THE TFP CHANNEL OF CREDIT SUPPLY SHOCKS

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Abstract

Recent work stresses a potentially important relation between credit supply shocks and aggregate TFP based on input misallocation. I examine this relation using state-of-the-art credit supply shock and aggregate TFP measures. An adverse credit supply shock has a weak and very short-lived effect on aggregate TFP. This finding suggests that the TFP channel of credit supply shocks has a very transient and limited role in their transmission to the real economy. The response of input reallocation to credit supply shocks along the firm size and good durability dimensions is consistent with a weak TFP channel of credit supply shocks.

JEL classification: E23,E32,E44

Key words: Credit Supply Shocks, Total Factor Productivity, Input misallocation

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1 Introduction

The recent financial crisis has generated a new wave of interest in research on the role of credit supply shocks in the business cycle. Models with financial frictions mostly stress the link between credit supply shocks and interest-sensitive spending, such as investment, as the basic channel by which these shocks propagate into the real economy. Recently, however, considerable work has emerged studying the potentially important role that input-misallocation-induced changes in aggregate total factor productivity (TFP) may have in amplifying/moderating credit supply shocks' effects on the real economy (see, e.g., Buera et al. (2011), Petrosky-Nadeau (2013), Pratap and Urrutia (2012), Khan and Thomas (2013), Buera and Moll (2015), Buera et al. (2015), Gopinath et al. (2017), Buera and Shin (2017), and Manaresi and Pierri (2017)).

What This Paper Does. A direct estimation of the effect of credit supply shocks on aggregate TFP in the data, while using state-of-the-art measures of these two objects, serves as a natural litmus test to determine the quantitative importance of the TFP channel of credit supply shocks. However, to the best of my knowledge, such direct estimation has not been done despite the fact that such measures have been readily available for several years now. Instead, researchers have generally opted to study this relation within micro-founded structural models which contain both financial frictions and some form of agents' heterogeneity.

I take a different, model-free approach that is capable of directly ascertaining the significance of the TFP channel of credit supply shocks. Within a VAR that includes the excess bond premium (EBP) measure from Gilchrist and Zakrajek (2012) and the utilization-adjusted TFP measure from Fernald (2014), along with various other macroeconomic variables, I identify a credit supply shock as the reduced form VAR innovation in EBP.[1] My findings can be summarized as follows. While adverse credit supply shocks are found to produce significant declines in real economic activity, they have very modest effects on TFP. Specifically, these shocks account for roughly only 3% of the

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[1]Gilchrist and Zakrajek (2012) use micro-level data to construct a credit spread index which they decompose into a component that captures firm-specific information on expected defaults and a residual component that they term as the excess bond premium. As argued in that paper, the latter component can be interpreted as capturing exogenous variation in the pricing of default risk and as such constitutes an appropriate measure of structural credit supply shocks.

forecast error variance of TFP at business cycle frequencies, having insignificant effects on TFP at all horizons except the second horizon. Hence, these results clearly fail to pass the aforementioned litmus test.

Much of the motivation for studying the TFP channel of credit supply shocks lies in the significantly lower TFP growth rates observed during the financial crisis across much of the developed economies. But, as discussed in Buera et al. (2015) in the U.S. context, this observation mainly applies to TFP that is not adjusted for input-utilization changes; once TFP is adjusted for such changes as in the case of the Fernald (2014) utilization-adjusted TFP measure, the difference in growth rates between the financial crisis period and other periods is much less stark. I provide VAR evidence consistent with this important unconditional observation: adverse credit supply shocks significantly reduce unadjusted TFP and account for about 20% of its variation at business cycle frequencies. That these effects effectively vanish for the utilization-adjusted TFP series indicates that credit supply shocks produce sizable unobserved-input-utilization-induced changes in aggregate unadjusted TFP movements as opposed to generating reallocation-induced changes in true TFP.

To more formally forcefully argue against the reallocation based mechanism that is at the core of the theoretical works cited above, I proceed by estimating the response of employment by firm size, available from the Bureau of Labor Statistics (BLS) National Business Employment Dynamics database, to my identified credit supply shock series. The reasoning behind by focus on firm size lies in its well accepted interpretation as a proxy for financial constraints' intensity, which in turn allows me to examine whether financial constraints can potentially matter for input-reallocation-induced TFP changes. Notably, I find that small firms' employment responds by much less than employment of medium and large firms, with differences being very persistent and both economically and statistically significant. This starkly contrasts with the underlying notion of much of the theoretical work studying the TFP channel of credit supply shocks that financial frictions amplify input-misallocation-induced TFP losses in the presence of adverse credit supply shocks.

Building on the literature on returns to scale heterogeneity across the durable and nondurable goods industries (see, e.g., Basu and Fernald (1997, 2001), Basu et al. (2001), and Nekarda and Ramey (2011)), I also investigate the response of reallocation involving these two industries while

exploiting returns to scale estimates from this literature to calibrate a theory-consistent reallocation term based on returns to scale heterogeneity. Further bolstering the evidence against the reallocation based mechanism, I show that reallocation involving the durable and nondurable goods industries moves in an insufficient manner in response to credit supply shocks so as to generate meaningful TFP variation.

The fact that we do not obtain meaningful aggregate TFP responses to credit supply shocks in the data tells us that there is likely no such sufficiently significant reallocation mechanism taking place in response to these shocks. And the findings that, *i*) the relative magnitude of small firms' employment response with respect to that of large firms goes in the opposite direction of the one implied by a meaningful TFP channel of credit supply shocks and *ii*) heterogenous-returns-to-scale-induced reallocation in the presence of credit supply shocks is not large enough to generate a noticeable TFP change, both reinforce my baseline VAR findings' interpretation. Therefore, the main takeaway from the evidence put forward in this paper is that the TFP channel of credit supply shocks is nearly non-existent, suggesting caution in placing too much focus on building theoretical models whose core relies on a meaningful TFP channel of credit supply shocks. (This statement has not the intention to dispute the significant intellectual value of studying this channel, which is definitely worth pursing from an intellectual curiosity standpoint; rather, it has the intention of stressing that such pursuit may ultimately have limited policy implications.)

Related Literature. To the best of my knowledge, as already mentioned above, this paper constitutes the first empirical investigation of the TFP channel of credit supply shocks that is based on directly observable, state-of-the-art data on credit supply shocks and TFP. Nevertheless, considerable work has been undertaken in recent years building structural models that highlight the potential role of input misallocation in the transmission of credit supply shocks to aggregate TFP changes and in turn to fluctuations in the real economy.

Much of this literature has developed DSGE models that find an amplifying role of aggregate TFP in the transmission of credit supply shocks.[2] In these models TFP is endogenized as a function

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[2]This literature can be viewed as a subset of the broader literature that studies the general relation between aggregate TFP and input misallocation (see, e.g., Basu and Fernald (2002), Hsieh and Klenow (2009), and Restuccia and Rogerson (2013)).

of financial frictions, by assuming some type of heterogeneity coupled with some form of financial frictions which together amplify the effects of credit supply shocks through their effect on input misallocation. While Pratap and Urrutia (2012) impose heterogeneity between intermediate and final goods in the sense that financial frictions only apply to the purchasing of the former, where final-goods producing firms need to finance part of their intermediate-goods purchases,[3] other works have emphasized heterogeneity across borrowing firms/entrepreneurs in terms of the financial frictions and associated borrowing costs facing them (see, e.g., Buera et al. (2011), Gilchrist et al. (2013), Khan and Thomas (2013), Midrigan and Xu (2014), Moll (2014), Buera and Moll (2015), Buera et al. (2015), and Buera and Shin (2017)).[4]

By contrast, some other work has found a *moderating* role for input misallocation in transmitting credit supply shocks. Modeling the creation and destruction of jobs in the presence of heterogeneity in firm productivity and financial frictions, Petrosky-Nadeau (2013) finds that adverse credit supply shocks destroy the least productive jobs and slow job creation, thus raising aggregate TFP. Moreover, focusing on an exogenous decline in the real interest rate as a proxy for favorable credit supply shocks and allowing for a borrowing constraint that depends on firm size, Gopinath et al. (2017) find that favorable credit supply shocks actually lead to a short-run decline in TFP (which accords well with the experience of southern Europe in the early 1990s) owing to unconstrained, less productive firms increasing their capital more so than more productive, credit constrained firms.[5]

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[3]Importantly, Pratap and Urrutia (2012) define aggregate TFP in an open economy setting as a Solow residual that does not account for intermediate inputs, facilitating the drop in their aggregate TFP measure as a result of input mix misallocation when the economy is hit by an adverse credit supply shock.

[4]In the context of news shocks about future technology, Chen and Song (2013) develop a model with financial frictions and entrepreneurs that are heterogenous in their initial level of net worth, where positive news shocks produce TFP-increasing capital reallocation by which capital flows in a procyclical manner to the more productive, credit constrained entrepreneurs.

[5]Using a rich set of cross-sectional and time-series observations from establishment-level data and focusing on idiosyncratic productivity shocks, rather than credit supply shocks, Midrigan and Xu (2014) find fairly small aggregate losses from misallocation across producers; also focusing on idiosyncratic productivity shocks but allowing for a self-financing mechanism on the part of entrepreneurs, Moll (2014) argues that the persistence level of these shocks determines the size of long-run TFP losses from misallcoation as well as the speed of transition to the new steady state: more persistent productivity shocks result in smaller long-run TFP losses (owing to the entrepreneurs having more time to substitute for external financing with self-financing) and a faster transition to the new steady state.

Outline. The remainder of the paper is organized as follows. In the next section the details of the empirical strategy are laid out. Section 3 begins with a description of the data, after which it presents the main empirical evidence followed by a sensitivity analysis section. The final section concludes.

2 Methodology

Prior to presenting the empirical strategy in detail, I first explain the underlying framework of the analysis employed in this paper.

2.1 Underlying Framework

To fix ideas and form a suitable conceptual base for my empirical analysis, it is useful to consider the rather general decomposition of aggregate TFP growth (ΔTFP_t) as the sum of technological growth and various reallocation terms developed in the seminal work of Basu and Fernald (2002):

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\begin{aligned}
\Delta TFP_t &= \sum_i \omega_i \Delta a_{it} + (\bar{\mu}^v - 1)\Delta x_t^v + \sum_i \omega_i (\mu_i^v - \bar{\mu}^v)\Delta x_{it}^v + \\
&+ \sum_i \omega_i (\mu_i^v - 1)\left(\frac{s_{mi}}{1 - s_{mi}}\right)(\Delta m_{it} - \Delta y_{it}) + \bar{\mu}^v \sum_i \omega_i s_{ki}^v \left(\frac{P_{ki} - P_k}{P_{ki}}\right)\Delta k_{it} + \\
&+ \bar{\mu}^v \sum_i \omega_i s_{li}^v \left(\frac{P_{li} - P_l}{P_{li}}\right)\Delta l_{it},
\end{aligned}
\tag{1}
$$

where ω_i is firm i's share of nominal value added; $\sum_i \omega_i \Delta a_{it}$ is the growth rate of aggregate technology; μ_i^v is firm i's "value added markup" of price over marginal cost, where its relation to markup μ_i is given by $\mu_i^v = \mu \frac{1 - s_{mi}}{1 - \mu s_{mi}}$, with s_{mi} representing firm-level materials inputs share in nominal gross output, i.e., $s_{mi} = \frac{P_{mi}M_i}{PY}$; $\bar{\mu}^v$ is the weighted average value added markup across firms (i.e., $\sum_i \omega_i \mu_{it}^v$); Δx_t^v is the weighted average of the growth rates of aggregate capital and labor inputs, where the shares are the aggregate cost of each input divided by total nominal output, and Δx_{it}^v is the corresponding weighted average of growth rates of capital and labor inputs in firm i; Δy_{it} is firm i's growth rate of output; s_{ji}^v, Δj_{it}, P_{ji}, and P_j are the firm-level input j's share in nominal gross output divided by $1 - s_{mi}$, firm-level input j's growth rate, firm-level input j's price, and aggregate input j's price, respectively, where $j = k, l, m$ (representing capital, labor, and materials inputs, respectively).

Decomposition (1) shows that aggregate TFP growth is affected by pure, aggregate technology (the first term); aggregate markups (second term); and factor inputs reallocation, where the third terms represents markup-reallocation changes, the fourth term is a materials-reallocation term reflecting the extent to which measured real value added depends on the intensity of intermediate-input use, and the fifth and sixth terms represent capital- and labor-input-reallocation terms, respectively. If all firms are perfectly competitive and pay the same price for factors, then all terms other than the technological term are zero.

Much of the above-cited literature on the relation between factor misallocation and credit supply shocks has focused on the potential role that the capital-reallocation term (the fifth term) in Equation (1) plays in transmitting credit supply shocks to aggregate TFP changes. E.g., in frameworks that allow for heterogenous wealth levels of entrepreneurs and a financial friction that limits their borrowing capacity as a function of their wealth, one can obtain a meaningful way by which credit supply shocks produce capital misallocation (see, e.g., Khan and Thomas (2013), Buera et al. (2015), and Buera and Moll (2015)). The general mechanism is as follows: Since more credit-constrained firms have less capital and a correspondingly higher capital rental price, an adverse credit supply shock lowers aggregate TFP by further moving capital away from more productive, more credit-constrained firms to less productive, less credit-constrained firms. (The higher capital rental price results from the effectively higher cost of acquiring capital due to higher borrowing costs; as apparent from Equation (1), without this heterogeneity in capital prices there would be no aggregate TFP loss from adverse credit supply shocks.)

From an empirical standpoint, under the fairly weak assumption that aggregate technology does not move in response to credit supply shocks and that average markups in the U.S. economy are rather small (see, e.g., Basu and Fernald (1997, 2002)), a direct implication of Decomposition (1) is that aggregate TFP movements driven by credit supply shocks must be due to input reallocation changes. I.e., for the reallocation-induced TFP channel of credit supply shocks to be meaningful, a suitable measure of aggregate TFP must significantly move following such shocks. Hence, what remains to be done other than to utilize a state-of-the-art TFP measure, is to come up with a proper way of identifying credit supply shocks. This is what I turn to describing next.

2.2 Identifying Credit Supply Shocks

To identify credit supply shocks, I make use of the state-of-the-art credit supply shock series constructed by Gilchrist and Zakrajek (2012). Using the structural "distance to default" model based on the seminal work of Merton (1973), Gilchrist and Zakrajek (2012) purge micro-level credit spread data of their endogenous default risk component and interpret the residual component (termed excess bond premium, or EBP in short)) as a credit supply shock that represents exogenous movements in the pricing of risk. Accordingly, I include EBP in a VAR with a TFP measure (to be described in the data section below) and other commonly considered macroeconomic variables and identify EBP reduced form innovations as credit supply shocks.

Specifically, let y_t be a kx1 vector of observables and let the VAR in the observables be given by

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + ... + B_p y_{t-p} + B_c + u_t, \tag{2}$$

where B_i are kxk matrices, p denotes the number of lags, B_c is a kx1 vector of constants, and u_t is the kx1 vector of reduced-form innovations with variance-covariance matrix Σ. It is assumed that there exists a linear mapping between the reduced-form innovations and economic shocks, v_t, given by

$$u_t = A v_t, \tag{3}$$

with $E(v_t) = 0$ and $var(v_t) = I$, where I is the identity matrix. The impact matrix A must satisfy $AA' = \Sigma$. There are, however, an infinite number of impact matrices that solve the system. In particular, for some arbitrary orthogonalization, C (e.g, the Cholesky factor of Σ), the entire space of permissible impact matrices can be written as CD, where D is a k x k orthonormal matrix ($D' = D^{-1}$, which entails $D'D = DD' = I$).

I place the EBP variable in the first position in the VAR and identify the credit supply shock as the unrestricted VAR innovation in EBP. The idea behind this simple identification strategy is based on the reasonable notion that the credit supply shock is the only shock which has a contemporaneous effect on EBP.[6] I follow the conventional Bayesian approach to estimation and infer-

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[6]Gilchrist and Zakrajek (2012) identified a credit supply shock by restricting the EBP shock to have a zero contemporaneous effect on output, consumption, investment, and inflation. I refrain from imposing such restrictions as they are mostly at odds with economic theory's implications for credit supply shocks.

ence by assuming a diffuse normal-inverse Wishart prior distribution for the reduced-form VAR parameters.

3 Empirical Evidence

In this section the main results of this paper are presented. I first provide a brief description of the data used in my analysis, followed by the main empirical results from my baseline VAR.

3.1 Data

The baseline VAR includes eight variables: EBP, RPI, output, hours, consumption, investment, inflation, and interest rates. For the TFP series, I employ the real-time, quarterly series on total factor productivity (TFP) for the U.S. business sector, adjusted for variations in factor utilization (labor effort and capital's workweek), constructed by Fernald (2014).[7] The adjustment Fernald (2014) makes for factor utilization changes is an important element underlying the construction of his TFP measure, greatly contributing to it being the state-of-the-art TFP measure used in the literature.

As discussed above, the variable I use to measure credit supply shocks is the excess bond premium (EBP) from Gilchrist and Zakrajek (2012), who use micro-level data to construct a credit spread index which they decompose into a component that captures firm-specific information on expected defaults and a residual component that they term as the excess bond premium (EBP). The most updated series of the EBP variable, available from Favara et al. (2016),[8] is my measure of credit supply shocks in this paper. It is in quarterly frequency and covers the sample period 1973:Q1 to 2017:Q3. Quarterly values are averages of corresponding raw monthly values.

The nominal series for output, consumption, and investment are taken from the Bureau of Economic Analysis (BEA). Output is measured as GDP in the non-farm business sector, consumption as the sum of non-durables and services, and investment is the sum of personal consumption expenditures on durables and gross private domestic investment. The nominal series are converted

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Nevertheless, my baseline results are robust to adding such restrictions, as shown in Section 4.

[7]http://www.frbsf.org/economics/economists/staff.php?jfernald.

[8]The permanent link for this updated excess bond premium series is
https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv.

to per capita terms by dividing them by the civilian non-institutionalized population aged sixteen and over. I use the corresponding chain-weighted deflators to obtain the real series. The hours series is log of per capita total hours worked in the non-farm business sector. Inflation is measured as the percentage change in the CPI for all urban consumers and the nominal interest rate is the three month Treasury Bill rate.[9] The data series span the period 1973:Q1-2017:Q3.

3.2   Baseline Results

I first present the impulse responses and variance decomposition results with respect to the credit supply for the baseline VAR, which includes utilization-adjusted TFP; I then present results from a VAR that includes instead a TFP measure that does not adjust for utilization changes; and, lastly, after that I turn to a reconciliation of the baseline results with the observed behavior of employment reallocation by firm size and hours reallocation by good durability conditional on a credit supply shock.

Impulse Responses and Variance Decompositions.   My empirical VAR includes eight variables: EBP, TFP, output, investment and durables, non-durables and services consumption, hours worked, inflation, and interest rates. All variables enter the system in levels. The Akaike information and Hannan-Quinn criteria favor three lags whereas the Schwartz information criteria and Likelihood-Ratio test statistic favor two and eight lags, respectively. As a benchmark, I choose to estimate a VAR with four lags. The results are robust to using a different number of lags.

Figures 1a and 1b depict the median and 97.5th and 2.5th percentiles of the posterior distributions of impulse responses and contribution to forecast error variance (FEV) at all horizons up to the 5 year one, respectively. Similar to the results from Gilchrist and Zakrajek (2012), an adverse credit supply shock (of one standard deviation) produces a significant recession accompanied by a drop in inflation and interest rates, with output, investment, consumption, and hours dropping by 0.40%, 1.67%, 0.23%, and 0.53%, respectively, after one year. The respective median FEV shares are also economically large for these variables, with the one-year FEV shares standing at 20%, 25%,

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[9]To convert monthly population, inflation, and interest rate series to quarterly series, I take the average over monthly observations from each quarter.

10%, and 21%.

The main novelty of the results from these figures lies in the TFP response. While TFP exhibit a statistically significant drop of -0.15% in the second quarter following the shock, its responses at all other horizons are insignificant and negligible. The corresponding FEV shares stress the very weak, almost non-existent TFP channel of credit supply shocks borne out by the data, with median FEV shares hovering around 3%-4%. These results clearly indicate that the mechanism by which credit supply shocks affect the business cycle is likely unrelated to the much focused upon input misallocation channel.

VAR With Unadjusted TFP measure.   Owing to the common lack of TFP measures that properly account for unobserved factor utilization changes, researchers often look at unadjusted TFP measures for motivation and also more formal analysis. (This is true mainly for non-U.S. studies, although at least from a motivational standpoint this point also at times applies to U.S. focused studies, as is done e.g. in Buera et al. (2015).) The main merit of the Fernald (2014) utilization-adjusted TFP measure is the fact that it accounts for unobserved factor utilization changes. As such, it provides for a clean, purified measure of aggregate TFP that serves well for the purposes of this paper. To study the TFP channel of credit supply shocks, which is based on a factor reallocation mechanism, one must employ a TFP measure that is not contaminated by cyclical utilization changes. This is made very clear by looking at the behavior of utilization-adjusted TFP alongside unadjusted TFP, both from Fernald (2014), during recession periods and in particular the Great Recession period.

Figure 2 serves this purpose, depicting the logs of the two variables for 1947:Q1-2017:Q3 with shaded areas representing recession periods. Notably, unadjusted TFP tends to drop by much more during recessions than utilization-adjusted TFP, and this is especially evident from the recent Great Recession episode during which credit supply shocks were large. (The fairly large discrepancies between the two series are consistent with the rather low correlation between the series (in first-difference terms), which stands at 0.44.) Hence, wrongly focusing on unadjusted TFP to inform us about the relevance of the TFP channel of credit supply shocks is likely to lead to erroneous inference. Clearly, factor utilization is strongly countercyclical and renders it impor-

tant to control for its variation when trying to ascertain the relevance of the TFP channel of credit supply shocks.

I now show conditional evidence that accords well with the unconditional evidence from Figure 2 on the importance of controlling for factor utilization changes for the purposes of this paper. Figures 3a and 3b correspond to Figures 1a and 1b, only that unadjusted TFP replaces utilization-adjusted TFP in the VAR. While results for the other variables are robust to this replacement, it is clear that the unadjusted TFP measure behaves very differently from the utilization-adjusted one, significantly falling for six quarters following the shock. The decline in unadjusted TFP is both statistically and economically significant, bottoming at -0.28% after 3 quarters. The corresponding FEV shares tell a similar tale: credit supply shocks account for about 20% of the business cycle variation in unadjusted TFP. Taken together, these results stress that unobserved factor utilization is strongly affected by credit supply shocks and not accounting for this may lead to erroneously inferring that a reallocation-based mechanism is at work in response to adverse credit supply shocks while in fact it is the mere decline in unobserved factor utilization that drives the negative response of unadjusted TFP.

Credit Supply Shocks and Financial-Frictions-Induced Reallocation.   The findings shown so far indicate that the reallocation-based TFP channel of credit supply shocks has a very limited role in transmitting credit supply shocks to the real economy. Interpreted through the lens of the structural models usually used to study the credit-supply-TFP nexus, these results indicate that financial frictions are not likely to play an important role in producing meaningful input reallocation in the presence of credit supply shocks. To reinforce this interpretation, it could prove useful to look into the response of actual reallocation to credit supply shocks in a way that is informative about the relevance of financial frictions for the amplification of reallocation-induced TFP changes. One way to go about this is to consider the popular emphasis on firm size as a proxy for financial frictions' intensity, where small firms are considered to be much more credit-constrained than large ones. This emphasis was initiated, at least from a macroeconomic standpoint, by the seminal work of Gertler and Gilchrist (1994) who provided evidence from the US Census Bureau's Quarterly Financial Report (QFR) that firm size serves as a proxy for financial constraints, as small firms

are more likely to be bank-dependent and less likely to have access to broader capital markets.[10]

This firm-size-based dichotomy is merely one way to divide the economy's production, and by no means the only one. (See, e.g., Buera et al. (2015) for a firm-age-based dichotomy, which is naturally associated with size but still not perfectly so; and Basu and Fernald (1997) and Nekarda and Ramey (2011), who focused on a durable-nondurable goods dichotomy in the context of heterogenous returns to scale (an analysis of the implications of this type of dichotomy for credit supply shocks appears below).) However, its arguably conclusive relation to financial constraints' intensity renders the firm-size-based dichotomy a potentially informative device for learning about the relevance of financial frictions for TFP-reducing input reallocation in the presence of adverse credit supply shocks. As such, it can be a helpful means by which to support the interpretation of the previous VAR-based findings on the irrelevance of the TFP channel of credit supply shocks.

Toward this end, I make use of employment data for various firm sizes available from the Bureau of Labor Statistics (BLS) National Business Employment Dynamics database, covering the sample 1993:Q1-2017:Q2. I define employment in small firms as corresponding to firms employing 1-49 employees; medium-sized firms are defined as firms employing 50-249 employees; and large firms are defined as firms employing more than 249 employees. Figure 4 presents the responses of per capita employment of small, medium, and large firms to credit supply shocks, as well as the responses of the ratios of small to medium firms' employment, small to large firms' employment, and medium to large firms' employment. I apply here the Bayesian estimation algorithm for strong block recursive VAR models put forward by Zha (1999), where the likelihood function is broken into the different recursive blocks and the log-first-differences of the per capita employment variables are effectively regressed on 3 own lags and current and 3 lagged values of the exogenous median credit shock series from my baseline VAR specification.[11]

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[10]As discussed in Crouzet and Mehrotra (2017), measuring financial constraints in empirical work in corporate finance effectively always involves the use of firm size, either by itself or as part of a constructed financial constraints index (see Farre-Mensa and Ljungqvist (2016) and references therein).

[11]In my case, I only have two blocks, where the first consists of a single equation in which the credit supply shock series is equal to itself, and the second block contains a three equation VAR for the employment variables in which the credit supply shock series enters the right hand side of these equations both contemporaneously and in lagged form. As shown in Zha (1999), this kind of block separation along with the standard assumption of a normal-inverse Wishart prior leads to a normal-inverse Wishart posterior distribution for the block recursive VAR parameters.

The results from Figure 4 can be summarized as follows. As to be expected, employment for all firm sizes significantly declines in response to an adverse credit supply shock. Importantly, this decline is increasing in firm size, especially when moving from small firms to medium and large firms. While medium and large firms' employment levels respond similarly, the difference between the employment of small firms and that of medium and large firms is very persistent and also economically and statistically significant, with a much stronger fall in medium and large firms' employment. Specifically, large firms' employment falls by 0.5% more than small firms' employment does two years following the shock, with this difference being very persistent, effectively plateauing out at this significant gap; and a similar gap is observed for small firms relative to medium firms.

How should the much stronger decline in large and medium firms' employment relative to small firms should be interpreted from a structural standpoint? Since theories that point to a strong TFP channel of credit supply shocks are usually based on the notion that the latter induce bigger changes in inputs of more credit-constrained firms who are at the same time also more productive due to their underinvesting, we should expect the employment of small firms (which should be more credit-constrained) to decline by more than medium and large firms' employment for this theoretical mechanism to be true. That we actually see the opposite is an indication that financial frictions are unlikely to be playing a meaningful role in transmitting credit supply shocks to aggregate TFP through input misallocation.[12] More generally, taken together with the preceding findings on the largely muted TFP response to these shocks in the data, we can deduce that the TFP channel of credit supply shocks is likely to be of limited importance.

Reallocation Based on Heterogenous Returns to Scale. As mentioned above, the division of the economy's production according to firm size is by no means the only one; an additional, notable dichotomy often used to divide the economy's production is through a distinction between

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[12]A potential caveat worthwhile mentioning here is that, since capital misallocation is the main element from a modeling standpoint behind the TFP channel of credit supply shocks, the arguably ideal variable one would want to look at is investment, rather than employment, by firm size. Due to data availability issues I have resorted to using employment data. However, given that theory largely implies that labor input should move in tandem with capital conditional on an adverse credit supply shock (see, e.g., Buera et al. (2015)), it seems rather sensible to consider employment by firm size to inform us about the relevance of the TFP channel of credit supply shocks.

durable and nondurable goods production. And, importantly, this way of dividing the economy's production has been often applied in the context of studying the reallocation-productivity nexus (see, e.g., Basu and Fernald (1997, 2001), Basu et al. (2001), and Nekarda and Ramey (2011)), generally yielding the finding that the production of durable goods exhibits larger returns to scale than that of nondurable goods while the aggregate economy exhibits roughly constant returns to scale.[13] Therefore, the durable versus nondurable goods dichotomy can be a potentially informative device for learning about the direct relation between factor-reallocation-induced TFP changes and credit supply shocks; and, as such, it can be used as a means to further reinforce this paper's finding that the reallocation-based TFP channel of credit supply shocks is weak.

Given that pure economic profits are mostly found to be close to zero and that returns to scale are equal to the product of markup and one minus the ratio of economic profits to total revenue (Basu and Fernald (1997)), one can innocuously replace the markup parameter μ^v appearing in Equation (1) with a corresponding value added returns to scale parameter which I shall denote by γ^v and which I shall define below. This in turn emphasizes that the third term appearing in Equation (1) represents reallocation changes induced by heterogenous returns to scale, which for convenience is rewritten here (now accounting for the replacement of the markup parameter with the returns to scale parameter):

$$\sum_i \omega_i (\gamma_i^v - \bar{\gamma}^v) \Delta x_{it}^v, \tag{4}$$

where ω_i is firm i's share of nominal value added; γ_i^v is firm i's "value added returns to scale", where its relation to returns to scale γ_i is given by $\gamma_i^v = \gamma \frac{1-s_{mi}}{1-\gamma s_{mi}}$, with s_{mi} representing firm-level materials inputs share in nominal gross output, i.e., $s_{mi} = \frac{P_{mi} M_i}{PY}$; $\bar{\gamma}^v$ is the weighted average returns to scale across firms (i.e., $\sum_i \omega_i \gamma_{it}^v$); Δx_t is the weighted average of the growth rates of aggregate capital and labor inputs, where the shares are the aggregate cost of each input divided by total nominal output; and Δx_{it}^v is the corresponding weighted average of growth rates of capital and labor inputs in firm i.

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[13]Focusing on the role of increasing returns to scale and unmeasured input utilization in explaining procyclical productivity growth, Inklaar (2007) finds similar results on returns to scale. Importantly, Inklaar (2007) also finds that services-producing sectors exhibit roughly constant returns to scale, making their exclusion in the estimations I perform below innocuous for my purposes.

The reallocation term appearing in Equation (4) can be used to quantify the effect of credit supply shocks on TFP due to heterogenous-returns-to-scale-induced reallocation changes. Such quantification can further reinforce the interpretation of my baseline finding that TFP moves by little in response to credit supply shocks as representing a weak, almost non-existent reallocation based TFP channel of credit supply shocks.

Toward this end, I proceed in two steps. First, I make use of data on hours worked in the durable and nondurable goods sectors available from the BLS (covering 1987:Q1-2017:Q3) to estimate the response of Δx_{it}^v to credit supply shocks. Note that I ignore here the response of capital in these sectors, owing to lack of data; this effectively implies my assuming that capital input changes in the same proportion as hours worked. Also note that due to lack of data on services' hours worked, I ignore the latter's response in my analysis. However, as explained in Footnote 13, since both the services sector as well as the overall economy seem to exhibit roughly constant returns to scale, I can innocuously ignore services' hours worked response as the term relating to it effectively vanishes due to the aforementioned rough equality between the overall economy's and services' returns to scale.

Second, I use direct estimates of $\bar{\gamma}^v$ for the aggregate private economy and γ_i^v for the durable and nondurable goods industries from the reallocation-corrected OLS estimates reported in Table 3 of Basu and Fernald (1997). They estimate a value added returns to scale parameter of 1.03 for the overall private economy, 1.36 for durable goods industries, and 0.81 for nondurable goods industries. To measure ω_i, I use annual industry level value added data from the Bureau of Economic Analysis (BEA) to compute the average shares of durable and nondurable goods value added in total private industries value added over the sample 1947-2016, which stand at 13.6% and 9.6%, respectively. I then compute the estimated TFP loss from reallocation implied by the calibrated version of Equation (4).

Figure 5 presents the responses of hours worked in the durable and nondurable goods sectors to credit supply shocks, as well as the responses of the ratio of durable goods hours worked to nondurables goods hours worked and the reallocation-induced TFP loss implied by the calibrated version of Equation (4). As in the previous estimation exercise involving employment by firm size, I apply here the Bayesian estimation algorithm for strong block recursive VAR models put

forward by Zha (1999), where the likelihood function is broken into two recursive blocks and the log-first-differences of the hours worked variables are effectively regressed on 3 own lags and current and 3 lagged values of the exogenous median credit shock series from my baseline VAR specification.

The results from Figure 5 clearly indicate that hours worked in the durable goods sector fall by much more than their corresponding counterpart of the nondurable goods sector. Specifically, two years after the shock, the former fall by -1.5% compared to a -0.6% decline for the latter, with this difference being statistically significant and very persistent. But are these responses sufficiently different so as to generate noticeable reallocation-induced TFP losses? The last sub-figure of Figure 5 provides a negative answer to this question. While reallocation does lower TFP in a statistically significant manner, this decline is clearly not economically insignificant, being lower than -0.04% for the first year and then hovering at -0.05% afterwards. The rather small response of the reallocation-induced TFP loss accords well with the results shown so far, all of which indicate that credit supply shocks are unlikely to produce significant reallocation-induced TFP changes.

4   Robustness Checks

This section examines the robustness of the baseline results along four main dimensions.[14] The first speaks to the possibility that there may not exist a perfect linear mapping between VAR innovations and economic shocks. The second is that over the entire sample period VAR innovations may not be homoscedastic and VAR coefficients may not be stable. The third relates to the exclusion of the Great Recession and zero lower bound (ZLB) periods. And the fourth regards the robustness of the results to the different Cholseky ordering used in Gilchrist and Zakrajek (2012).

Addressing Potential Invertibility Issues.   As emphasized in Fernandez-Villaverde et al. (2007), for there to be a linear mapping between VAR innovations to economic shocks, as it is assumed in Mapping (3), the observables ought to be capable of perfectly forecasting any unob-

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[14]I have also confirmed that the main results of the paper are robust to different numbers of lags in the VAR. These results are available upon request from the author.

served state variables present in the true model. If this is the case, the moving average (MA) process of the true model is said to be invertible, or fundamental.

Given that non-invertibility is fundamentally a product of informational deficiency, one practical approach to testing whether non-invertibility is affecting one's results is by checking whether the VAR contains sufficient information such that the true MA process is invertible. Following this reasoning, Forni and Gambetti (2014) have developed a formal statistical test of the null hypothesis of invertibility that is based on checking for orthogonality of the identified shock at hand with respect to the past values of the principal components of a large macroeconomic data set. Forni and Gambetti (2014) have shown that the null of invertibility is rejected if and only if orthogonality is rejected, in which case the identified shock cannot be considered a structural shock.

To conduct the invertibility test for my identified credit supply shock, I extract the principal components from the large quarterly FRED-QD database consisting of 254 quarterly macroeconomic and financial series, all of which have been transformed to induce stationarity.[15] The series span the period 1959:Q1-2015:Q3. Consistent with the invertibility test proposed and used in Forni and Gambetti (2014) and Forni et al. (2014), Table 1 reports the p-values of the F-test of the regression of the median credit supply shock series on three lags of the first n principal components, where n goes from 1 to 8. I truncate n at 8 as the first eight principal components explain 53% of the total variance of the FRED-QD data set. In all specifications the null of invertibility cannot be rejected at even the 10% level, indicating that the identified credit supply shock passes the invertibility test.

Moreover, Table 1 also reports the R^2s associated with each regression in line with the important message from Beaudry et al. (2015) that one must look at the explanatory power of lagged principal components in addition to the standard F-test p-values so as to ascertain the quantitative importance of any potential non-invertibility. Beaudry et al. (2015) show that non-invertibility is likely to be quantitatively unimportant in terms of its effect on identification precision even for R^2s in the order of 0.2. Hence, that the R^2s of my regressions never exceed 0.17 is encouraging and enhances confidence that the results of this paper are not driven by potential non-invertibility.

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[15]The data was downloaded from Michael McCracken's webpage at https://research.stlouisfed.org/econ/mccracken/fred-databases/.

Results for Post-1982 Sub-Sample. One may be concerned that the VAR coefficients may not be stable over the entire sample period. Moreover, the VAR innovations may not be homoskedastic. Hence, I now present results from applying my methodology to a post-1982 sub-sample where it is demonstrated that these sub-sample results, which are much less likely to suffer from potential heteroskedasticity (see, e.g., Stock and Watson (2007)), are very similar to the larger sample results.

Figures 6a and 6b show the impulse responses and FEV contributions from this estimation. It is apparent the main results are mostly unchanged for the post-1982 sub-sample period: the credit supply shock affects TFP significantly only in the first two periods and accounts for small shares of its business cycle variation. As in the baseline case, the TFP channel seems to only matter in the very short-run, effectively becoming non-existent from the third quarter onwards.

Excluding the Great Recession and ZLB Periods. An additional potential concern regarding the baseline results is that they are driven in part by the inclusion of the Great Recession period and the associated ZLB period. One may argue that such inclusion biases the results owing to the fact that the Great Recession period was a very unique episode in terms of the large credit supply shocks it saw; one may also want to consider results that are based on more normal, non-crisis periods where credit supply shocks are of normal size. Moreover, when interest rates are at their zero lower bound the structure of the economy changes, in turn inducing possible changes in the transmission of credit supply shocks. Hence, a useful robustness check is to run the VAR estimation for a sample that excludes the Great Recession and ZLB periods. The results from this exercise are presented in Figures 7a and 7b, which correspond to Figures 1aand 1b except that now the sample is truncated at 2007:Q3.

It is apparent that the baseline results are robust to the exclusion of the Great Recession and ZLB periods. Credit supply shocks significantly move TFP only in the second period, being both economically and statistically insignificant at all other horizons. These results indicate that the main message of the paper is robust to excluding from the analysis the large credit supply realizations of the 2008-2009 period as well as the associated ZLB period of 2009-2015.

Gilchrist and Zakrajek (2012)'s Cholesky Ordering.   As discussed in Footnote 6, I ordered EBP first in my baseline VAR, rather than fifth (after output, consumption, investment, and inflation) as in Gilchrist and Zakrajek (2012), to allow for the theory-consistent possibility of credit supply shocks having contemporaneous effects on all variables in my system. Specifically, broadly in line with theory, my differing from Gilchrist and Zakrajek (2012)'s identification scheme allows for credit supply shocks to have an immediate effect on both the real economy as well as inflation. That said, it still seems worthwhile to confirm that my baseline results are robust to ordering EBP fifth after output, consumption, investment, and inflation, which in turn shuts down credit supply shocks' contemporaneous effects on these variables.

The results from this exercise are presented in Figures 8a and 8b, which correspond to Figures 1a and 1b except that now the Cholesky ordering from Gilchrist and Zakrajek (2012) is used. It is apparent that credit supply shocks continue to have a limited, very short-lived effect on TFP, with correspondingly low contributions to the business cycle variation in TFP. Hence, we can infer from this exercise that the main result of this paper is robust to using the alternative Cholskely ordering employed in Gilchrist and Zakrajek (2012) for the identification of credit supply shocks.

5   Conclusion

This paper has made an important contribution to our understanding of the quantitative importance of the reallocation-based TFP channel of credit supply shocks by providing robust evidence of a weak, short-lived response of aggregate TFP to credit supply shocks. To obtain this evidence, I used state-of-the-art credit supply shock and TFP measures and found that the former move the latter in a significant way only in the second period after the shock, making it unlikely that a meaningful TFP-reducing factor input misallocation mechanism takes place in the presence of adverse credit supply shocks. To further reinforce this finding, I provided two additional pieces of evidence. First, I made use of employment data by firm size and showed that small firms' employment falls by much less that medium and large firms' employment in response to adverse credit supply shocks. Given that firm size is a reasonable proxy for financial frictions' intensity, these results indicate that financial frictions are unlikely to produce significant TFP losses from

input misallocation in the presence of adverse credit supply shocks. And second, I showed that heterogenous-returns-to-scale-induced reallocation involving the durable and nondurable goods industries is insufficiently large for producing significant TFP changes.

Importantly, the results of this paper were obtained using a largely model-free approach that does not place considerable restrictions on the data, but instead lets the data indicate rather freely whether there is a meaningful TFP channel of credit supply shocks. As such, this identification approach is arguably sufficiently reliable - in terms of the credibility of the results it produces - for guiding model builders in developing theories that accord with its results. Notably, despite being reduced-form in nature, the analysis undertaken in this paper was able to shed structural light on my results by interpreting them through the lens of the general framework underlying much of the theoretical work on the credit-supply-TFP nexus. It is my hope that this structural light can help bring closer data and future theories as well as inform policymakers in determining the optimal set of policy tools for mitigating the effects of credit supply shocks. While it is rather clear that policies directed at reducing input misallocation in general, and in particular that induced by financial frictions, can produce significant long-term welfare gains, the evidence put forward in this paper suggests that specific policies enacted to counteract potential input misallcoation in the presence of credit supply shocks may be unwarranted.

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Table 1: **F-Test and R^2 of Regression of Credit Supply Shock Series on Lagged Principal Components.**

	Principal Components (from 1 to n)							
	1	2	3	4	5	6	7	8
P-Value	0.95	0.21	0.41	0.47	0.13	0.15	0.14	0.24
R^2	0	0.05	0.06	0.07	0.13	0.12	0.17	0.17

Notes: Column n reports the p-value of the F-test of the regression of the median credit supply shock series on three lags of the first n principle components extracted from the FRED-QD comprehensive quarterly data set, where n goes from 1 to 8.

Figure 1: **Baseline VAR: (a) Impulse Responses ; (b) Contribution to FEV**
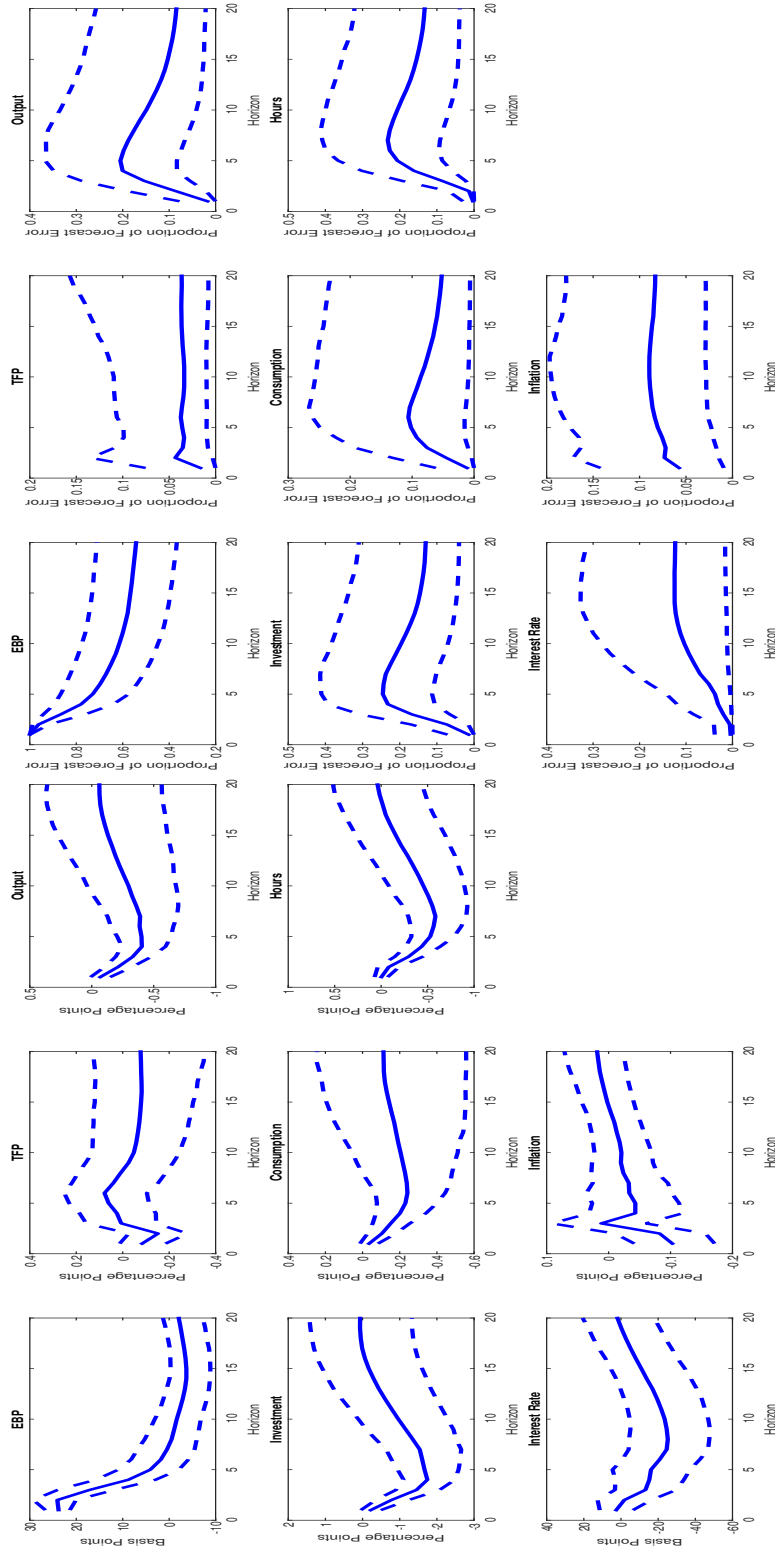
(a) **The Median and 97.5th and 2.5th percentiles of the Impulse** (b) **The Median and 97.5th and 2.5th Percentiles of the Contri-
Responses to Credit Supply Shock.** **bution of Credit Supply Shock to the Forecast Error Variance
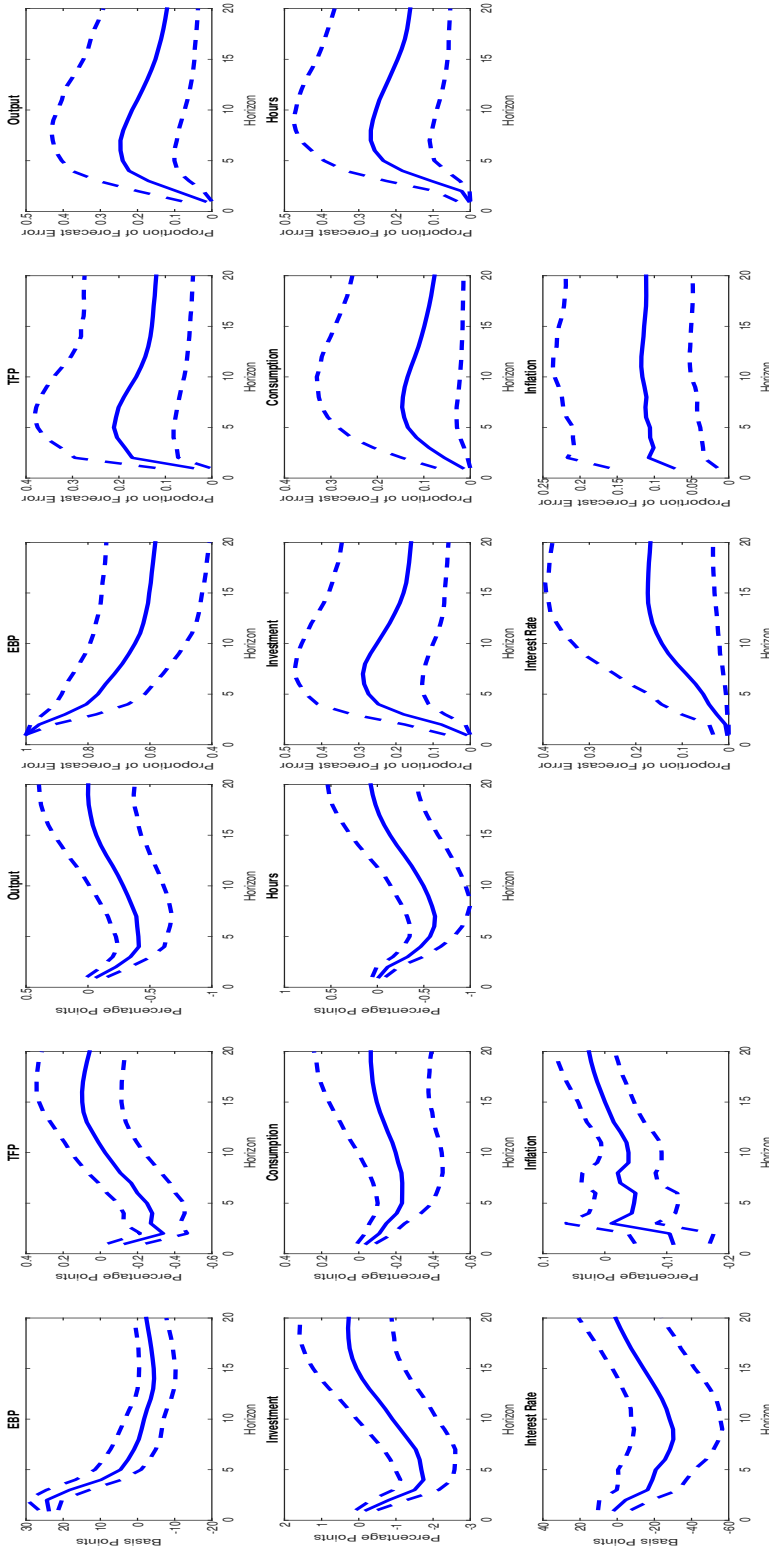of the Variables.**

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 97.5th 2.5th percentiles
of the posterior distributions of impulse responses. Panel (b): The solid line is the median FEV contribution and the
dashed lines are the 97.5th 2.5th percentiles of the posterior distribution of FEV contributions.

Figure 2: **Time Series of Utilization-Adjusted TFP and Unadjusted TFP.**
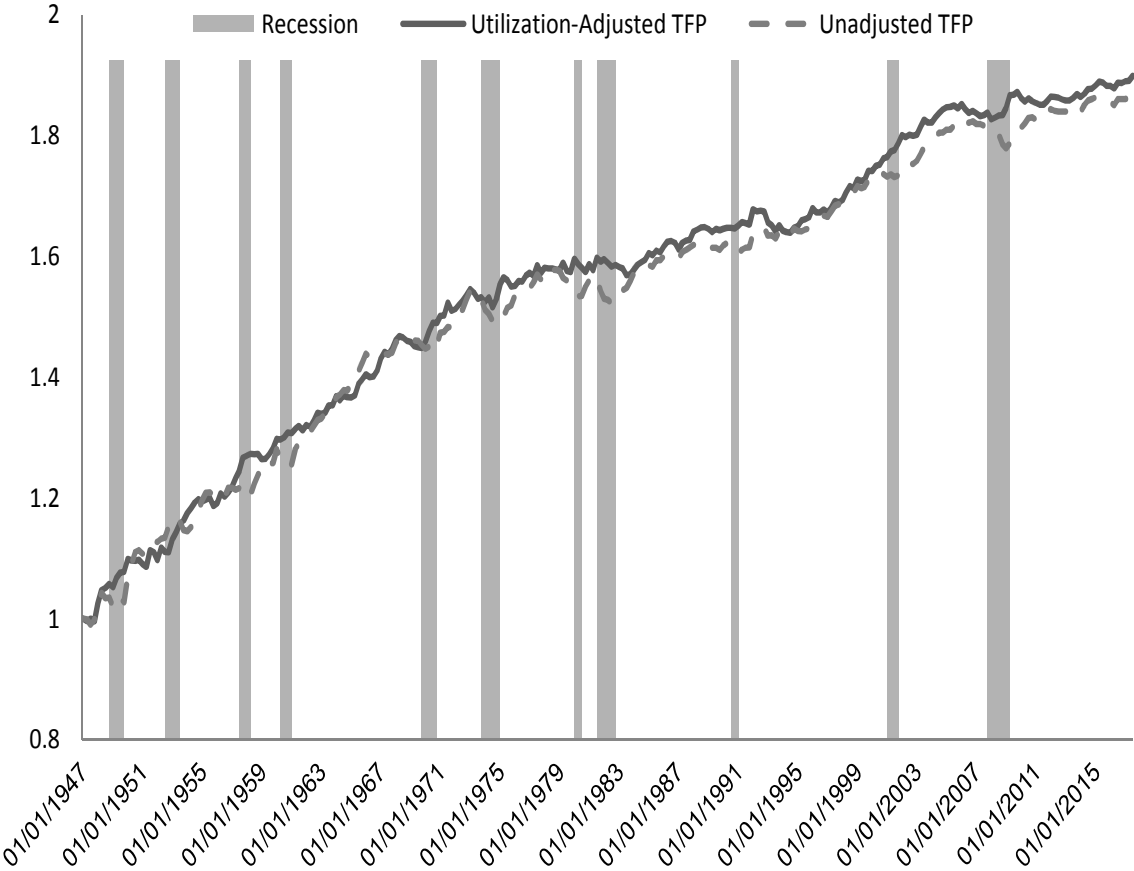
Notes: This figure presents the time series of logs of utilization-adjusted TFP (solid line) and unadjusted TFP (dashed line), where the latter is a TFP measure that does not account for factor utilization changes. Both measures are taken from Fernald (2014) and cover the period 1948:Q1-2017:Q3. U.S. recessions are represented by the shaded areas.

Figure 3: **VAR With Unadjusted TFP: (a) Impulse Responses ; (b) Contribution to FEV**

(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to Credit Supply Shock.

(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shock to the Forecast Error Variance of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 97.5th and 2.5th percentiles of the posterior distributions of impulse responses from a VAR with the Fernald (2014) unadjusted TFP measure, i.e., one that does not adjust for factor utilization changes. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 97.5th and 2.5th percentiles of the posterior distribution of FEV contributions from a VAR with the Fernald (2014) unadjusted TFP measure, i.e., one that does not adjust for factor utilization changes.

Figure 4: **Employment Response to Credit Supply Shocks By Firm Size**.
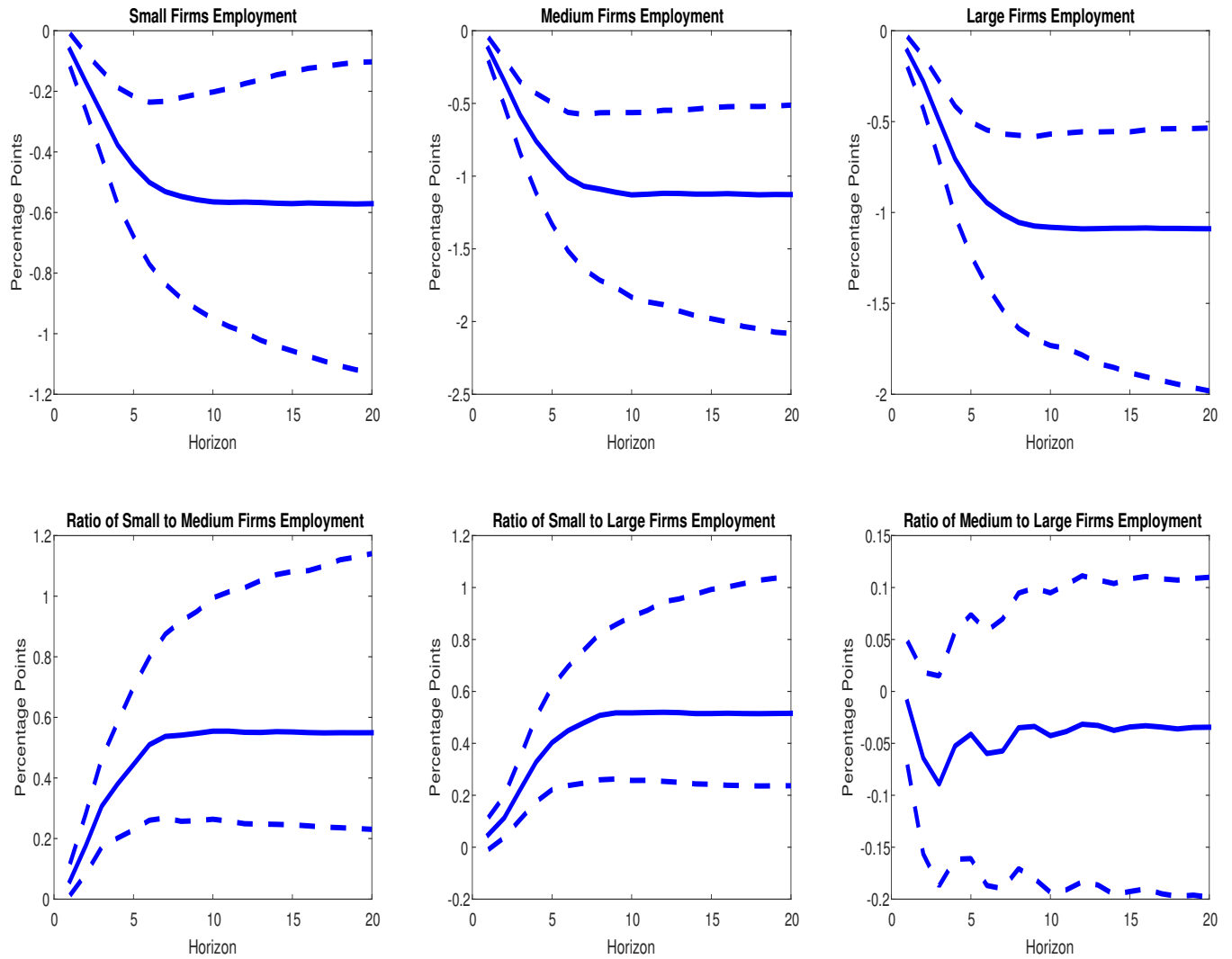
Notes: This figure presents the impulse responses of per capita employment of small, medium, and large firms to credit supply shocks. Solid lines are median impulse responses and the dashed lines are the 97.5th and 2.5th percentiles of the posterior distributions of impulse responses. Small firms are those employing less than 50 employees; medium firms are those employing 50-249 employees; and large firms are those employing more than 249 employees. The first three sub-figures present the responses of employment for each firm size, while the last three sub-figures show the responses of the ratios of the employment variables.

Figure 5: **Hours Worked Response to Credit Supply Shocks By Good Durability and Implications for Reallocation-Induced Changes in TFP**.
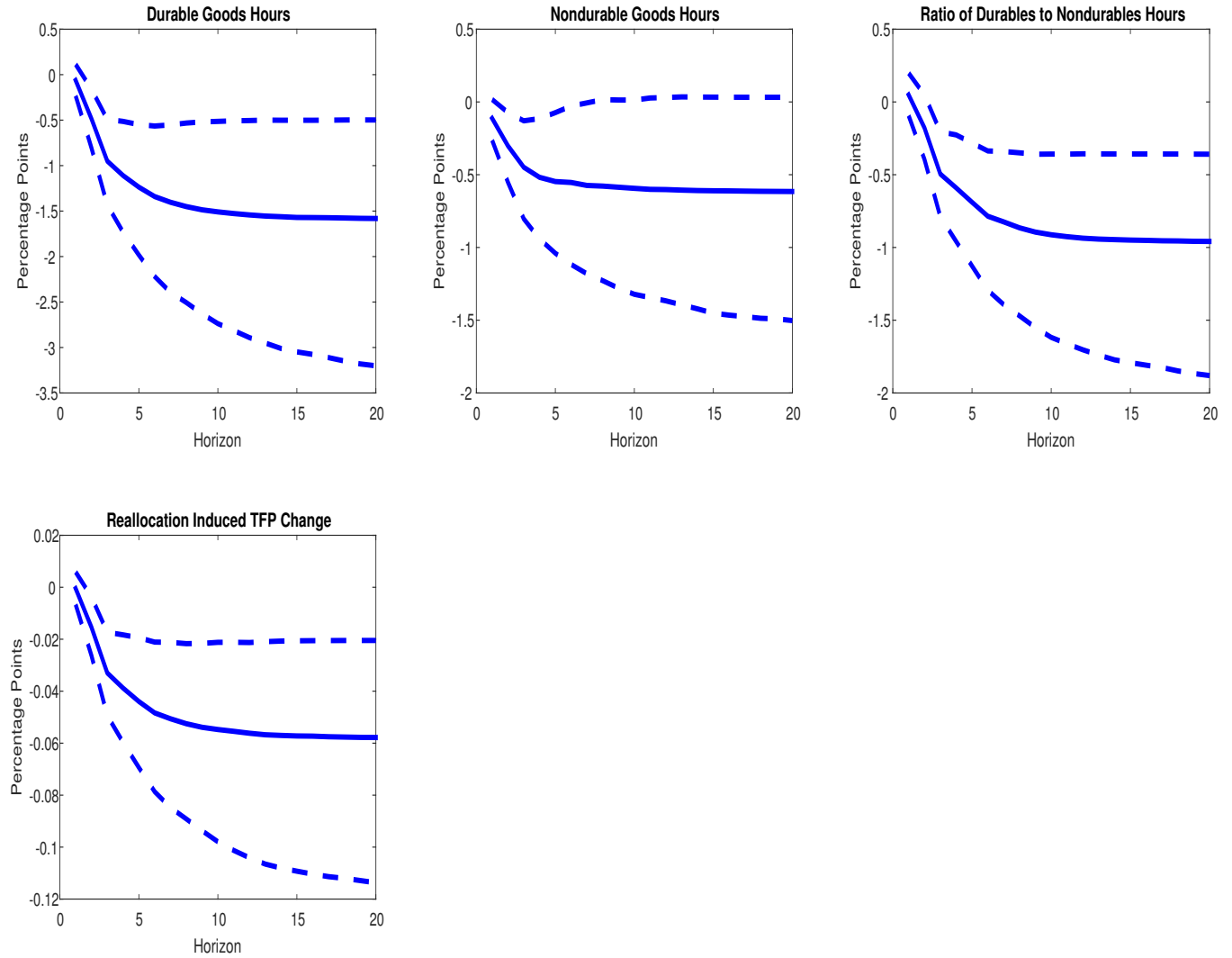
Notes: This figure presents the impulse responses of hours worked in the durable and nondurable goods industries along with the implied TFP change from reallocation, based on the calibrated version of Equation (4). Solid lines are median impulse responses and the dashed lines are the 97.5th and 2.5th percentiles of the posterior distributions of impulse responses. The first two sub-figures present the responses of hours worked for each sector, the third sub-figure shows the response of the ratio of durable goods hours worked to nondurable goods hours worked, and the last sub-figure depicts the implied TFP loss due to reallocation (computed from the calibrated version of Equation (4)).
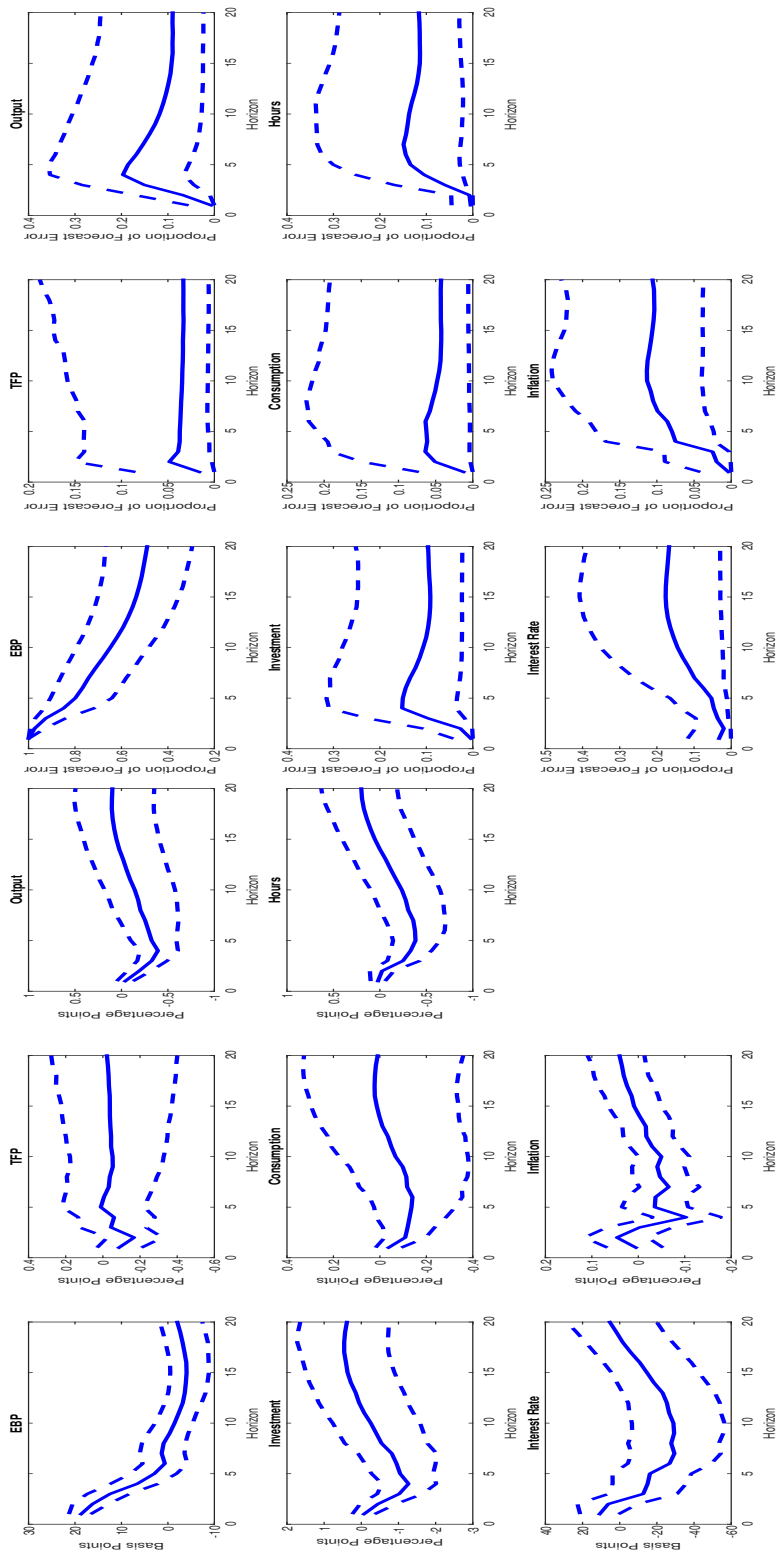
Figure 6: Post-1982 VAR: (a) Impulse Responses ; (b) Contribution to FEV
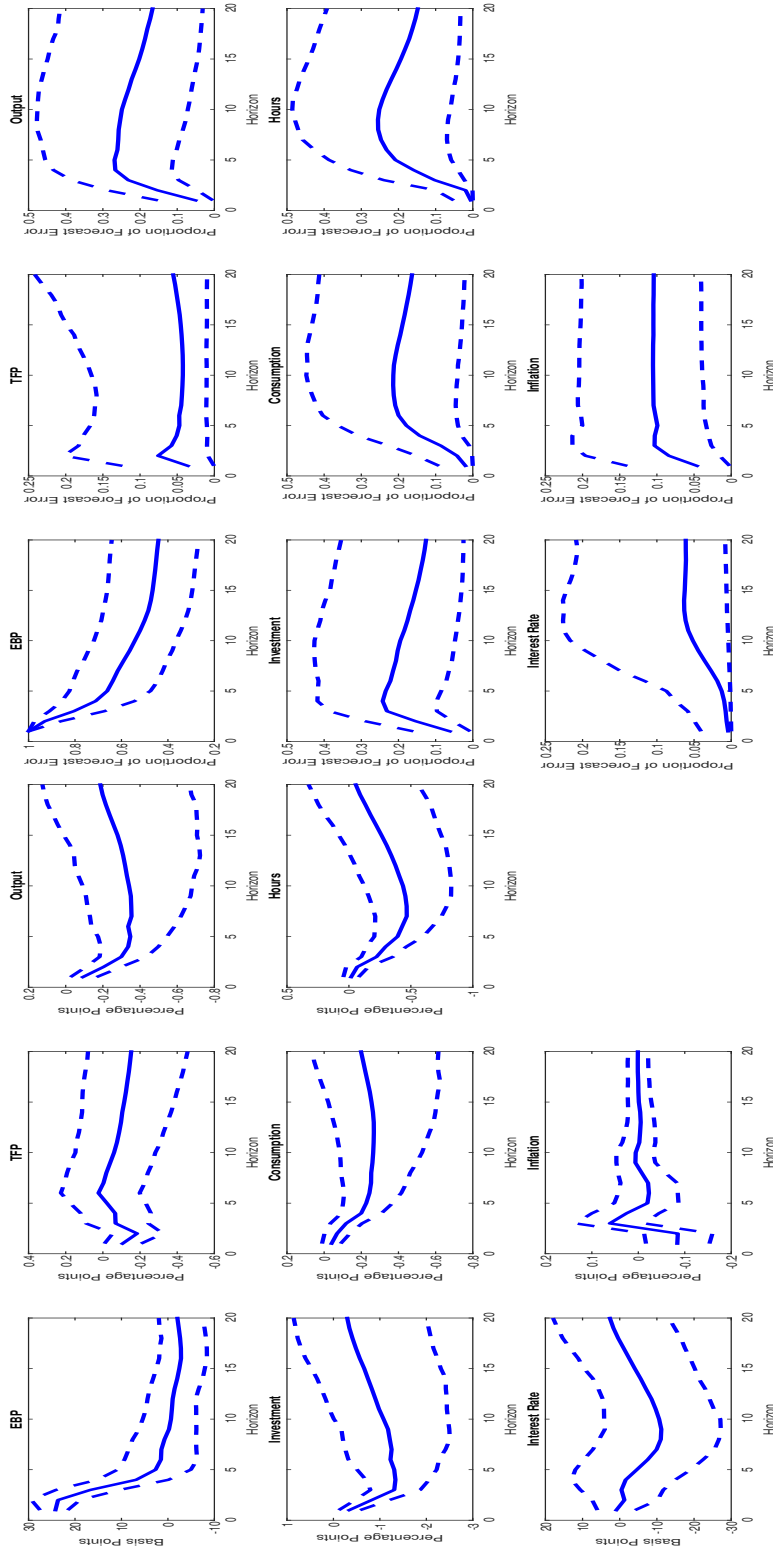
(a) The Median and 97.5th and 2.5th percentiles of the Impulse (b) The Median and 97.5th and 2.5th Percentiles of the Contri-
Responses to Credit Supply Shock.   bution of Credit Supply Shock to the Forecast Error Variance
of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 97.5th and 2.5th per-
centiles of the posterior distributions of impulse responses from a post-1982 VAR. Panel (b): The solid line is the
median FEV contribution and the dashed lines are the 97.5th and 2.5th percentiles of the posterior distribution of
FEV contributions from a post-1982 VAR.

Figure 7: Excluding the Great Recession and ZLB Periods: (a) Impulse Responses ; (b) Contribution to FEV

(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to Credit Supply Shock.

(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shock to the Forecast Error Variance of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 97.5th and 2.5th percentiles of the posterior distributions of impulse responses from a VAR whose sample is truncated at 2007:Q3. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 97.5th and 2.5th percentiles of the posterior distribution of FEV contributions from a VAR whose sample is truncated at 2007:Q3.

Figure 8: Using the Choleky Ordering from Gilchrist and Zakrajek (2012): (a) Impulse Responses ; (b) Contribution to FEV
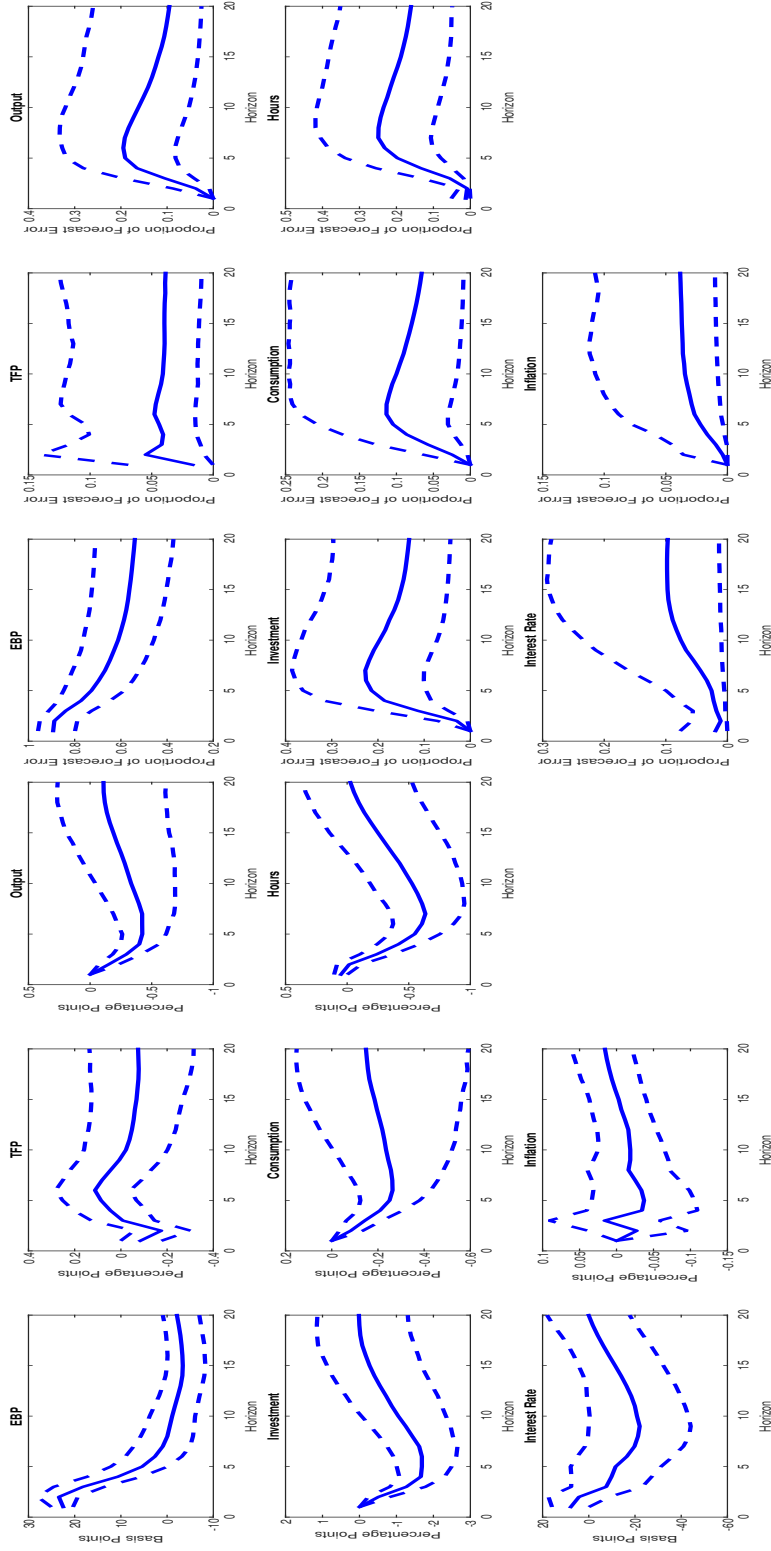
(a) The Median and 97.5th and 2.5th percentiles of the Impulse
Responses to Credit Supply Shock.

(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shock to the Forecast Error Variance
of the Variables.

Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 97.5th and 2.5th percentiles of the posterior distributions of impulse responses from a VAR whose Cholesky ordering places EBP fifth after output, consumption, investment, and inflation. Panel (b): The solid line is the median FEV contribution and the dashed lines are the 97.5th and 2.5th percentiles of the posterior distribution of FEV contributions from a VAR whose Cholesky ordering places EBP fifth after output, consumption, investment, and inflation.