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

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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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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 the crisis, the US, UK and Euro area 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, Romer and 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]

We show that 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 Gilchrist and 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 (Mendoza, 2010; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014). In contrast, narrative accounts implicitly allow for asymmetric effects, because they only focus on adverse financial conditions, i.e., negative "shocks".

We then consider an empirical model, a Vector Moving-Average model (VMA) model, de-

[1]See also Cerra and Saxena (2008), Jordà, Schularick and Taylor (2011), Bordo and Haubrich (2017), Ball (2014), Reinhart and Rogoff (2014), Blanchard, Cerutti and Summers (2015), Krishnamurthy, Muir and Yale (2015).

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

signed to address these separate limitations, i.e., we (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 Romer and 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 somewhat 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 and Euro area data, and we obtain very similar conclusions. For the UK, we follow the same identification strategy as in the US, using data on the excess bond premium from Bleaney, Mizen and Veleanu (2016) and the narrative measure of exogenous monetary policy changes from Cloyne and Hürtgen (2016). For the Euro area, we follow the approach of Gilchrist and Mojon (2018) and use Monfort and Renne's (2013) *KfW-Bund spread* as an external proxy for the unobserved financial shock. 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 or Euro area output and its pre-crisis trend is likely due 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 Barnichon and 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 literature on the effects of financial market disruptions; Section 3 presents our empirical model, our method to approximate impulse responses using Gaussian basis functions and our strategy to identify financial shocks; Section 4 presents our baseline evidence from US data; Section 5 presents evidence on the asymmetric effects of financial shocks from UK and Euro area data; Section 6 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 Cerra and Saxena (2005) and Reinhart and 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 Jordà (2005)'s local projection method. The particular specification they estimate is

$$Y_{j,t+h} = \alpha_j^h + \gamma_t^h + \beta^h F_{j,t} + \sum_{l=1}^{4} \phi_l^h F_{t,t-l} + \sum_{l=1}^{4} \theta_l Y_{j,t-l}, \text{ for } h = 0, 1, ..., 10 \tag{1}$$

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 behaviour 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.[4]

Figure 3(a) plots the IRs 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 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.

[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.

[4] More generally, we note that the EBP impulse response can serve to benchmark the magnitude of the financial strains implied by RR's narrative index and thus allows researchers to use the RR distress index to discipline quantitative models with financial frictions.

Structural VARs

The second strand in the literature uses structural Vector AutoRegressions (VARs) to try to identify the causal effects of shocks originating in financial markets. 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. 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]

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 (ii) much more persistent.

Going back to the recent financial crisis, we note that the two approaches lead to very

[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 Gilchrist, Sim and Zakrajek (2014). Similar results hold for the major Euro area countries (Germany, France, Italy and Spain) with Gilchrist and 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.

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 Estimating the effects of adverse financial shocks

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—, (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 conditions, i.e., negative "shocks".[8]

To address these two issues, we estimate a model designed to (i) identify the causal effects of financial shocks, and (ii) take into account the possible asymmetric effects of financial shocks. Specifically, we consider a Vector Moving-Average model (VMA) model that can be easily generalized to allow for asymmetric effects of shocks (unlike VARs), and we establish causality by using an identification strategy that builds on but also expand GZ.

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

[8] Another limitation of the VAR approach is that the size of the shock affects economic activity in a linear fashion, that is there is no size dependence in the effects of financial shocks. Interestingly, RR explored the possibility of such non-linearities in the impulse responses to their financial distress index but found little evidence of any size-dependence. We also explored the possibility of size dependence in our model, but similarly found little evidence.

3.1 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

$$\boldsymbol{y}_t = \sum_{k=0}^{K} \boldsymbol{\Psi}_k(\boldsymbol{\varepsilon_{t-k}})\boldsymbol{\varepsilon_{t-k}}, \tag{2}$$

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 (2) 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 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 (2), the existence of a VAR is compromised, because inverting (2) 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 (2).

3.2 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 (2) 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 (1), i.e.

$$\boldsymbol{y}_t = \sum_{k=0}^{\infty} \boldsymbol{\Psi}_k \boldsymbol{\varepsilon_{t-k}}. \tag{3}$$

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

$$\psi(h) = \sum_{n=1}^{N} a_n e^{-(\frac{h-b_n}{c_n})^2}, \quad \forall h \geq 0 \tag{4}$$

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 4, 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 rebound 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

$$\boldsymbol{y}_t = \sum_{k=0}^{K} \left[\boldsymbol{\Psi}_k^+ (\boldsymbol{\varepsilon_{t-k}} \odot \mathbf{1}_{\boldsymbol{\varepsilon_{t-k}>0}}) + \boldsymbol{\Psi}_k^- (\boldsymbol{\varepsilon_{t-k}} \odot \mathbf{1}_{\boldsymbol{\varepsilon_{t-k}\leq 0}})\right] \tag{5}$$

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

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

response function ψ^+ would write

$$\psi^+(k) = \sum_{n=1}^{N} a_n^+ e^{-\left(\frac{k-b_n^+}{c_n^+}\right)^2}, \quad \forall k > 0 \tag{6}$$

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.

3.3 Identification

To identify financial shocks from innovations to the EBP, we build on GZ and include in our vector $\boldsymbol{y}_t$ macroeconomic variables (output, inflation), an EBP measure and a measure of the monetary stance (e.g., 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 $\boldsymbol{\Psi}_0$ 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.

Different from GZ or previous approaches in the literature, we do not impose a recursive ordering between the EBP and monetary policy but allow for contemporaneous feedback between the two. Absent any other information, financial shocks and monetary shocks cannot be separately identified. To identify changes 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 (2):

$$m_t = \mu^m + \alpha^m \varepsilon_t^m + u_t^m \tag{7}$$

where $u_t^m \sim_{iid} N(0, \sigma^2_{u^m})$ 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 ε_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 Caldara and Herbst (2016) identification of monetary shocks in a VAR.

4 The effects of financial shocks, US evidence

In this section, we estimate the effects of financial shocks using US data. We use the FAIR methodology as our baseline, but we also check the robustness of our results using Jordà's (2005) local projection method as an (imperfect) alternative to FAIR.

4.1 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—as a likelihood-ratio test favors a FAIR(2) over a FAIR(1) or a FAIR(3) (Table 1). A FAIR(2) is particularly relevant here because it allows us to capture the mean-reverting pattern of output.

The data are monthly and cover 1973m1–2016m12.[10] When the federal funds rate are

[10]As a robustness check, we estimated our model over 1973-2006, i.e., excluding the global financial crisis

at the zero lower bound, we capture the stance of monetary policy with the Wu and Xia (2016) shadow rate.[11] As instrument for monetary shocks, we use the Romer and Romer monetary policy instrument extended to 2007 by Wieland and Yang (2016). Following standard practice in the literature (Stock and Watson, 2012; Gertler and Karadi, 2015; Caldara and Kamps, 2017), we infer the contemporaneous effect of monetary policy on the EBP from the subsample for which the instrument is available.

Allowing for asymmetric effects of credit shocks leads to a large improvement in the goodness of fit of the model. Table 2.1 summarizes the log likelihood of alternative FAIR models, and we can see that allowing for asymmetric effects substantially increases the log likelihood (comparing columns (1) and (2)). Since the FAIR models are nested, we can compare them with likelihood-ratio tests, and we can reject the symmetric FAIR model in favor of the asymmetric FAIR model.

Figure 5 presents the estimated impulse responses to credit supply 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 and CPI from the cumulative impulse responses of ΔIP and ΔCPI. 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. 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

and the period over which the fed funds rate was at the zero lower bound. Our key results remain unchanged, and the impulse responses are very similar, as shown in Figure A1 in the Appendix.

[11] 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.

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. Interestingly, asymmetry is also present in the response of inflation with only contractionary shocks generating a significant disinflationary episode.[12]

4.2 Digging deeper

To dig deeper into the effects of financial shocks on the economy, we now explore the asymmetric impulse response functions of five additional macroeconomic variables: (i) real GDP; (ii) real personal consumption expenditures (C); (iii) real business fixed investment (I); (iv) the unemployment rate (U); (v) business investment in research and development ($R\&D$).[13]

To study the effects of financial shocks on variables not included in $\boldsymbol{y_t}$, we proceed in two steps. First, we extract the financial shocks, denoted $\{\hat{\varepsilon}_t\}$, that we identified from our baseline specification.[14] Second, we estimate a univariate model - a univariate FAIR - capturing the impulse response of the additional variables. Specifically, denoting y_t a variable of interest, we estimate

$$y_t = \sum_{k=0}^{K} \psi(k)\hat{\varepsilon}_{t-k} + u_t, \tag{8}$$

where ψ captures the impulse response function to the financial shock 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. Then, we use parametrize the impulse response ψ using

[12] Note that the response of the fed funds rate cannot explain the asymmetric responses of output growth and inflation, because monetary policy is more accommodative following a contractionary shock, which should dampen the asymmetry.

[13] We use private domestic investment in research and development.

[14] More specifically, the Bayesian estimation of the vector-FAIR model described by Equation 5 and 6 delivers a posterior distribution of the financial shocks $\{\hat{\varepsilon}_t\}$.

FAIR. We estimate the model with y set to, respectively, ΔGDP,[15] ΔC, ΔI, $\Delta R\&D$ or U, and we use a FAIR(2) to have enough flexibility to capture the (potentially) mean-reverting pattern of our variables. We allow for asymmetric effects of financial shocks by estimating two impulse response functions —ψ^+ and ψ^-—, and we also estimate a linear FAIR(2) model to use as a linear benchmark.

Figure 6 summarizes our results and shows strongly asymmetric impulse responses for our five variables. The effects of a contractionary financial shock on real GDP, consumption, investment or R&D spending are much larger and more persistent than the effects of an expansionary financial shock.

The strong and persistent effect of financial market disruptions on R&D spending is interesting and deserves further exploration. While the response of R&D spending could be driven solely by the strong decline in output, the behavior of R&D also provides a natural link from business cycle fluctuations to long-term economic performance. For instance, it has been argued that adverse transitory shocks that lower R&D spending can inhibit economic performance in the long run (see e.g. Comin and Gertler, 2006; Bianchi and Kung, 2014). In this context, a decline in R&D spending could cause a persistent decline in output.

4.3 Taking stock

We now contrast our FAIR estimates with those of narrative accounts and VARs. Figure 7 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

[15] Since GDP is only available at quarterly frequency, we regress the log-difference of real GDP on the quarterly average of the monthly financial shocks.

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 overestimate any adverse causal impact of financial distress on output (as acknowledged by Romer and Romer 2017, page 3114).

Interestingly, 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. Indeed, 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.[16] Removing some of the endogenous component of financial distress reduces the magnitude of the response of GDP (Figure 7) and in fact brings it remarkably in line with our FAIR estimates. The impulse responses of GDP are on top of each other over the first 2.5 years, diverging only slightly at longer horizons. In other words, once we take into account the issues of causality and asymmetry, narrative accounts and structural time series analysis become remarkably consistent.

4.4 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.[17] Importantly, for this exercise we use our VMA model estimated

[16]See e.g., Barnichon and Brownlees (2018) for more details on how to impose recursive identifying assumptions in the context of local projections. Note that the plausibility of this identification approach is severely limited by the semi-annual frequency of the RR dataset.

[17]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 FAIR(2).

over 1973-2006, i.e., excluding any information from the great financial crisis and its aftermaths.[18] Thus, the behavior of US GDP since 2007 has no influence on our counter-factual 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.

Figure 8 plots the actual paths of GDP and the EBP along with their counterfactual median paths implied by our FAIR estimates along with the 68th and 90th 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 end 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 (Coibion, Gorodnichenko and Ulate, 2017).

4.5 Robustness check: evidence from local projections

To the best of our knowledge, the FAIR approach used in this paper is the only operational way of identifying structural shocks when the Data Generating Process (DGP) is nonlinear with asymmetric impulse responses.

However, since our approach relies on the parametrization of the impulse response func-

[18] The impulse responses estimated over 1973-2006 are displayed in the appendix, figure A1. They are very similar to the impulse responses estimated with the full sample.

tions with Gaussian basis functions, in this section, we examine the robustness of our results to this parametrization. The idea of the robustness check is to not rely on a FAIR but instead to use a nonparametric method—Jordà's (2005) Local Projections (LP)—which imposes little structure on the Data-Generating Process (DGP) and is thus more robust to misspecification than a FAIR model (at the cost of efficiency). The drawback of this approach is that it requires a series of previously identified financial shocks.

We thus use a "VAR-LP" procedure that proceeds in two steps: First, we estimate a standard structural VAR to identify financial shocks denoted $\{\widetilde{\varepsilon}_t\}$. We use the same identification strategy as for FAIR. That is, we estimate a proxy VAR in which Romer and Romer's (2004) narrative measure of exogenous monetary policy changes serves as an external instrument for the latent monetary shock. Second, we estimate the dynamic effects of these shocks using Local Projections, possibly allowing for asymmetric effects. While such a hybrid VAR-LP procedure is flawed (in fact, not internally consistent since the VAR shocks are identified under the assumption that the DGP is linear), we see it as a useful robustness check of our results based on FAIRs. We come back to this point at the end of the section.

To first have a linear benchmark for the effects of financial shocks, we run linear Local Projections, i.e., we estimate $H + 1$ equations

$$y_{t+h} = \alpha_h + \beta_h \widetilde{\varepsilon}_t + \gamma' x_t + u_{t+h}, \qquad h = 0, 1, ..., H \tag{9}$$

where y_{t+h} is the variable of interest, x_t contains 12 lags of y_t, and $\widetilde{\varepsilon}_t$ is our VAR-based estimate of the financial shock at time t. The impulse responses are then given by $\beta^0, \beta^1, ..., \beta^H$. We use a horizon of $H = 60$ months (or 5 years). We report Newey and West (1987) standard errors allowing for autocorrelation of order h in the error terms.

To allow for asymmetric effects of financial shocks, we allow for sign dependence in β_h, that is we estimate the $H + 1$ equations

$$y_{t+h} = \alpha_h + \beta_h^+ \widetilde{\varepsilon}_t^+ + \beta_h^- \widetilde{\varepsilon}_t^- + \gamma' x_t + u_{t+h}, \qquad h = 0, 1, ..., H \tag{10}$$

where β_h^+ is the response to a positive financial shock $\widetilde{\varepsilon}_t^+$, and β_h^- is the response to a negative financial shock $\widetilde{\varepsilon}_t^-$ at horizon h.

We estimate Equation (9) and (10) for the log-difference of industrial production and the log-difference of the CPI price index, and Figure 9 plots the corresponding impulse responses. Overall, the results are very similar to the results obtained with FAIR models: the effects of adverse financial shocks are larger than implied by linear estimates and highly persistent, reducing IP by about 4ppt after 5 years, like our FAIR estimate. Favorable financial shocks, on the other hand, have no significant effects on our variables.

To put these estimates in the context of the 2007-2008 financial crisis, we can do a back-of-the-envelope calculation using the 2007-2008 VAR-identified financial shocks. The sum of exogenous impulses to the EBP in 2007-2008 is approximately 2ppt. According to our hybrid VAR-LP estimates, a 2ppt exogenous increase in the EBP implies a $2 * 4 = 8$ppt output loss, which is close to our counter-factual estimate from FAIR on the effect of the 2007-2008 financial crisis on output.

As a final remark, note that while the hybrid VAR-LP approach is attractive because it relies only on standard linear regression techniques, it is flawed for two reasons. First, if the data are generated by a nonlinear process, a linear model to identify the structural shocks is misspecified and we cannot estimate consistently the true structural shocks. To do so, one should explicitly account for the nonlinearities in the data-generating process. These two drawbacks can, however, be overcome with FAIR. Second, to perform the Local Projection exercise laid out above, one needs to know the structural shocks. Here, we take the shocks identified from the structural VAR as given. They are, however, the result of a first stage estimation and therefore the standard errors obtained from Local Projections are incorrect.[19]

[19] Despite its shortcomings, we think of our proposed hybrid VAR-Local Projection approach as a useful tool. First, it can be used as a quick test for nonlinearities in the impulse response functions to shocks estimated from a linear VAR. Therefore, one might see it as (visual) test for misspecification in terms of omitted nonlinearities. Second, once structural shocks are estimated from any model (for instance from a VAR or FAIRs), Local Projections can be used to examine whether relaxing the dynamic structure (i.e., the parametric restrictions) imposed by the model alters the results substantially.

5 The effects of financial shocks, international evidence

In this section, we provide independent evidence that adverse financial shocks have large and persistent effects by using alternative sources of variations. Specifically, we study the effects of financial shocks in (i) the United Kingdom (UK) and (ii) the Euro area (EA).

5.1 United Kingdom

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 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 A4), 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 10 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. 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.

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. Similarly to the US, we find that absent the series of financial shocks that raised the UK EBP by about 2ppt overall,[20] 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.

5.2 Euro Area

Since the EBP measure by Bleaney, Mizen and Veleanu (2016) is too short for the Euro area (EA), we use another approach to obtain exogenous variations in financial conditions in the EA. Specifically, we follow Gilchrist and Mojon (2018) and Monfort and Renne (2013), and we identify liquidity shocks affecting the Euro area from movements in the KfW-Bund spread, the spread between the KfW, a German Government-owned development bank whose debt is guaranteed by the Germand government, and the Bund.[21] Because KfW debt is less liquid than the Bund, a widening of the KfW-Bund spread signals a rise in the liquidity premium that is then transmitted to other bond market yields, notably euro area credit spreads. Since movements in the KfW-Bund spread are arguably exogenous to private sector credit risk, we can interpret a rise in the KfW-Bund spread as an exogenous tightening of financial constraints in the EA.[22]

To identify the effects of liquidity shocks in FAIR, we order the KfW-Bund spread first in $\boldsymbol{y}_t$, and we assume that $\boldsymbol{\Psi}_0$ has its first row filled with 0 except for the diagonal coefficient, i.e., the KfW-Bund does not react contemporaneously to other shocks, which is consistent

[20]See Figure A5 in the appendix

[21]The KfW-Bund spread data from 1997 to 2010 are from Schuster and Uhrig-Homburg (2013). We extend this time-series to 2013 using data from Monfort and Renne (2013).

[22]Note that liquidity shocks are unlikely to be the only source of exogenous movements in financial constraints in EA. As stated by Monfort and Renne (2013), a liquidity shock may occur as a result of unexpected cash shortages, a need to rebalance a portfolio in order to maintain a hedging or diversification strategy, or a change in capital requirements. Thus, liquidity shocks likely only form a subset of the financial shocks that hit the EA.

with the idea that movements in the KfW-Bund spread are exogenous to private sector credit risk.

Our specification uses five variables: (i) KfW-Bund; (ii) IP growth; (iii) CPI inflation; (iv) the Euro OverNight Index Average rate (EONIA); and (v) the Euro area bank credit spread series constructed by Gilchrist and Mojon (2018) and shown in Figure A6.

$$\boldsymbol{y_t} = [KfW\text{-}Bund_t, \Delta IP_t, \Delta CPI_t, EONIA_t, Spread_t]$$

As with the US and the UK, we estimate an asymmetric FAIR(2), and Figure 11 plots the estimated impulse responses to a one-standard deviation bank spread shock. In line with our US and UK results, an adverse financial shock causes a large and persistent decline in output, but a favorable shock has no sizable effect.[23]

6 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 influen-

[23]Unfortunately, we cannot conduct a counter-factual exercise on the effects of the financial crisis on Euro output, as we did with the US or UK, since liquidity shocks are likely only a subset of the financial shocks that hit the EA.

tial 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).

To see through these seemingly conflicting results, we propose and 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.

An important goal for future research is to understand the reasons for the asymmetry and the large and persistent effects of adverse financial shocks. One possibility is the highly non-linear behavior of economies with financial frictions. As shown by Brunnermeier and Sannikov (2014), with financial frictions, a large adverse shocks can take the economy away from its steady-state for a very long (but finite) time. Another possibility, consistent with our finding of large drops in R&D following adverse financial shocks, is that financial distress episodes could force firms to cut on research expenditures or prevent high-growth potential start-ups to emerge (e.g., Sedlacek, 2015; Sedlacek and Sterk, 2017). In this context, another important goal is to better understand the implication of the asymmetric effects of adverse financial shocks for the conduct of monetary policy, as highlighted in a speech by Federal Reserve Governor Jeremy Stein (2014).

Appendix

Estimation

We now briefly describe how we use Bayesian methods to estimate a multivariate linear FAIR(N) model with a short-run restriction. The extension to nonlinear models is relatively straightforward bar some technical details.[24]

The key to estimating a moving-average model (2) is the construction of the likelihood function $p(\boldsymbol{y}^T|\boldsymbol{\theta})$ of a sample of size T for a moving-average model with parameter vector $\boldsymbol{\theta}$ and where a variable with a superscript denotes the sample of that variable up to the date in the superscript.

We use the prediction error decomposition to break up the density $p(\boldsymbol{y}^T|\boldsymbol{\theta})$ as follows:[25]

$$p(\boldsymbol{y}^T|\boldsymbol{\theta}) = \prod_{t=1}^{T} p(\boldsymbol{y}_t|\boldsymbol{\theta}, \boldsymbol{y}^{t-1}). \tag{11}$$

Then, to calculate the one-step-ahead conditional likelihood function $p(\boldsymbol{y}_t|\boldsymbol{\theta}, \boldsymbol{y}^{t-1})$, we assume that all innovations $\{\boldsymbol{\varepsilon_t}\}$ are Gaussian with mean zero and variance one, and we note that the density $p(\boldsymbol{y}_t|\boldsymbol{y}^{t-1}, \boldsymbol{\theta})$ can be re-written as $p(\boldsymbol{y}_t|\boldsymbol{\theta}, \boldsymbol{y}^{t-1}) = p(\boldsymbol{\Psi}_0\boldsymbol{\varepsilon_t}|\boldsymbol{\theta}, \boldsymbol{y}^{t-1})$ since

$$\boldsymbol{y}_t = \boldsymbol{\Psi}_0\boldsymbol{\varepsilon}_t + \sum_{k=1}^{K} \boldsymbol{\Psi}_k\boldsymbol{\varepsilon}_{t-k}. \tag{12}$$

Since the contemporaneous impact matrix is a constant, $p(\boldsymbol{\Psi}_0\boldsymbol{\varepsilon}_t|\boldsymbol{\theta}, \boldsymbol{y}^{t-1})$ is a straightforward function of the density of $\boldsymbol{\varepsilon}_t$.

To recursively construct $\boldsymbol{\varepsilon_t}$ as a function of $\boldsymbol{\theta}$ and $\boldsymbol{y}^t$, we need to uniquely pin down the value of the components of $\boldsymbol{\varepsilon_t}$, that is we need that $\boldsymbol{\Psi}_0$ is invertible. We impose this restriction by only keeping parameter draws for which $\boldsymbol{\Psi}_0$ is invertible. It is also at this stage that we impose the identifying restriction: We order the variables in $\boldsymbol{y}$ such that the EBP

[24] See Barnichon and Matthes (2018).

[25] To derive the conditional densities in decomposition (11), our parameter vector $\boldsymbol{\theta}$ thus implicitly also includes the K initial values of the shocks: $\{\boldsymbol{\varepsilon}_{-K}...\boldsymbol{\varepsilon}_0\}$. We will keep those fixed throughout the estimation and discuss our initialization below.

is ordered third—after output growth and inflation, but before the fed funds rate—and we add the equation describing our proxy for the monetary policy shock to the system. Finally, to initialize the recursion, we set the first K values of $\boldsymbol{\varepsilon}$ to zero.[26]

We use flat (improper) priors, and to explore the posterior density, we use a Metropolis-within-Gibbs algorithm (Robert and Casella, 2004) with the blocks given by the different groups of parameters in our model; a, b, and c. Using a flat prior allows us to interpret our results as outcomes of a maximum likelihood estimation. To initialise the Metropolis-Hastings algorithm in an area of the parameter space that has substantial posterior probability, we follow a two-step procedure: first, we estimate a standard VAR using OLS on our data set, calculate the moving-average representation, and we use the impulse response functions implied by the VAR as our starting point.[27] In the nonlinear models, we initialize the parameters capturing asymmetry and state-dependence at zero (i.e., no nonlinearity). This approach is consistent with the starting point (the null) of this paper: shocks have linear effects on the economy, and we are testing this null against the alternative that shocks have nonlinear effects.

Additional supporting evidence

Figure A1 presents the asymmetric impulse responses to a financial shock estimated using only data up to 2006, i.e., excluding data from the financial crisis and its aftermmaths. That is, the restricted sample covers 1973m1 to 2006m12. We can see that the impulse responses are very similar to our baseline results using the full sample (see Figure 5).

Figure A2 plots the time series and a histogram of the US financial shocks estimated from FAIR(2). The distribution is roughly symmetric with respect to positive and negative shocks. The 2007-2008 financial crisis shows up as a series of positive (i.e., adverse) financial

[26]When K, the lag length of the moving average (2), is infinite, we truncate the model at some horizon K, large enough to ensure that the lag matrix coefficients $\boldsymbol{\Psi}_K$ are "close" to zero. Such a K exists since the variables are stationary.

[27]Specifically, we set the parameters of our FAIR model (the a, b, and c coefficients) to minimize the discrepancy (sum of squared residuals) between the impulse responses implied by FAIR and those implied by the estimated VAR.

shocks in 2007, representing an exogenous increase in the EBP of about 2ppt.

Figure A3 plots the impulse responses of GDP and the RR financial distress index to an innovation of +7 to the RR index. The blue lines denote estimates obtained using the full set of OECD countries (as in RR), and the red lines denote the estimates using only US data. We can see that tee impulse responses are similar with the same drop in output (about -4.5ppt) 5 years after the impulse.

Figure A4 shows the evolution of the UK EBP over 1996-2010, and Figure A5 shows the distribution of UK financial shocks identified with FAIR. Figure A6 shows the evolution of the Euro area bank credit spread over 1999-2016, and Figure A7 shows the distribution of Euro area liquidity shocks identified with FAIR.

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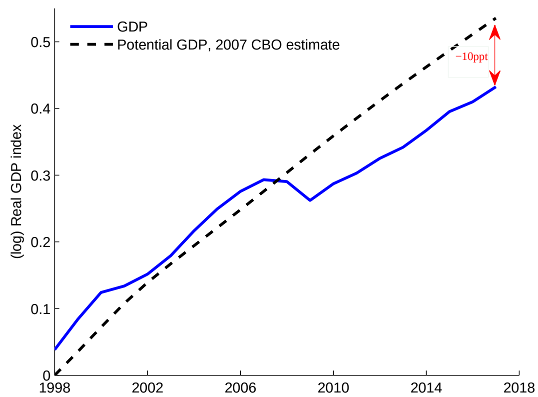
Table 1: Log likelihood of alternative models

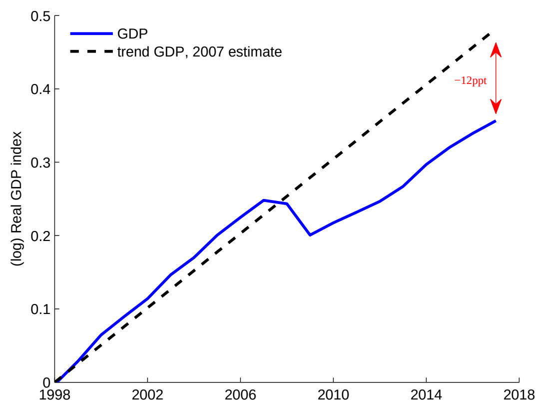
	FAIR(2) Symmetric	FAIR(1) Asymmetric	FAIR(2) Asymmetric	FAIR(3) Asymmetric
	(1)	**(2)**	**(3)**	**(4)**
log likelihood	-2980	-2593	-2467	-2465
LR test		(2) vs (1)	(3) vs (2)	(4) vs (3)
p-value		<0.01	<0.01	>0.1

Note: FAIR model with $\Delta log(IP), \Delta log(CPI), EBP, FFR$ estimated with data from 1973 to 2016. (1) is a symmetric model using a two Gaussian parametrization (FAIR(2)) of the impulse responses. (2) is a model that allows for asymmetric effects of financial shocks using a one Gaussian parametrization (FAIR(1)) of the impulse responses. The LR test is between (2) and (1). (3) is a model that allows for asymmetric effects using a two Gaussian parametrization (FAIR(2)). The LR test is between (3) and (2). (4) is a model that allows for asymmetric effects using a three Gaussian parametrization (FAIR(3)). The LR test is between (4) and (3).

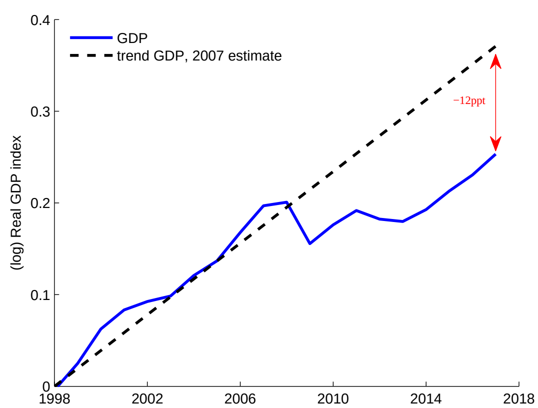
Figure 1: Output since the global financial crisis



(a) US



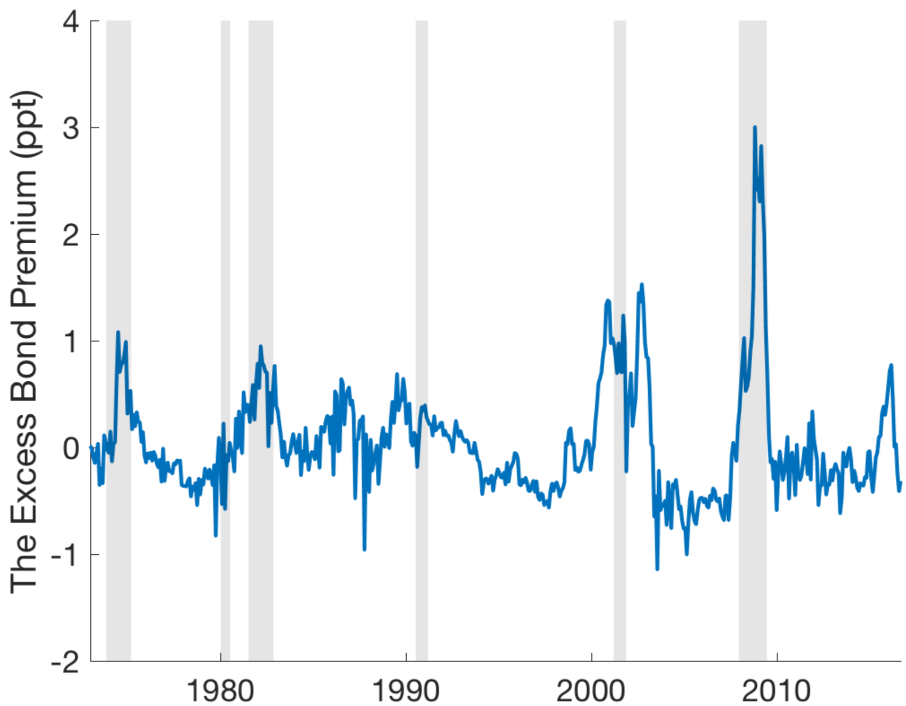
(b) UK



(c) Euro area

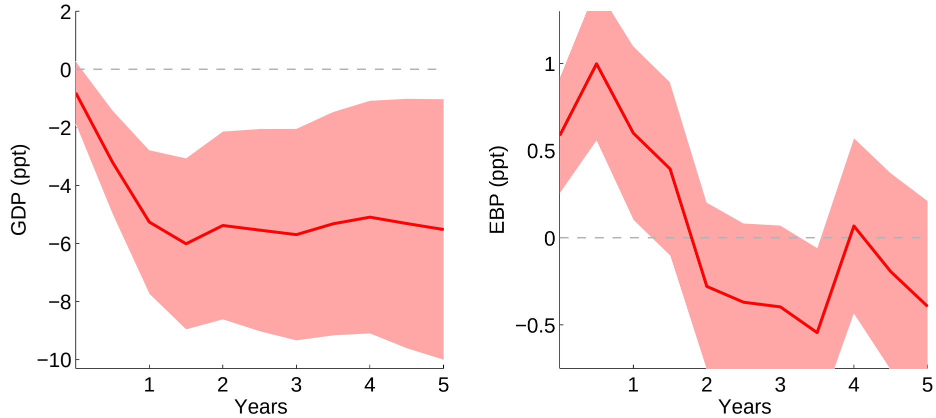
Notes: Real GDP since 1998 for US, UK and Euro area. Potential GDP for the US is the CBO estimate as of 2007. Trend GDP for the UK and Euro area is estimated from a linear trend over 1995-2007.

Figure 2: The US Excess Bond Premium

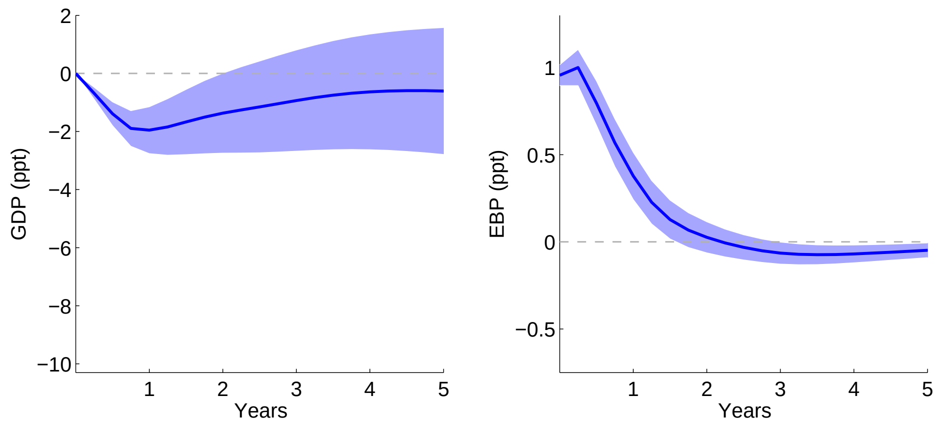


Notes: 1973-2016. Shaded areas mark NBER recession dates.

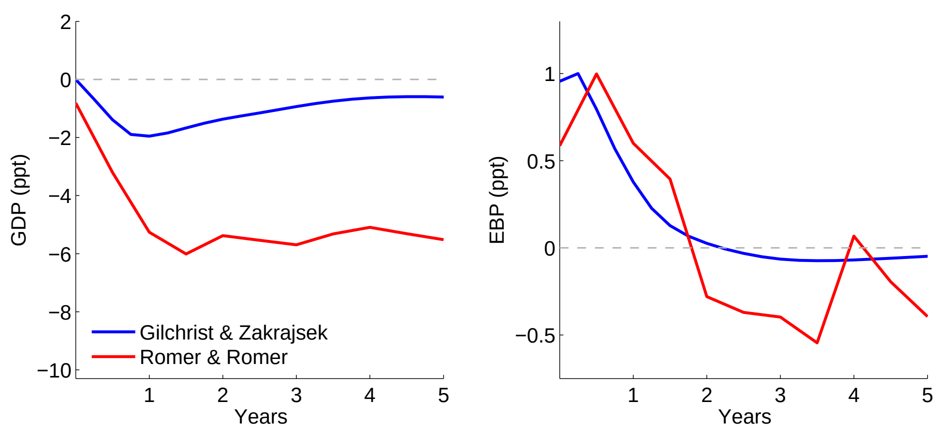
Figure 3: Financial strains and economic activity — state of the literature



(a) Romer and Romer (2017, RR) specification. Impulse response functions 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.



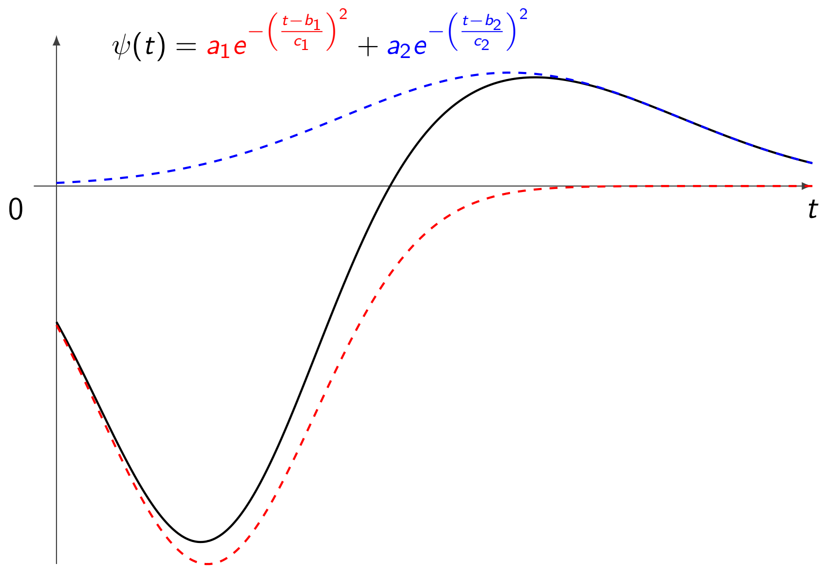
(b) Gilchrist and Zakrajšek (2012, GZ) specification. Impulse response functions of real GDP (GDP) and the excess bond premium (EBP) to a financial shock that raises the EBP by 1 ppt.



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

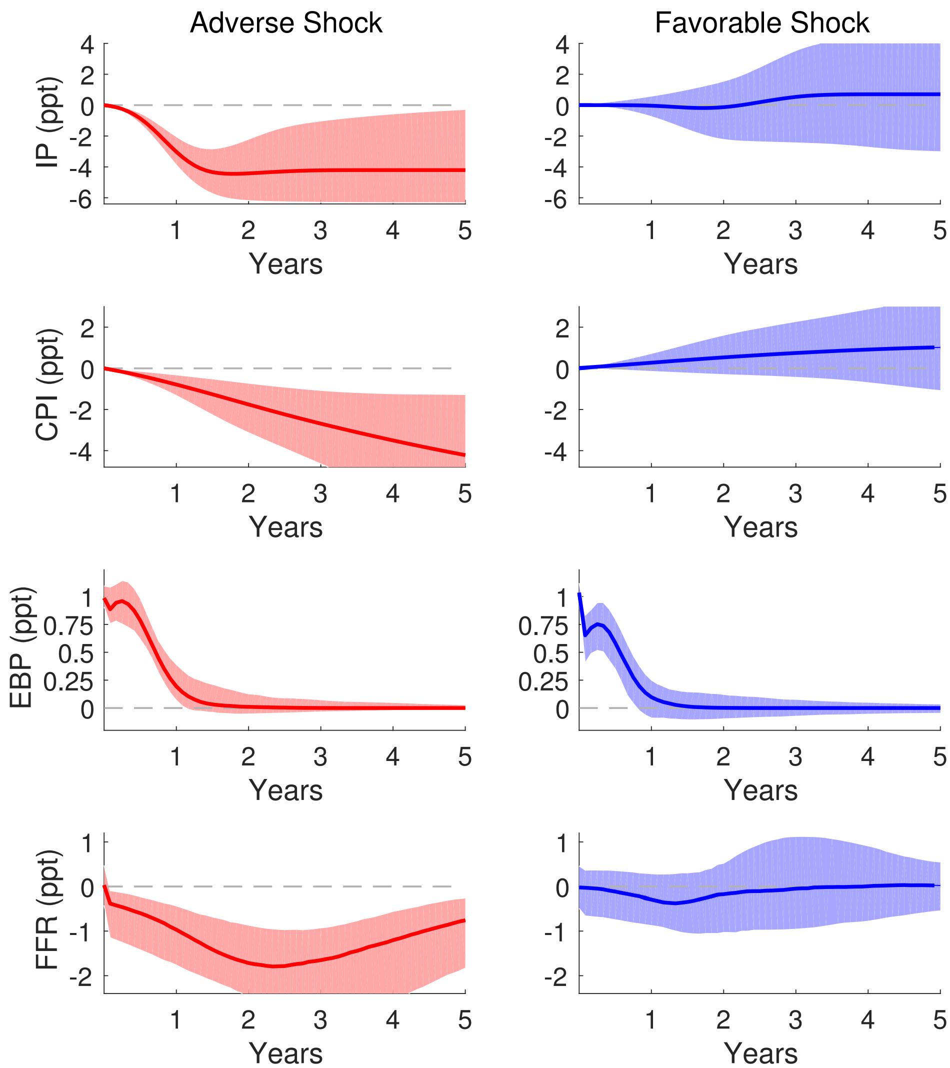
Notes: Shaded areas cover 90 percent of the posterior probability.

Figure 4: A functional approximation of an impulse response (FAIR)



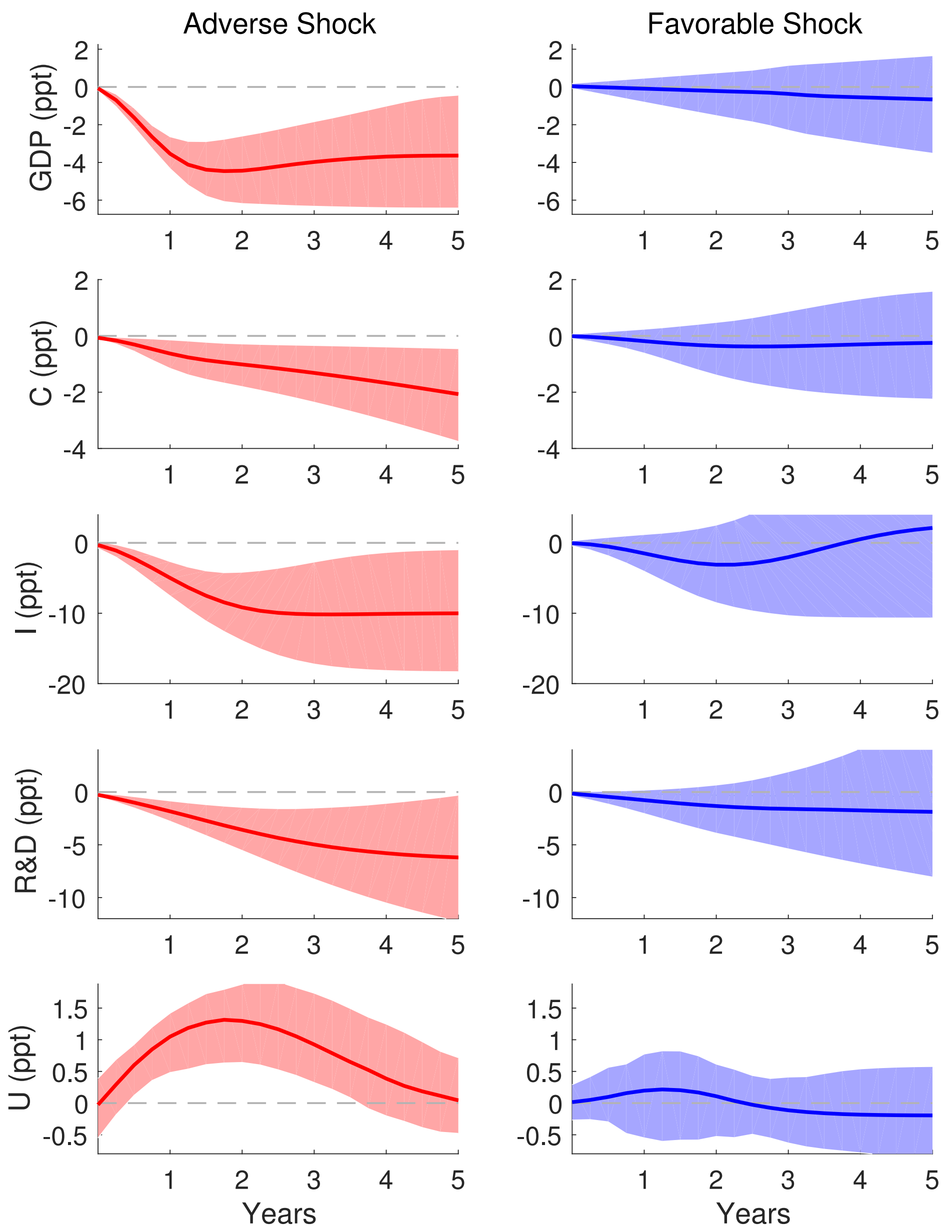
Notes: Example of how a FAIR(2) model can capture an oscillating impulse response.

Figure 5: The asymmetric effects of financial shocks — US evidence



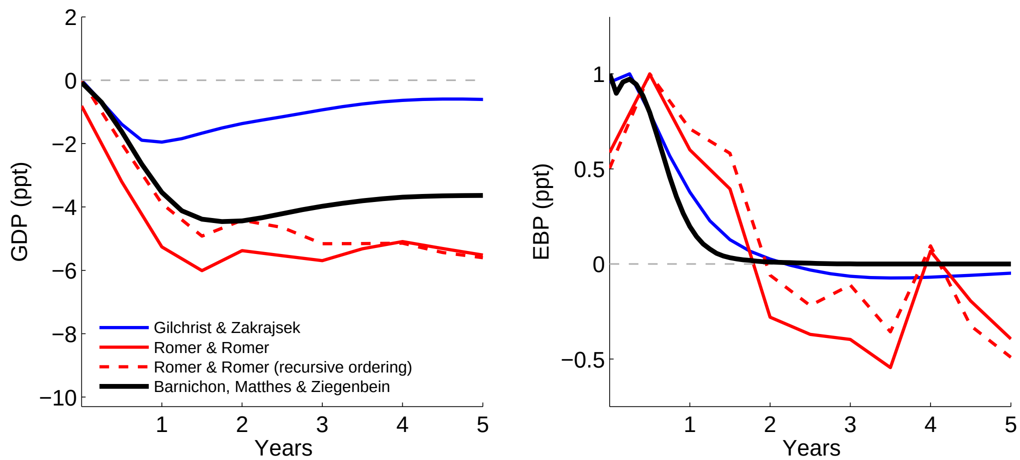
Notes: Impulse response functions of Industrial Production (IP), consumer prices (CPI), the excess bond premium (EBP) and the federal funds rate (FFR) to a unit shock to the excess bond premium. Estimation from a FAIR(2) (plain lines). The shaded bands cover 90% of the posterior probability. For ease 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. Estimating using US monthly data for the period 1973m1-2016m12.

Figure 6: The asymmetric effects of financial shocks, additional results — US evidence



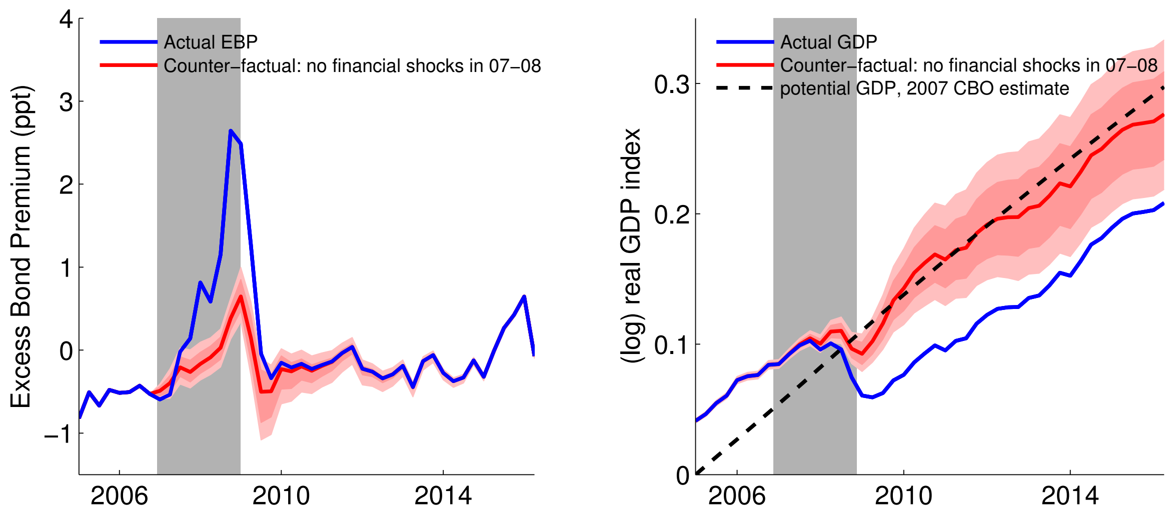
Notes: Impulse response functions of real GDP (GDP), personal consumption expenditures (C), business fixed investment (I), business spending in R&D, and the unemployment rate (U) to a unit shock to the EBP. Estimation from a FAIR(2) (plain lines). The shaded areas cover 90% of the posterior probability. 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. Estimation using US data for the period 1973-2016.

Figure 7: The effects of financial shocks across methods — US evidence



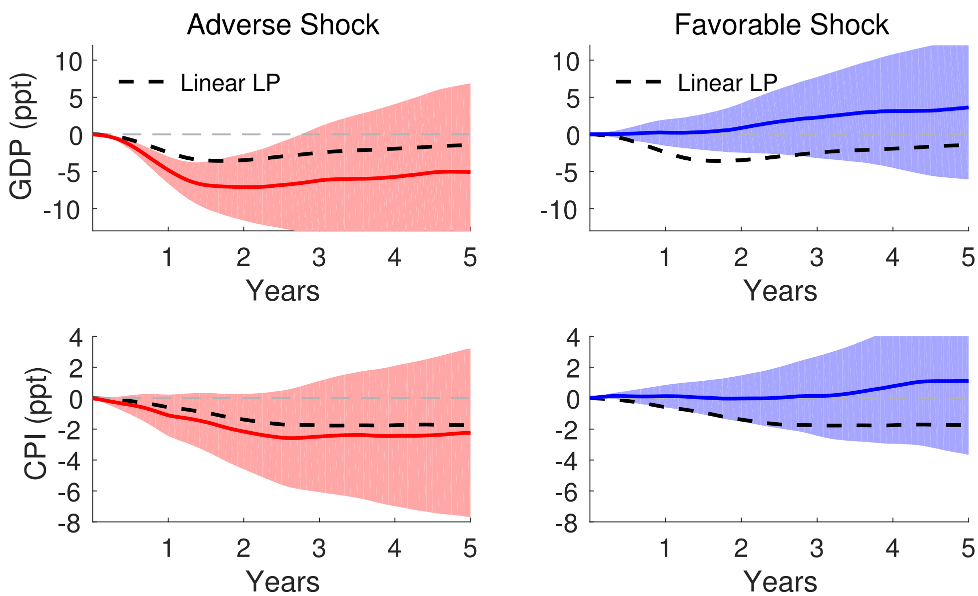
Notes: Impulse response functions of real GDP (GDP) and the excess bond premium (EBP) to a financial shock. Red lines: impulse responses to an innovation to Romer and Romer (2017) financial distress variable. Dashed-red line: same as red-line except that we impose that GDP does not react contemporaneously (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 8: The effects of the 2007-2008 financial crisis — counterfactual



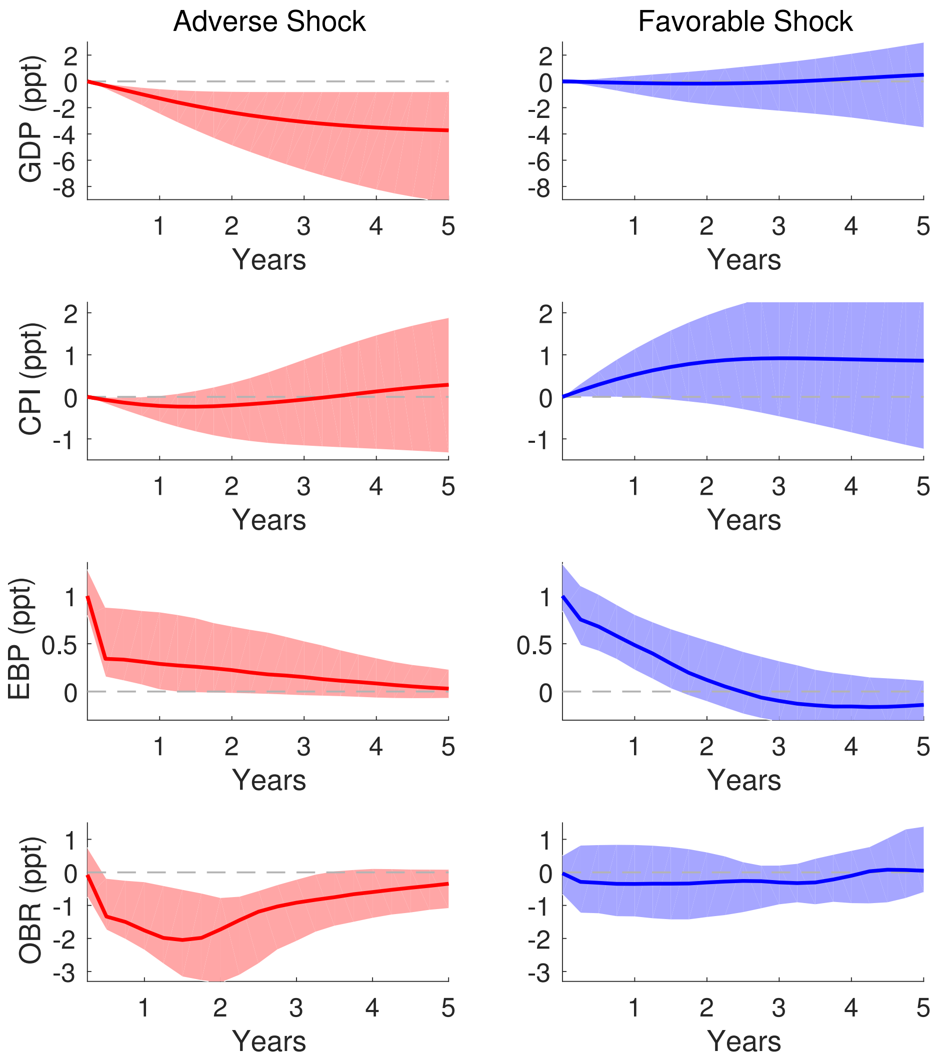
Notes: Blue lines: actual real GDP and EBP. Red lines: counterfactual simulated paths of real GDP and EBP assuming no financial shocks in 2007-2008 using parameter estimates from 1973-2006 only.

Figure 9: Robustness check — Estimates from hybrid VAR-LP, US evidence



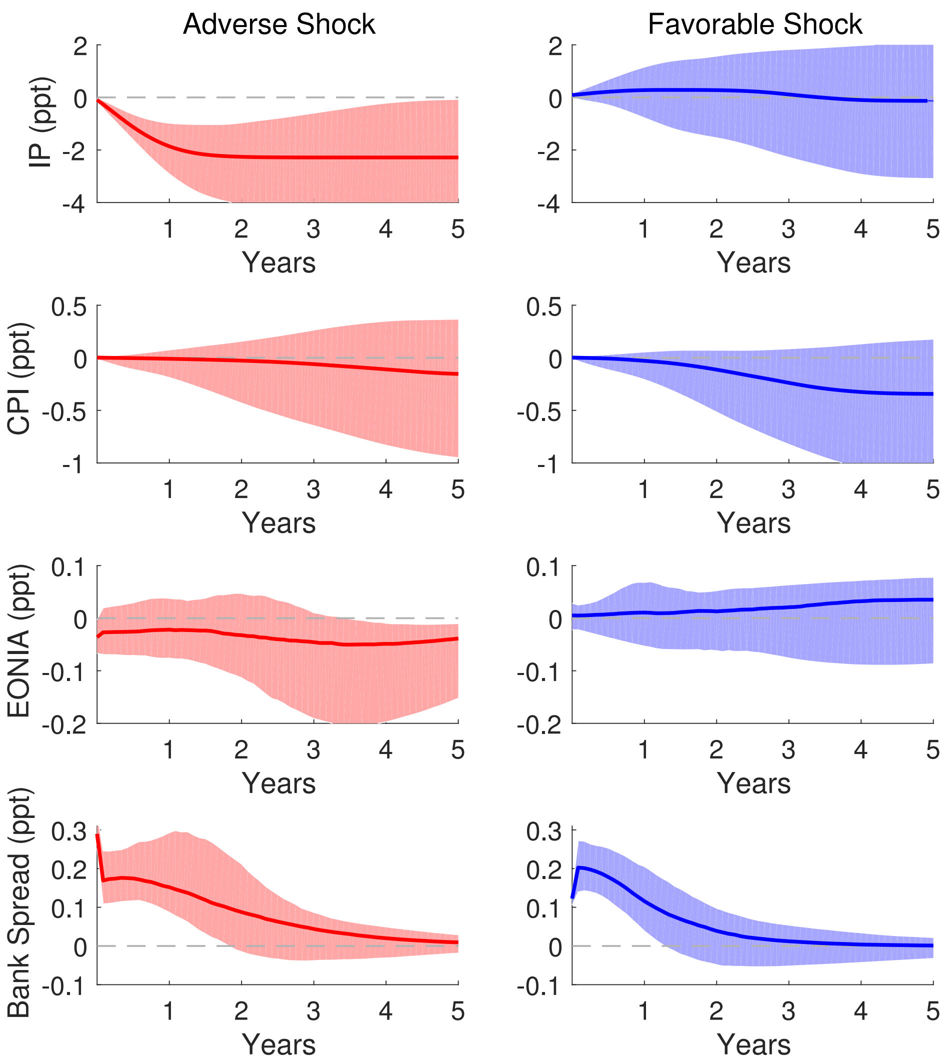
Notes: Impulse response functions of industrial production (IP) and consumer prices (CPI) to a unit shock to the EBP. Results from a symmetric model (dashed line) and from a model allowing for asymmetry (plain lines). The shaded areas span 90% confidence bands calculated using Newey-West standard errors. 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. Estimation using US monthly data covering 1973m1-2016m12.

Figure 10: The asymmetric effects of financial shocks — UK evidence



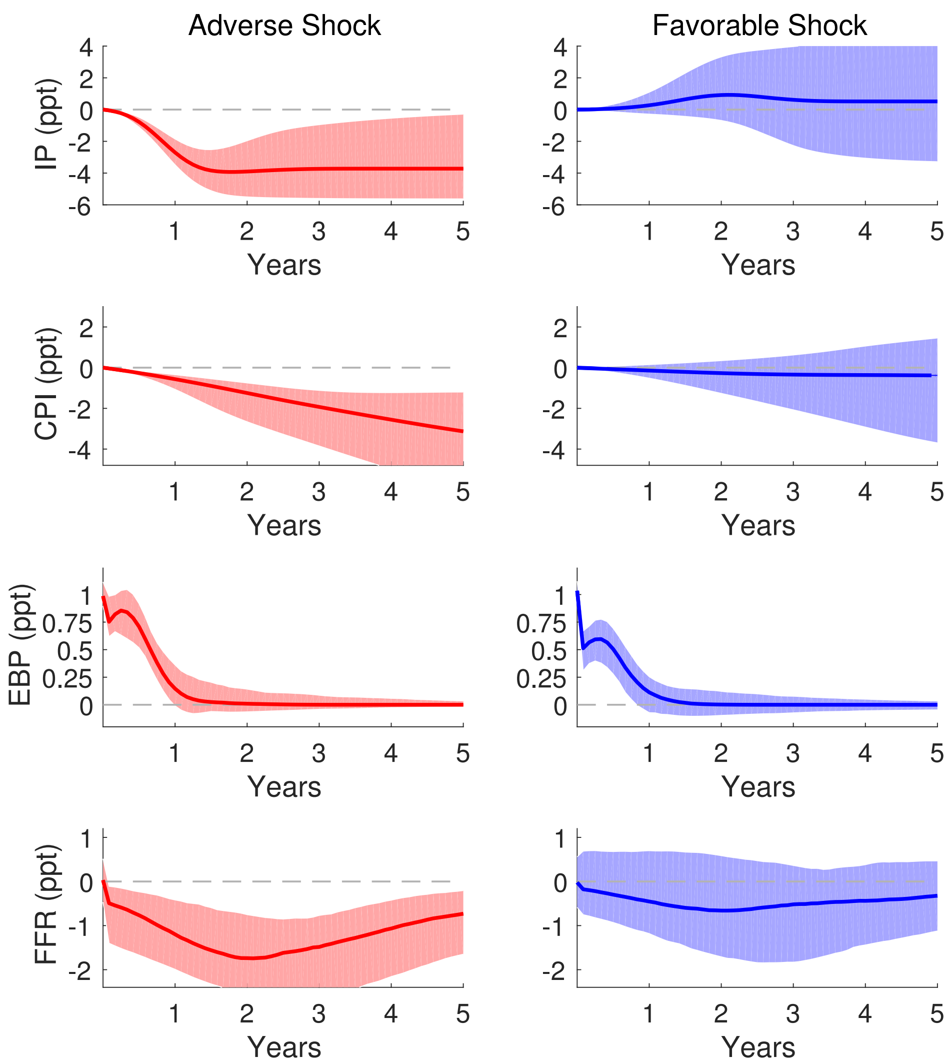
Notes: Impulse response functions of real GDP (GDP), consumer prices (CPI), the excess bond premium (EBP) and the official bank rate (OBR) to a unit shock to the excess bond premium. Estimation from a FAIR(2) (plain lines). The shaded bands cover 90% of the posterior probability. For ease of comparison 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. Estimation using UK quarterly data covering 1996q1-2010q2.

Figure 11: The asymmetric effects of financial shocks — Euro area evidence



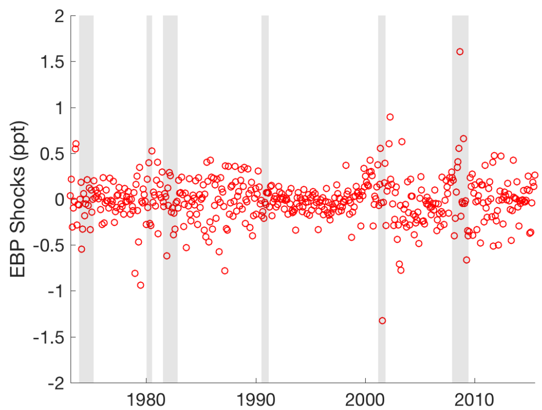
Notes: Impulse response functions of the 10-Year KfW-Bund Spread output, output growth (IP), CPI inflation, and the EONIA to a one-standard deviation shock to the KfW-Bund Spread. Estimation from a FAIR(2) (plain lines). The shaded bands cover 90% of the posterior probability. For ease of comparison between the left and right panels, the responses to a favorable financial shock (a decline in the KfW-Bund Spread) are multiplied by -1 in the right panels. Estimation using Euro area monthly data covering 1999m1-2016m8.

Figure A1: US evidence, robustness check — Excluding post-2006 data

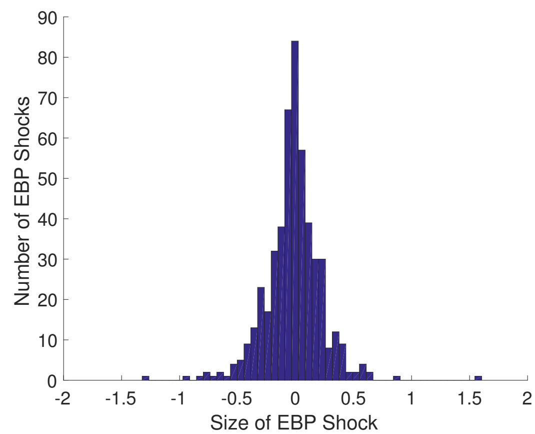


Notes: Impulse response functions of Industrial Production (IP), consumer prices (CPI), the excess bond premium (EBP) and the federal funds rate (FFR) to a unit shock to the excess bond premium. Estimation from a FAIR(2) (plain lines). The shaded bands cover 90% of the posterior probability. For ease 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. Estimating using US monthly data for the period 1973m1-2006m12.

Figure A2: The distribution of financial shocks

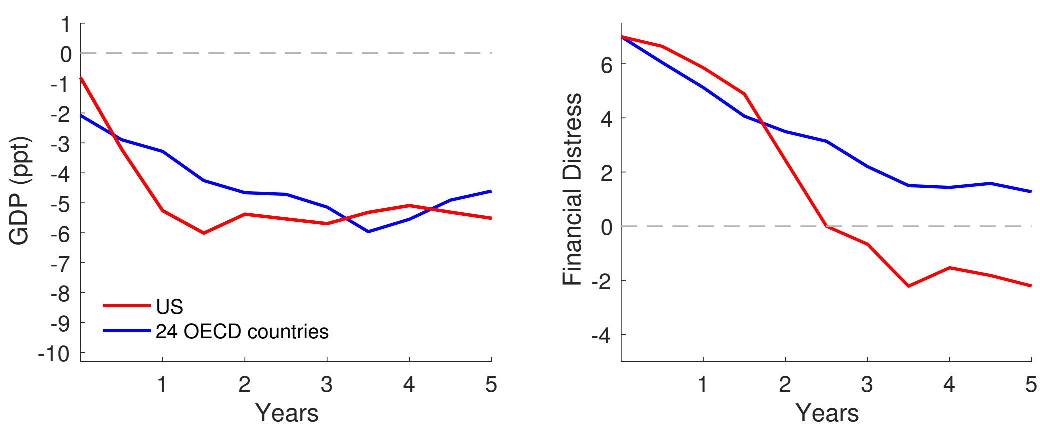


(a) Financial shocks (red dots) and NBER recession dates (grey areas).



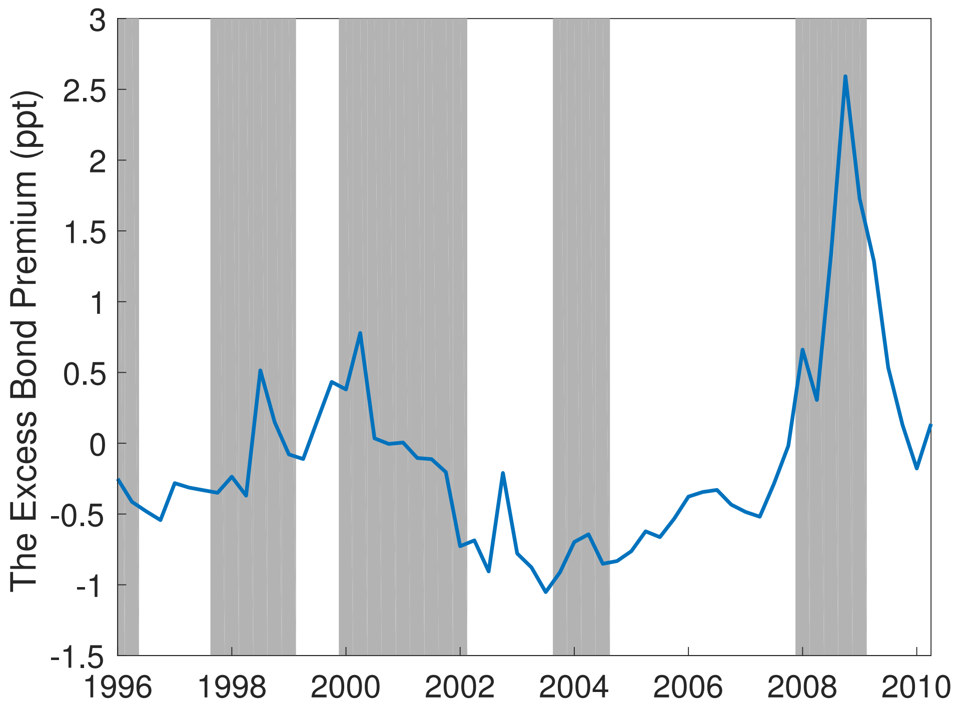
(b) Histogram of financial shocks.

Figure A3: RR specification — Robustness check



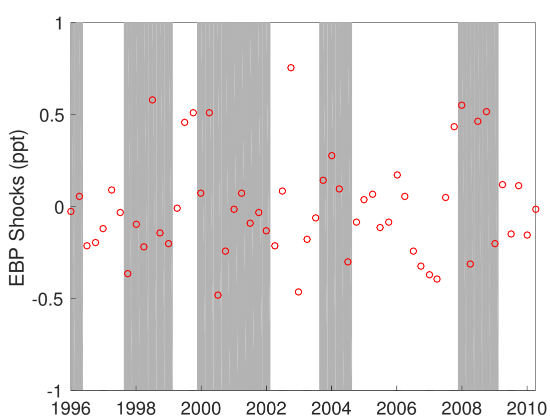
Notes: Impulse response functions of real GDP (GDP) and the Romer and Romer (2017) financial distress index to an impulse of 7 (*moderate financial crisis*) to the RR financial distress index. Blue lines: estimates using all data from Romer and Romer (2017) for 24 OECD countries. Red lines: estimates using data only for the US.

Figure A4: The UK Excess Bond Premium

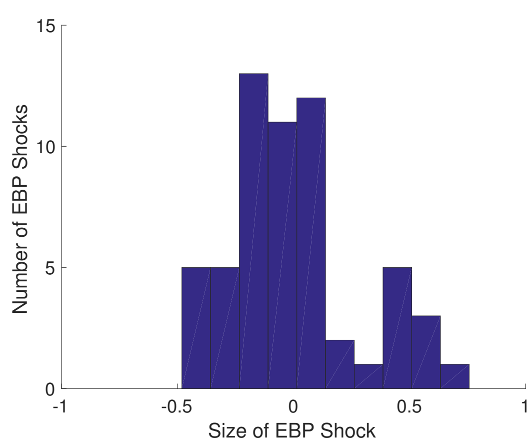


Notes: 1996-2010. Shaded areas mark OECD recession dates.

Figure A5: The distribution of UK financial shocks

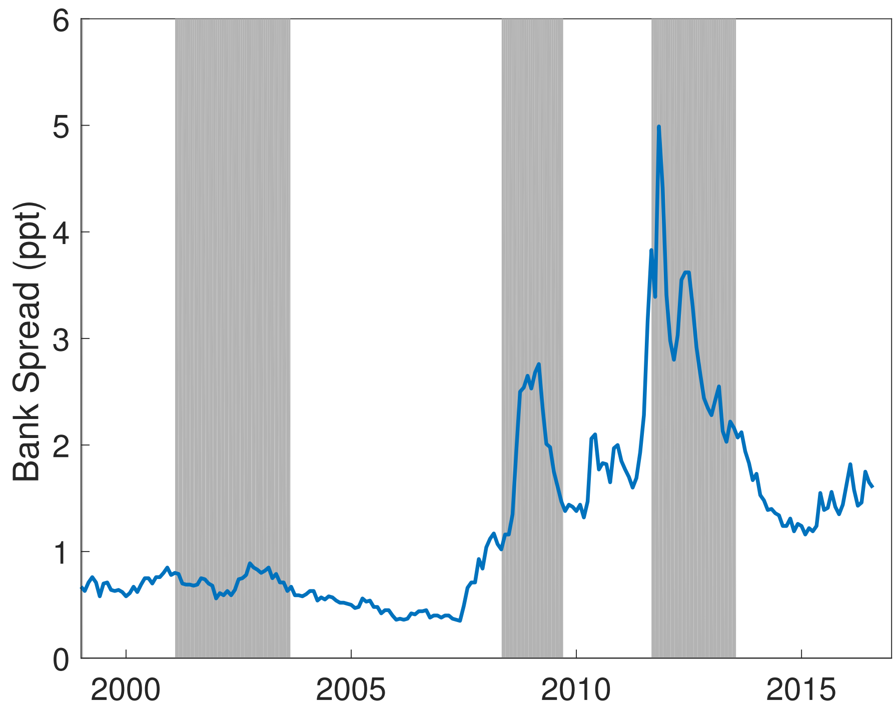


(a) Financial shocks identified from FAIR (red dots) and OECD recession dates (grey areas).



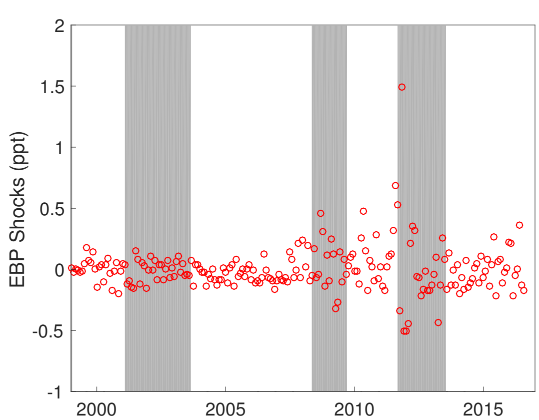
(b) Histogram of financial shocks identified from FAIR.

Figure A6: The Euro Area Bank Spread

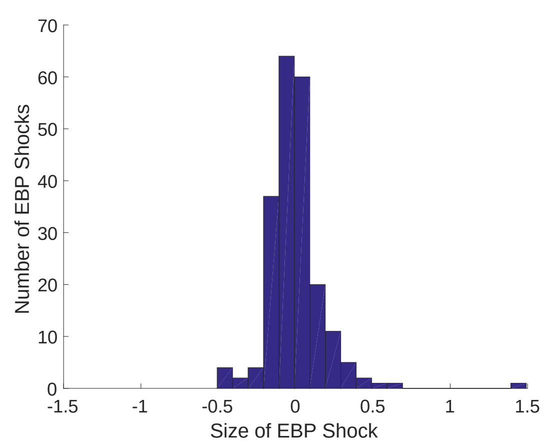


Notes: 1999-2016. Shaded areas mark OECD recession dates.

Figure A7: The distribution of Euro area liquidity shocks



(a) Liquidity shocks identified from FAIR (red dots) and OECD recession dates (grey areas).



(b) Histogram of liquidity shocks identified from FAIR.