol{\Psi}_k\}_{k=0}^{K}$ in (3) is very large or possibly infinite. To address this issue, we use Functional Approximations of Impulse Responses (Barnichon and Matthes, 2018), which consists in representing the impulse response functions as expansions in basis functions.

To illustrate the workings of FAIR, consider a linear version of (3), i.e.

$$\boldsymbol{y}_t = \sum_{k=0}^{\infty} \boldsymbol{\Psi}_k \boldsymbol{\varepsilon}_{t-k}. \tag{4}$$

Denote by $\psi(k)$ an element of matrix $\boldsymbol{\Psi}_k$, so that $\psi(k)$ is the value of the impulse response function ψ at horizon k. A functional approximation of ψ consists in decomposing ψ into a sum of basis functions, and in this work we will use Gaussian basis functions to write

$$\psi(h) = \sum_{n=1}^{N} a_n e^{-(\frac{h-b_n}{c_n})^2}, \quad \forall h \geq 0 \tag{5}$$

with a_n, b_n, and c_n parameters to be estimated.[9]

Gaussian basis functions can be particularly attractive in our context. For instance, two Gaussian functions can already approximate an oscillating impulse response function, say the impulse response of GDP growth following an adverse financial shock. As illustrated in Figure 5, the first Gaussian captures the first-round effect of the shock—an initial decline in output growth— while the second Gaussian captures the second-round effect—a later re-

[9]For flexibility reasons, we treat the contemporaneous impact coefficient $\psi(0)$ as a free parameter.

bound in output growth. The parsimony of the functional approximation has two important advantages. First, it will allow us to estimate the VMA model. Second, it will allow us to add more degrees of freedom and introduce possible asymmetric effects of shocks.

To allow for asymmetries in the VMA model, we let $\boldsymbol{\Psi}_k$ depend on the signs of the structural shocks, i.e., we let $\boldsymbol{\Psi}_k$ take two possible values: $\boldsymbol{\Psi}_k^+$ or $\boldsymbol{\Psi}_k^-$ and write

$$\boldsymbol{y}_t = \sum_{k=0}^{K} \left[\boldsymbol{\Psi}_k^+(\boldsymbol{\varepsilon_{t-k}} \odot \mathbf{1}_{\boldsymbol{\varepsilon}_{t-k}>0}) + \boldsymbol{\Psi}_k^-(\boldsymbol{\varepsilon}_{t-k} \odot \mathbf{1}_{\boldsymbol{\varepsilon}_{t-k}\leq 0})\right] \tag{6}$$

with $\boldsymbol{\Psi}_k^+$ and $\boldsymbol{\Psi}_k^-$ the lag matrices of coefficients for, respectively, positive and negative shocks and $\odot$ denoting element-wise multiplication. Then, denoting ψ^+, an impulse response function to a *positive* financial shock and similarly for ψ^-, a FAIR model of the impulse response function ψ^+ would write

$$\psi^+(k) = \sum_{n=1}^{N} a_n^+ e^{-\left(\frac{k-b_n^+}{c_n^+}\right)^2}, \;\; \forall k > 0 \tag{7}$$

with a_n^+, b_n^+, c_n^+ some constants to be estimated. A similar expression would hold for $\psi^-(k)$.

We leave the details of the estimation for the appendix, but in a nutshell the estimation boils down to the estimation of a truncated moving-average model (with a FAIR parametrization). The model can be estimated using maximum likelihood or Bayesian methods, and we recursively construct the likelihood by using the prediction error decomposition and assuming that the structural innovations are Gaussian with mean zero and variance one.

4.3 Identification

Our goal is to identify shocks to the risk-bearing capacity of the financial markets. For simplicity, we will refer to these shocks as "financial shocks". Building on GZ, our vector $\boldsymbol{y}_t$ will include macroeconomic variables (output, inflation) and financial variables (the EBP and the fed funds rate).

As GZ, we impose a recursive ordering between economic variables and financial variables, so that the EBP and the stance of monetary policy are ordered after the macro variables, and we impose that $\mathbf{\Psi}_0$ is lower triangular except for the block relating monetary policy shocks and financial shocks, as described below. To make this recursive ordering plausible, we will rely whenever possible on data at a monthly frequency.

A strong identification assumption made by GZ, however, is that financial shocks do not affect the fed funds rate on impact. In this work, we relax this assumption and do not impose a recursive ordering between the EBP and the fed funds rate.[10] Instead, to identify movements in the EBP that are not due to changes in monetary policy, we add external information on the contemporaneous effect of monetary policy on the EBP by using a proxy variable for the latent monetary policy shock, for instance the Romer and Romer's (2004) monetary shock series in the case of the US. More specifically, denote a proxy for the monetary policy shock by m_t and the actual monetary policy shock by ε_t^m. We add the following equation to our VMA model (3):

$$m_t = \mu^m + \alpha^m \varepsilon_t^m + u_t^m \tag{8}$$

where $u_t^m \sim_{iid} N(0, \sigma_{u^m}^2)$ captures measurement error in the proxy variable. The parameters of this equation are estimated jointly with all other parameters of the model in our Metropolis-Hastings algorithm. With this equation, we give our model information about which element of $\boldsymbol{\varepsilon}_t$ is the monetary policy shock and thus also which element is the financial shock. Although used in a different context, this strategy is similar in spirit to the Dario Caldara and Edward Herbst (2019) identification of monetary shocks in a VAR.

5 The effects of financial shocks, US evidence

In this section, we use the FAIR methodology to estimate the effects of US financial shocks.

[10] Thus, absent any other information, financial shocks and monetary shocks cannot be separately identified.

5.1 Evidence from FAIR

We consider a VMA model with four endogenous variables: (i) the log-difference of industrial production (IP); (ii) the log-difference of the CPI price index; (iii) the excess bond premium; (iv) the effective (nominal) federal funds rate:

$$\boldsymbol{y}_t = [\Delta IP_t, \Delta CPI_t, EBP_t, FFR_t]$$

We use a FAIR(2) model—two Gaussian functions per impulse response—, which allows us to capture the mean-reverting pattern of output.[11]

The data are monthly and cover 1973m1–2016m12. When the federal funds rate is at the zero lower bound, we capture the stance of monetary policy with the Jing Cynthia Wu and Fan Dora Xia (2016) shadow rate.[12] As instrument for monetary shocks, we use the Romer and Romer monetary policy instrument extended to 2007 by Johannes F. Wieland and Mu-Jeung Yang (2016). Following standard practice in the literature (James H Stock and Mark W Watson, 2012; Mark Gertler and Peter Karadi, 2015; Dario Caldara and Christophe Kamps, 2017), we infer the contemporaneous effect of monetary policy on the EBP from the subsample for which the instrument is available.

Figure 6 presents the estimated impulse responses to financial shocks. The thick lines are posterior mode estimates, and the shaded areas cover 90% of the posterior probability. We obtain the impulse responses of IP from the cumulative impulse response of ΔIP. The left panel shows the impulse responses following an adverse financial shock (an increase in the EBP), and the right panel shows the impulse responses following a favorable financial shock (a decrease in the EBP). When comparing impulse responses to positive and negative shocks, it is important to keep in mind that the impulse responses to favorable shocks (a decrease in the EBP) were multiplied by -1 to ease comparison across impulse responses.

[11] The posterior-odds ratio between a FAIR(2) and a FAIR(3) model supports the more parsimonious FAIR(2) model.

[12] The shadow rate is the hypothetical level of a federal funds rate not constrained by the zero lower bound, given the level of asset purchases and forward guidance. Wu and Xia (2016) construct an estimate of the shadow rate from the observed Treasury yield curve, i.e., by finding the level (positive or negative) of the policy rate that would generate the observed yield curve.

With this convention, when there is no asymmetry, the impulse responses are identical in the left panel (responses to an adverse shock) and the right panel (responses to a favorable shock).

Financial shocks have strongly asymmetric effects. An adverse financial shock causes a large decline in output, while a favorable shock generates little movements in output. In terms of magnitude, an increase of 1ppt in the EBP translates into a 4ppt persistent decline in IP. Moreover, while the GZ VAR estimates—discussed in Section 2—suggest a rebound in output one year after the financial shock, the FAIR estimates suggest that the rebound is weak following a contractionary shock. As a result, the level of output appears to be persistently affected by a contractionary financial shock, which is in line with the evidence from narrative studies discussed in Section 2.

In the online appendix, we present a number of robustness checks that confirm our findings. In particular, we show that our results are robust to (i) excluding the great financial crisis and the zero-lower bound period from the sample, and (ii) using an alternative identification of financial shocks.[13]

5.2 Taking stock

We now go back to the current state of the literature and contrast our baseline FAIR estimates with those of the literature —narrative accounts and VARs. Figure 9 plots the impulse responses to an innovation to the RR financial distress variable (estimated as in RR, red line); the impulse responses to a GZ financial shock (estimated as in GZ, blue line); and the FAIR estimate of the impulse responses to an adverse financial shock (black lines). All the impulse responses are scaled such that the peak response of the EBP equals +1ppt.

We can see that our FAIR estimates fall in the midrange between the smaller VAR estimates and the larger estimates from narrative studies. The peak effect of an adverse

[13]Specifically, we considered (i) the 1973-2006 sample period, (ii) the 1990-2006 sample with a high-frequency identification of monetary shocks (instead of the Romer and Romer proxy), and (iii) an alternative identification of financial shocks from William F Bassett, Mary Beth Chosak, John C Driscoll and Egon Zakrajšek (2014), who identify credit supply shocks from bank-level responses to the Federal Reserve's Loan Officer Opinion Survey (SLOOS).

financial shock on real GDP is -4.5ppt (after approximately 2 years), larger than the VAR estimates but smaller than the RR narrative estimates. After 5 years, real GDP is still -3.5ppt lower. The VAR estimates are smaller, likely because the large effect of adverse shocks are mixed with the small effects of favorable shocks. The RR estimates are larger, likely because the RR approach does not isolate exogenous episodes of financial distress and thus overestimates any adverse causal impact of financial distress on output (as acknowledged by Romer and Romer 2017, page 3114).

Although the RR exercise is not meant to identify the causal effect of financial shocks, one could use a recursive ordering similar to GZ in order to try to isolate the causal effect of financial distress on GDP: If financial distress takes more than six months to affect economic activity —a much stronger assumption than implied by our monthly recursive ordering—, adding the contemporaneous value of output as control in the RR local projections (1) should allow us to identify the causal effect of financial distress on output.[14] These "identified" RR results are in line with our structural VMA estimates. As shown in Figure 9, the impulse responses of GDP are on top of each other over the first 2.5 years, diverging only slightly at longer horizons.[15] In other words, narrative accounts and structural time series analysis give remarkably consistent results once we take into account the issues of causality and asymmetry.

5.3 US GDP since the financial crisis

To examine the recent behavior of US GDP in light of our estimates, we conduct a counterfactual experiment in which we turn off (i.e., set to zero) the sequence of financial shocks experienced in 2007-2008.[16] Importantly, for this exercise we use our baseline VMA model estimated over 1973-2006, i.e., excluding any information from the great financial crisis and

[14]See e.g., Regis Barnichon and Christian Brownlees (2018) for more details on how to impose recursive identifying assumptions in the context of local projections.

[15]As expected, removing some of the endogenous component of financial distress reduces the magnitude of the response of GDP.

[16]Specifically, we draw from the posterior distribution of FAIR parameter estimates and identified financial shocks to obtain a posterior distribution of counterfactual paths for output and the EBP. Figure A2 in the appendix plots the time-series and a histogram of the US financial shocks estimated from a FAIR(2).

its aftermath. Thus, the behavior of US GDP since 2007 has no influence on our counterfactual exercise, and our predicted GDP path is only driven by the typical path of output following a financial market disruption, as estimated over 1973-2006 (see the appendix for more details).

Remarkably, we find that the impulse responses estimated with data prior to the financial crisis are very similar in magnitude to our baseline estimates (based on data including the financial crisis). Thus, we do not find that the crisis had disproportionally larger effects on the economy.[17] Instead, our results indicate that the financial crisis is just a scaled up version of earlier (much smaller) financial shocks, and the crisis had large and persistent effects on output simply because it was a very large shock.

Next, Figure 10 plots the actual paths of GDP and the EBP along with their counterfactual median paths implied by our FAIR estimates along with the 68 and 90 percent posterior ranges. Without the large adverse financial shocks experienced in 2007 and 2008, the EBP would have displayed a much smaller increase (driven only by the endogenous response of the EBP to the other shocks behind the great recession), and the behavior of GDP would have been very different. The drop in output would have been relatively mild, and GDP would have reverted to its pre-crisis trend in about a year. As of the end of 2017, the gap between output and potential output (as estimated from the CBO in 2007) would only be 3ppt (instead of 10ppt), implying that the 2007-2008 financial crisis persistently lowered output by roughly 7ppt. Thus, according to our FAIR estimates, more than two thirds of the persistent output loss that ensued following the great recession was in fact *caused* by the large financial market shock that hit the economy. In other words, a substantial fraction of the gap between current GDP and its pre-crisis trend is unlikely to revert, providing some support for CBO's repeated downward revisions to its estimate of potential output (Olivier Coibion, Yuriy Gorodnichenko and Mauricio Ulate, 2017).

[17]For instance, the zero-lower bound constraint during the crisis could have restrained the typical reaction of monetary policy and led to disproportionally larger effects on output.

5.4 On the persistent effect of adverse financial shocks

A natural question in light of our result is the source of the persistent effects of adverse financial shocks. One possible story is that financial frictions give rise to strong non-linearities. As shown by Brunnermeier and Sannikov (2014), with financial frictions adverse shocks can take the economy away from its steady-state for a very long (but finite) time.

Alternatively, financing difficulties can prevent high-growth potential start-ups to emerge, leading to a "lost generation" of firms and to a persistent output loss (Petr Sedlacek and Vincent Sterk, 2017; Petr Sedláček, 2019).

Another possible explanation is that financial distress episodes force firms to cut back on R&D expenditures (see e.g. Diego Comin and Mark Gertler, 2006; Francesco Bianchi and Howard Kung, 2014), which could permanently affect the level of TFP and thus the level of output in the long-run.

To help discriminate between these possibilities, we estimate the impulse responses of employment, capital, TFP, R&D expenditures and firm entry.[18] In the appendix, we report the impulse responses of four additional macro variables: real GDP, consumption, investment, and the fed funds rate. Since these variables were not included in the VMA model of $\boldsymbol{y}_t$, we estimate their impulse responses in two steps. First, we extract the financial shocks, denoted by $\{\hat{\varepsilon}_t\}$, that we identified from our baseline specification.[19] Second, we estimate a univariate model - a univariate FAIR - capturing the impulse response of the additional variables. Specifically, denoting y_t the variable of interest, we estimate

$$y_t = \sum_{k=0}^{K} \psi^{\pm}(k)\hat{\varepsilon}_{t-k} + u_t \tag{9}$$

where $\psi^{\pm}$ captures the impulse response function to a positive or negative financial shock

[18]TFP is utilization-adjusted TFP from John G. Fernald (2014), available at an annual frequency. R&D is real gross private domestic investment in research and development from the BEA. Employment is total non-farm employment from the BLS CES. Capital is the real US capital stock from the Penn World Table. Firm entry is a yearly series over 1977-2016 compiled by Sedláček (2019) from Business Dynamics Statistics data. All variables enter the regression in log-differences and we report cumulated impulse responses.

[19]More specifically, the Bayesian estimation of the FAIR model(6)-(7) delivers a posterior distribution of the financial shocks $\{\hat{\varepsilon}_t\}$.

$\hat{\varepsilon}_t$ and u_t is the residual. Since the errors are likely serially correlated, we allow for serial correlation in u_t by positing that u_t follows an AR(1) process. To parametrize the impulse responses $\psi^{\pm}$, we use a FAIR(2) to have enough flexibility to capture the (potentially) mean-reverting pattern of our variables.[20]

Figure 7 displays the results. Following an adverse financial shock, both capital and labor decline in roughly equal proportion. To put these numbers in the context of the latest financial crisis (an increase in the EBP of about 2), the $2 * 4$ percent decline in employment corresponds to about 11 million lost jobs. With the 2018 unemployment rate back to (even below) its pre-crisis level, this represents about 4 percentage points of labor force participation in 2018.

Interestingly, we do dot detect any significant or asymmetric response of TFP, even though R&D displays a strong asymmetric response, being persistently lower after an adverse financial shock. This last result seems to favor a non-linearity channel à la Brunnermeier and Sannikov (2014) or a "lost generation" channel. In fact, consistent with the "lost generation" hypothesis, an adverse financial shock leads to a sharp decline in firm entry with little signs of a rebound later. That being said, the effect of R&D on TFP could be present but so delayed (beyond 5 years) that we cannot detect it.[21]

6 The effects of financial shocks, UK evidence

In this section, we provide independent evidence that adverse financial shocks have large and persistent effects by focusing on the United Kingdom (UK).

While the EBP measure was originally constructed for the US, Bleaney, Mizen and Veleanu (2016) recently constructed EBP measures for some European countries. While the sample size is small for most countries (2003Q2-2010Q3 or even shorter), the EBP measure

[20]For variables only available at quarterly (yearly) frequency, we use as shock series the quarterly (yearly) average of the monthly financial shocks.

[21]In line with this possibility, Òscar Jordà, Sanjay R Singh and Alan M Taylor (2020) find with historical data that a negative aggregate demand shock has long-run effects on TFP, but the effect is not visible in the first five years, starting to materialize only after 6-7 years.

for the UK covers 1996Q1-2010Q2, offering hope that there might be enough variation to estimate our non-linear VMA with reasonable confidence intervals.

Similarly to the US, our specification uses four endogenous variables: (i) GDP growth (ii) CPI inflation, (iii) the UK excess bond premium (see Figure A8 in the appendix), and, (iv) the Official Bank Rate (OBR) of the Bank of England to measure the stance of monetary policy.

$$\boldsymbol{y}_t = [\Delta GDP_t, \Delta CPI_t, EBP_t, OBR_t]$$

We use the same identifying assumption as for the US. That is, we assume that macroeconomic variables react with a lag to financial shocks, and we use a proxy for monetary shocks —this time, the Cloyne and Hürtgen's (2016) narrative measure of exogenous monetary policy changes— to identify changes in the EBP that are not due to changes in the stance of monetary policy.

We estimate an asymmetric FAIR(2) model, and Figure 11 plots the corresponding impulse responses. The output effects of financial shocks are very similar to the ones we obtained for the US: An adverse financial shock leads to a large and persistent reduction in output. A favorable financial shock, on the other hand, has no significant effect on GDP.[22]

To get an estimate of the output loss created by the 2007-2008 financial crisis, we can proceed as with the US and simulate a counterfactual path for GDP without financial shocks in 2007-2008. For that exercise, we use parameter values estimated over 1996-2006 only, and Figure 12 shows the results. Similarly to the US, we find that absent the series of financial shocks that raised the UK EBP by about 2ppt overall, GDP would have been about 8ppt higher today. Thus, as with the US, we find that the 2007-2008 financial market disruptions in the UK can account for a large fraction of the gap between current GDP and its pre-crisis trend.

[22]As with the US, the asymmetry cannot be explained by the response of the interest rate, since the latter is more accommodative following an adverse financial shock (not shown).

7 Conclusion

Most advanced economies are still suffering from the aftermaths of a global financial crisis that started 10 years ago: GDP figures remain far from their pre-crisis trend. These disappointing performances as well as more systematic narrative studies (Reinhart and Rogoff, 2014; Romer and Romer, 2017) led many academics and policy makers to suspect (and worry) that output might not revert back to its pre-crisis trend (Ball, 2014). This mindset is most apparent in the series of downward revisions made by the Congressional Budget Office (CBO) to its estimate of potential output. The revisions have been so dramatic over the past 10 years that the CBO now estimates that US GDP is at potential, even though GDP never displayed any catch up towards its pre-crisis trend (Coibion, Gorodnichenko and Ulate, 2017). In other words, taking the 2007 CBO estimate of potential output at face value, the financial crisis appears to have led to a permanent loss in output.

We show that this conclusion stands in sharp contrast with the results of another influential literature on the importance of financial markets for economic activity. Multivariate time series models (i.e., structural VARs) find relatively mild and short-lived effects of financial market disruptions on output (Gilchrist and Zakrajšek, 2012).

We estimate a non-linear model designed to address some important shortcomings of previous approaches, namely (i) we identify the causal effects of financial shocks (unlike narrative studies), and (ii) we take into account the possible asymmetric effects of financial shocks (unlike VAR studies). We find that adverse financial shocks have large and persistent effects on output, while positive shocks have little effects. In a counter-factual exercise based on model estimates from pre-2007 data, we find that a large fraction of the gap between current output and its pre-crisis trend is due to the 2007-2008 adverse financial shocks and is unlikely to reverse itself, in line with CBO's repeated downward revisions to its estimate of potential output.

While we discussed some possible channels behind the asymmetric and persistent effects of financial shocks, an important goal for future research is to use theoretical and quantitative models to help sort out the different hypotheses and ultimately better understand the implications of these non-linearities for the conduct of monetary policy (Jeremy Stein, 2014).

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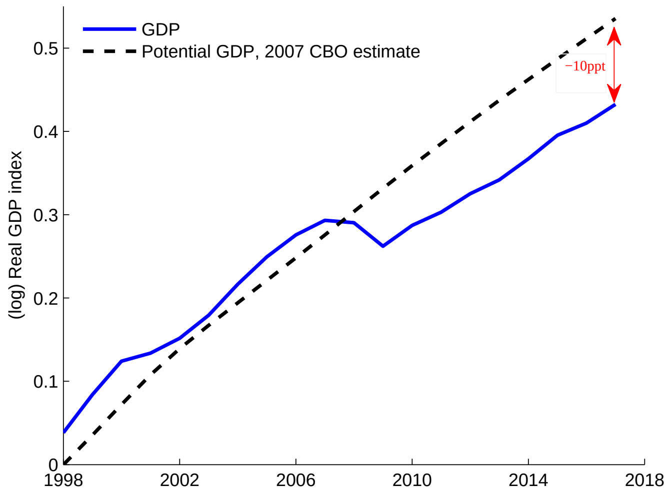
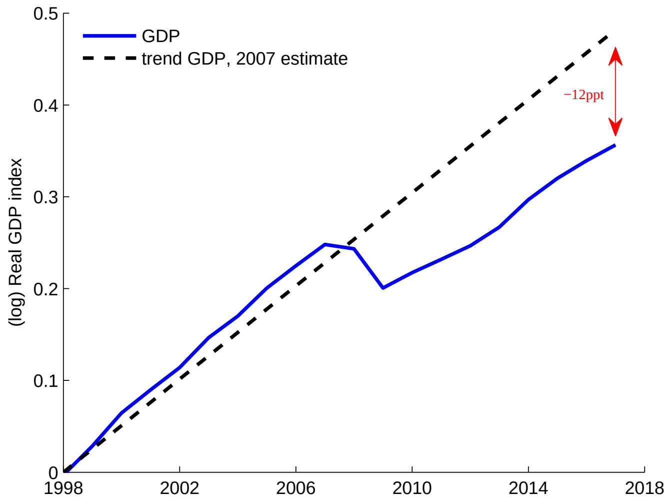
Figure 1: Output since the global financial crisis



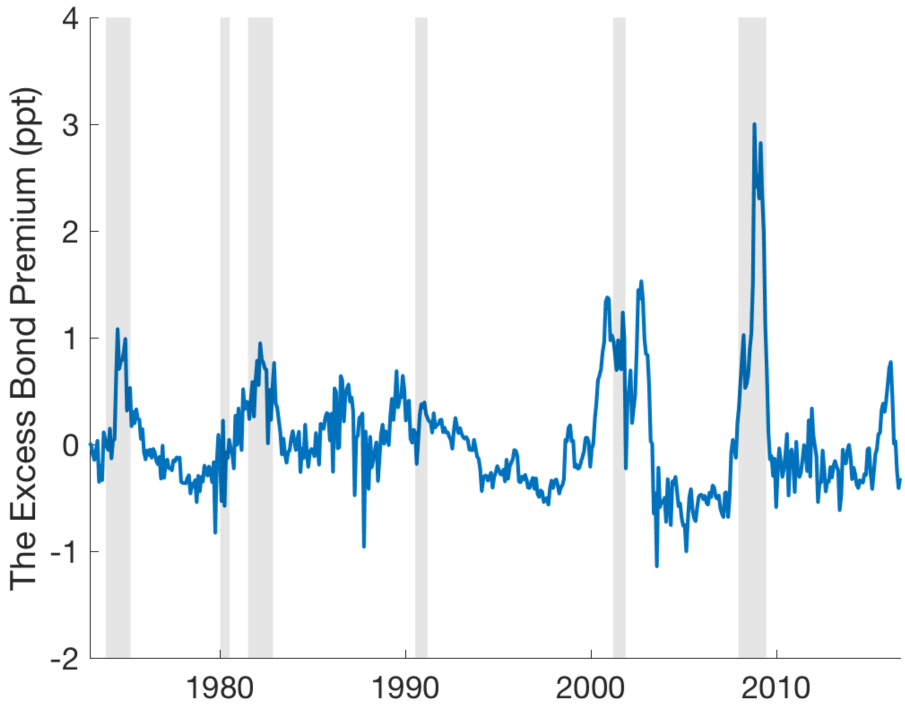
(a) US



(b) UK

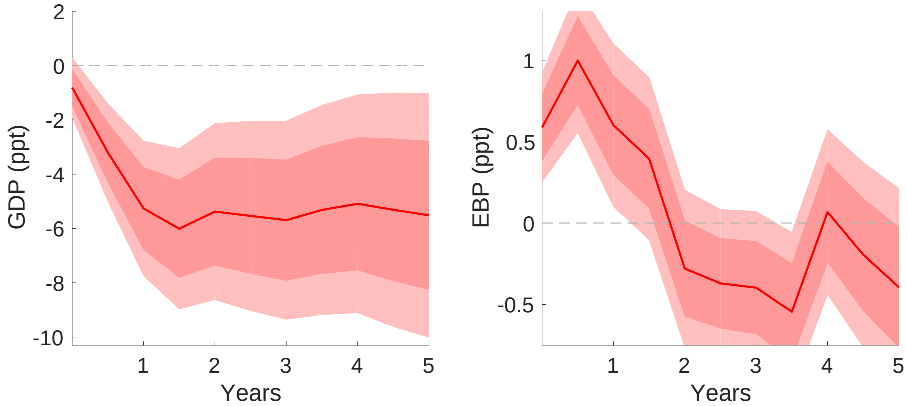
Notes: Real GDP since 1998 for US and UK. Potential GDP for the US is the CBO estimate as of 2007. Trend GDP for the UK is estimated from a linear trend over 1995-2007.

Figure 2: The US Excess Bond Premium

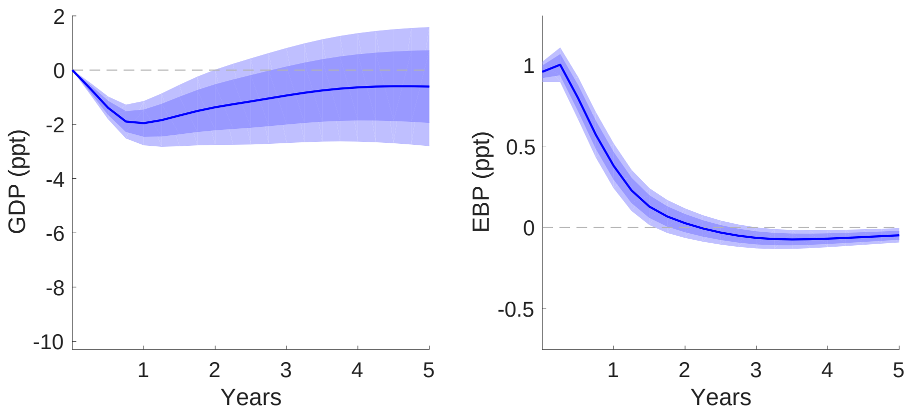


Notes: 1973-2016. Shaded areas mark NBER recession dates.

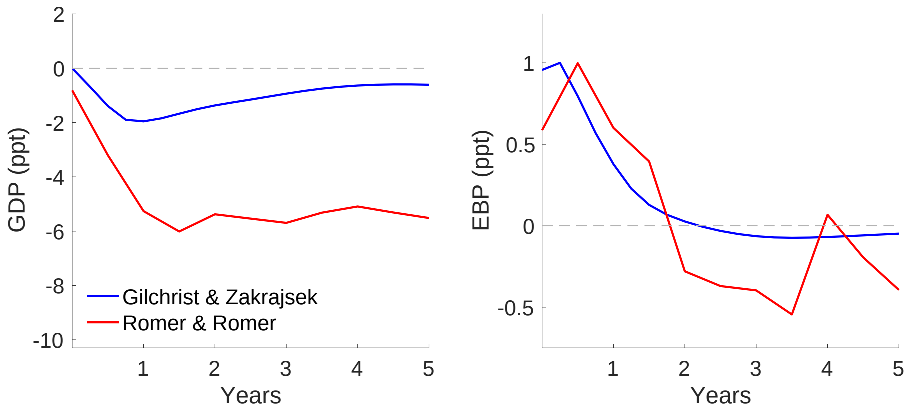
Figure 3: Financial strains and economic activity — state of the literature



(a) Romer and Romer (2017, RR) specification. Impulse responses of real GDP (GDP) and the excess bond premium (EBP) to an innovation in the RR financial distress index that raises the EBP by 1 ppt.



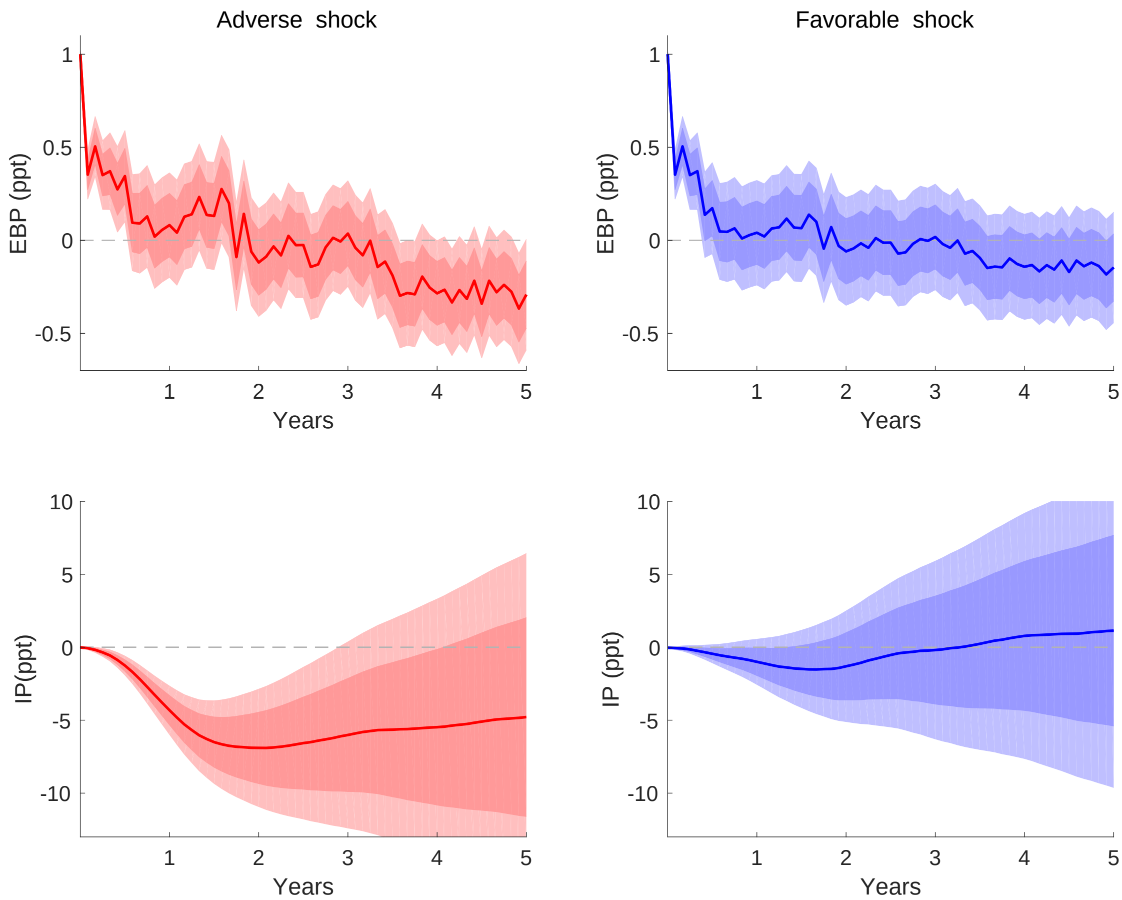
(b) Gilchrist and Zakrajšek (2012, GZ) specification. Impulse responses of real GDP (GDP) and the excess bond premium (EBP) to a financial shock that raises the EBP by 1 ppt.



(c) Comparison of Romer and Romer (2017) estimates (red lines) and Gilchrist and Zakrajšek (2012) (blue lines).

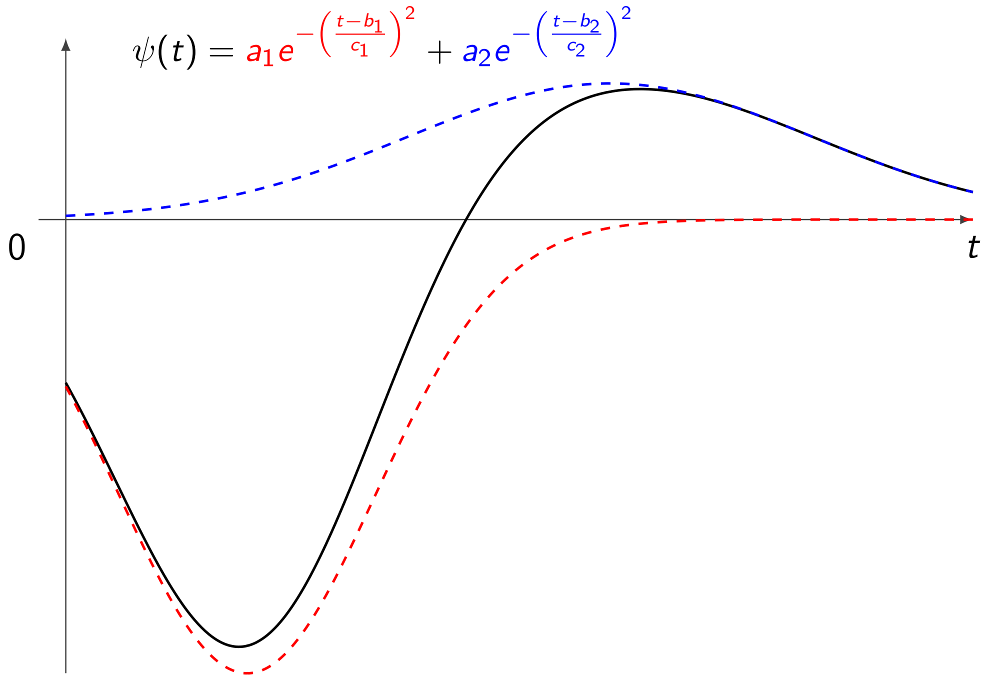
Notes: Shaded areas cover 68% and 90% of the posterior probability.

Figure 4: The asymmetric effects of financial shocks — A first pass



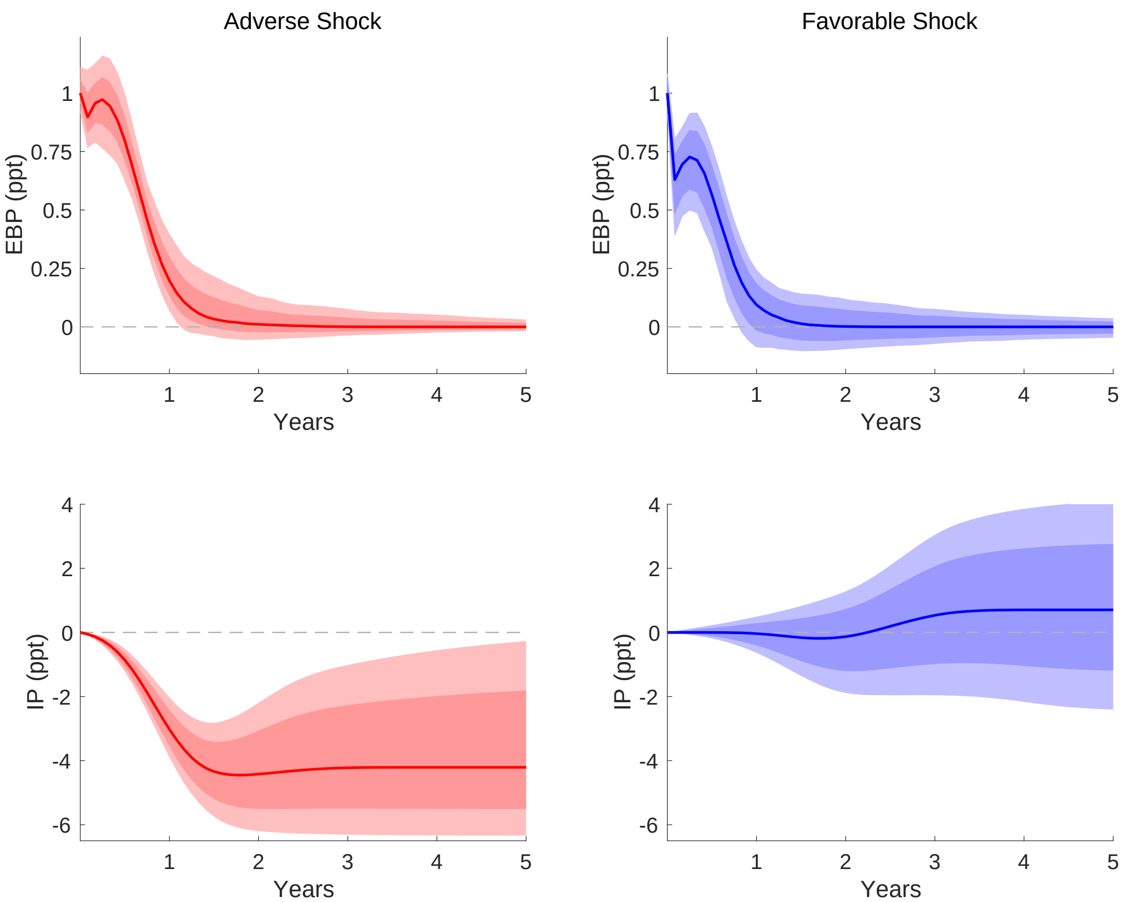
Notes: Impulse responses of the excess bond premium (EBP) and industrial production (IP) to a unit EBP shock identified from a VAR as in Gilchrist and Zakrajšek (2012). Impulse responses estimated by local projections (Jordà, 2005). The shaded areas cover the 68% and 90% confidence bands calculated using Newey-West standard errors. For ease of comparison between the left and right panels, the responses to a favorable financial shock (a decline in EBP) are multiplied by -1 in the right panels. US data, 1973m1-2016m12.

Figure 5: A functional approximation of an impulse response (FAIR)



Notes: Example of how a FAIR(2) model can capture an oscillating impulse response.

Figure 6: The asymmetric effects of financial shocks — 1973-2016



Notes: Impulse responses of the excess bond premium (EBP) and industrial production (IP) to a unit shock to the EBP. Estimation from a FAIR(2). The shaded bands cover 68% and 90% of the posterior probability. For ease of comparison between the left and right panels, the responses to a favorable financial shock (a decline in EBP) are multiplied by -1 in the right panels. US data, 1973m1-2016m12.

Figure 7: Decomposing the asymmetric effects of financial shocks

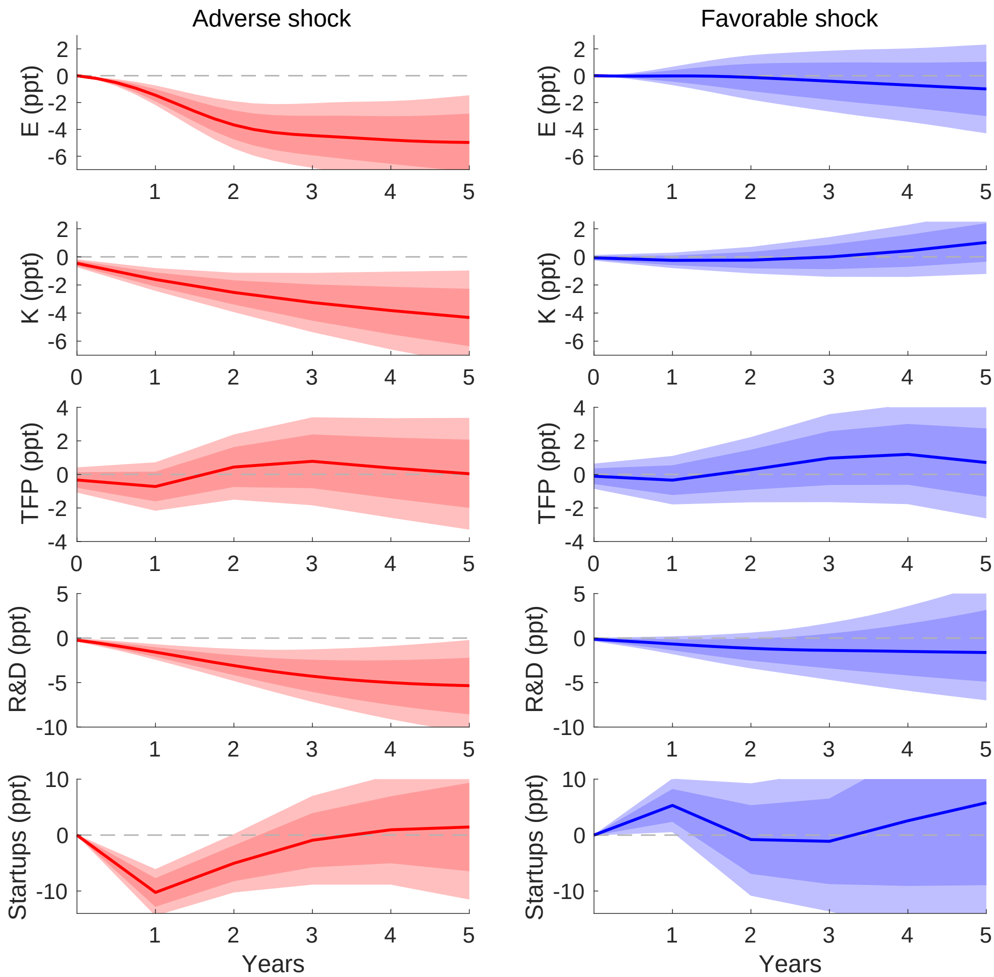
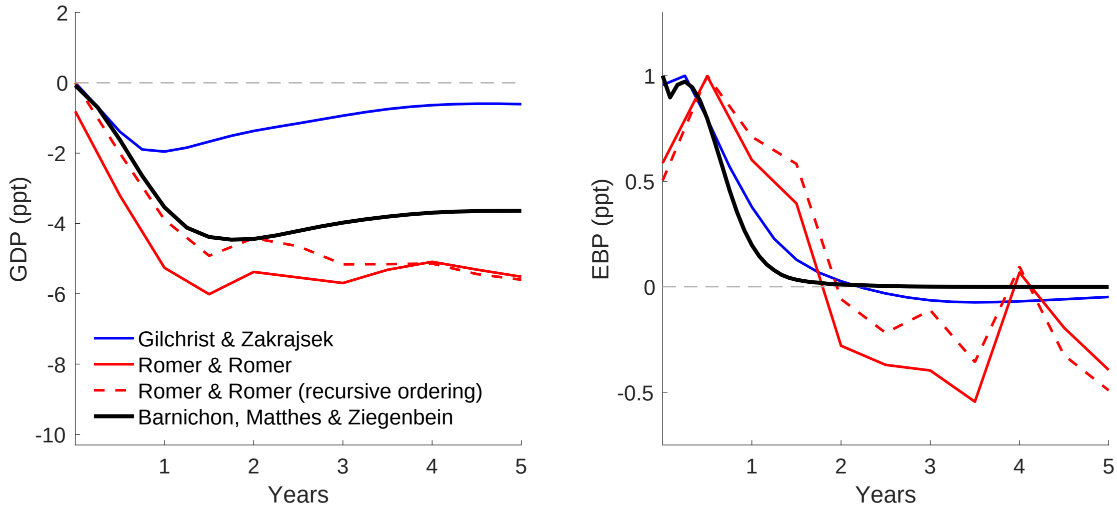


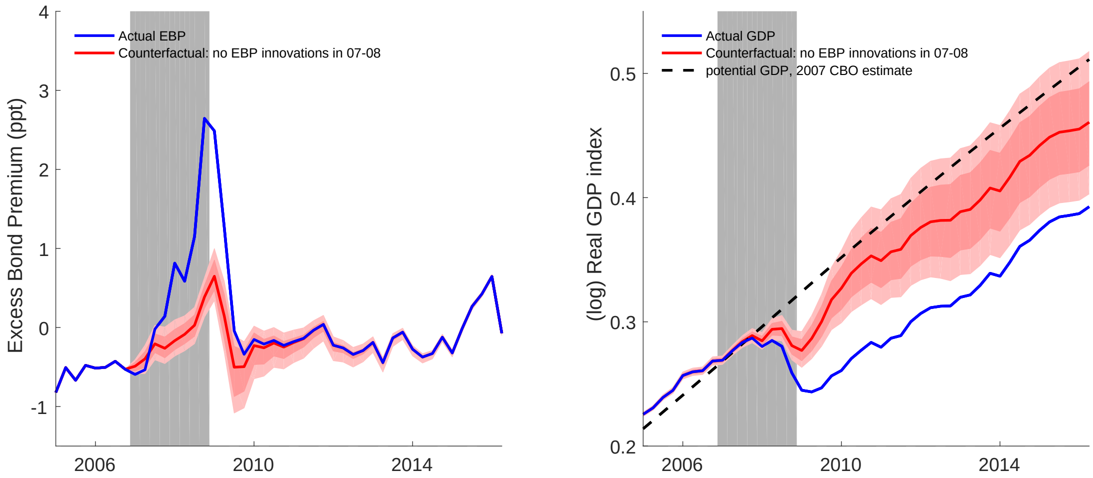
Figure 8: Impulse responses of total employment (E), the capital stock (K), Total Factor Productivity (TFP), business spending in R&D (R&D) and firm entry (Startups) to a unit shock to the EBP. Estimation from a FAIR(2). The shaded areas cover 68% and 90% of the posterior probability. For ease of comparison between the left and right panels, the responses to a favorable financial shock (a decline in EBP) are multiplied by -1 in the right panels.

Figure 9: The effects of financial shocks across methods



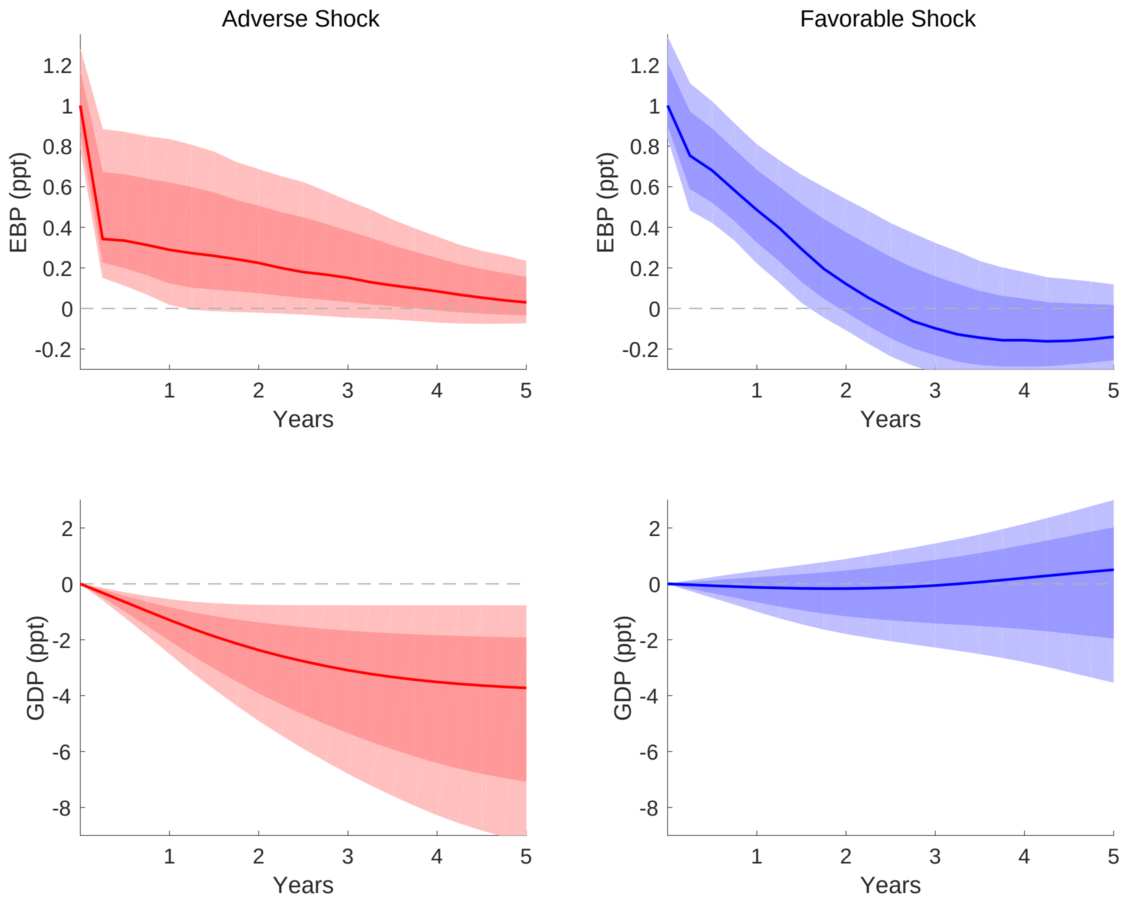
Notes: Impulse responses of real GDP (GDP) and the excess bond premium (EBP) to a financial shock. Red lines: impulse responses to an innovation to Romer and Romer (2017) financial distress variable. Dashed-red line: same as red-line except that we impose that GDP does not react contemporaneously (i.e., within the first six months) to an innovation in the financial distress variable. Blue lines: impulse responses to a financial shock from Gilchrist and Zakrajšek (2012)'s structural VAR. Black lines: impulse responses to an adverse financial shock (an increase in EBP) identified from an asymmetric FAIR(2). Responses are scaled such that the extremum effect on the EBP is equal to 1 ppt.

Figure 10: Counterfactual: the effects of the 2007-2008 financial crisis



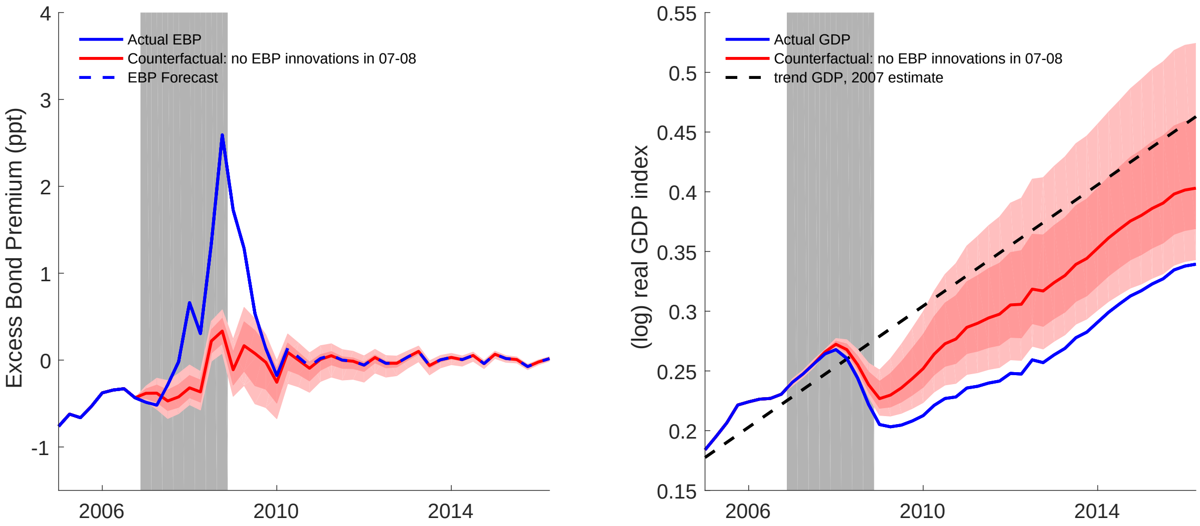
Notes: Blue lines: actual real GDP and EBP. Red lines: counterfactual simulated paths of real GDP and EBP assuming no financial shocks in 2007-2008 and using parameter estimates from 1973-2006 only.

Figure 11: The asymmetric effects of financial shocks — UK evidence



Notes: Impulse responses of the excess bond premium (EBP) and real GDP (GDP) to a unit shock to the excess bond premium. Estimation from a FAIR(2). The shaded bands cover 68% and 90% of the posterior probability. For ease of comparison between the left and right panels, the responses to a favorable financial shock (a decline in EBP) are multiplied by -1 in the right panels. UK data, 1996q1-2010q2.

Figure 12: Counterfactual: the effects of the 2007-2008 financial crisis — UK evidence



Notes: Blue lines: actual real GDP and EBP. Red lines: counterfactual simulated paths of real GDP and EBP assuming no financial shocks in 2007-2008 and using parameter estimated from 1996-2006 only.