Online Appendix for 'The TFP Channel of Credit Supply Shocks'

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Abstract

This online appendix consists of the following appendices: an appendix detailing the Bayesian estimation procedure for the bottom-up approach; an appendix presenting results from robustness checks for the baseline top-down analysis; an appendix with results from robustness checks for the baseline bottom-up capital misallocation channel analysis; and an appendix with results from robustness checks for the baseline bottom-up labor misallocation channel analysis.

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Appendix A Posterior Distribution of Parameters for Bottom-Up Estimation Approach

Since the Bayesian estimation of System (7)-(8) from the paper is done sequentially, estimating Equation (8) conditional on the estimation of the VAR in (7), I present here the estimation for (7) and (8) separately while taking as given the estimated posterior draw of the credit supply shock series from the VAR in (7) when estimating Equation (8).

Estimation of Credit Supply Shock. The VAR given by (7) can be written in matrix notation as follows:

$$Y = XB + U, \tag{A.1}$$

where $Y = [y_1, ..., y_T]'$, $X = [X_1, ..., X_T]'$, $X_t = [y_{t-1}, ..., y_{t-p}, 1]'$, $B = [B_1, ..., B_p, B_c]'$, k and p are the number of variables and lags, respectively, and $U = [u_1, ..., u_T]'$. B here represents the reduced form VAR coefficient matrix and Σ is the variance-covariance matrix of the reduced form VAR innovations. I follow the conventional approach of specifying a normal-inverse Wishart prior distribution for the reduced-form VAR parameters:

$$vec(B) \mid \Sigma \sim N(vec(\bar{B}_0), \Sigma \otimes N_0^{-1}), \tag{A.2}$$

$$\Sigma \sim IW_k(v_0 S_0, v_0), \tag{A.3}$$

where N_0 is a kpxkp positive definite matrix, S_0 is a kxk covariance matrix, and $v_o > 0$. As shown by Uhlig (1994), the latter prior implies the following posterior distribution:

$$vec(B) \mid \Sigma \sim N(vec(\bar{B}_T), \Sigma \otimes N_T^{-1}), \tag{A.4}$$

$$\Sigma \sim IW_k(v_T S_T, v_T), \tag{A.5}$$

where $v_T = T + v_0$, $N_T = N_0 + X'X$, $\bar{B}_T = N_T^{-1}(N_0 \bar{B}_0 + X'X\hat{B})$,
$S_T = \frac{v_0}{v_T} S_0 + \frac{T}{v_T}\hat{\Sigma} + \frac{1}{v_T}(\hat{B} - \bar{B}_0)' N_0 N_T^{-1} X'X(\hat{B} - \bar{B}_0)$, $\hat{B} = (X'X)^{-1}X'Y$,
and $\hat{\Sigma} = (Y - X\hat{B})'(Y - X\hat{B})/T$.

I follow the sign restrictions literature and use a weak prior, i.e., $v_0 = 0$, $N_0 = 0$, and arbitrary S_0 and $\bar{B}_0$. This implies that the prior distribution is proportional to $|\Sigma|^{-(k+1)/2}$ and that $v_T =$

T, $S_T = \hat{\Sigma}$, $\bar{B}_T = \hat{B}$, and $N_T = X'X$. Thus, the posterior simulator for B and Σ can be described as follows:

1. Draw Σ from an $IW_k(T\hat{\Sigma}, T)$ distribution.
2. Draw B from the conditional distribution $MN(\hat{B}, \Sigma \otimes (X'X)^{-1})$.
3. Repeat steps 1 and 2 a large number of times and collect the drawn B's and Σ's.

Once I have these draws at hand, I compute the standardized credit supply shock, which is the standardized residual from the first equation of the VAR (i.e., $\frac{\hat{u}_{1,t}}{\sqrt{\Sigma_{1,1}}}$) and feed it into the estimation of Equation (8), as described next.

Estimation of Equation (8). Drawing on the notation from the bottom of Page 15 of the paper, let the set of the parameters (coefficients matrix and residual standard deviation) to be estimated from Equation (8) be given by Q_h and $\sigma_{\epsilon,h}$. Equation (B.3) can then be written in companion form as follows:

$$Y_{i,h} = X_{i,h}Q_{i,h} + \zeta_{i,h}, \tag{A.6}$$

where $i = 1, ..., I$, indexing firms with $I = 2037$ for the capital misallocation channel analysis and firm size categories with $I = 6$ for the labor misallocation channel analysis; h is the regression's rolling horizon with $h = 1, ..., 20$; $Y_{i,h} = [y_{i,h} - y_{i,0}, y_{i,h+1} - y_{i,1}, ..., y_{i,T} - y_{i,T-h-1}]'$, with T being the time dimension of the sample; $X_{i,h} = [X_{i,1}, ..., X_{i,T-h}]'$, with $X_{i,t} = [\hat{u}_{i,1,t}, 1]'$;[1] $Q_h = [\Xi_{1,h}, ..., \Xi_{I,h}, \gamma_{1,h}, ..., \gamma_{I,h}]'$; and $\zeta_{i,h} = [\epsilon_{i,p-1+h}, ..., \epsilon_T]'$. Q_h here represents the coefficient matrix of Equation (8) from the paper and $\sigma^2_{\epsilon,h}$ is the variance of $\epsilon_{i,t+h}$.

I assume the following normal-inverse Wishart prior distribution for these parameters:

$$vec(Q_h) \mid \sigma^2_{\epsilon,h} \sim N(vec(\bar{Q}_{0,h}), \sigma^2_{\epsilon,h} \times N_0^{-1}), \tag{A.7}$$

$$\sigma^2_{\epsilon,h} \sim IW_k(v_0 S_{0,h}, v_0), \tag{A.8}$$

[1] Note that $\hat{u}_{i,1,t}$, which is denoting the credit supply shock series, is identical across the different i's. Nevertheless, keeping with the cross-sectional based notation is still of value here so as to remain consistent with the cross-sectional nature of the outcome variable and the fixed effects.

where N_0 is a $2(1+I)$ x $2(1+I)$ positive definite matrix; S_0 is a variance scalar; and $v_o > 0$. As shown by Uhlig (1994), the latter prior implies the following posterior distribution:

$$vec(Q_h) \mid \sigma^2_{\epsilon,h} \sim N(vec(\bar{Q}_h), \sigma^2_{\epsilon,h} \times N_h^{-1}), \tag{A.9}$$

$$\sigma^2_{\epsilon,h} \sim IW_k(v_h S_h, v_h), \tag{A.10}$$

where $v_h = I \times (T-h) + v_0$; $N_h = N_0 + \sum_i X'_{i,h} X_{i,h}$; $\bar{Q}_h = N_h^{-1}(N_0 \bar{Q}_{0,h} + \sum_i X'_{i,h} X_{i,h} \hat{Q}_h)$; $S_h = \frac{v_0}{v} S_{0,h} + \frac{I\times(T-h+1)}{v_h}\hat{\sigma}^2_{\epsilon,h} + \frac{1}{v_h}(\hat{Q}_h - \bar{Q}_{0,h})' N_0 N_h^{-1} \sum_i X'_{i,h} X_{i,h}(\hat{Q}_h - \bar{Q}_{0,h})$, where $\hat{Q}_h = (\sum_i X'_{i,h} X_{i,h})^{-1} (\sum_i X_{i,h})' Y$ and $\hat{\sigma}^2_{\epsilon,h} = \sum_i (Y_{i,h} - X_{i,h}\hat{Q}_h)'(Y_{i,h} - X_{i,h}\hat{Q}_h)/(I \times (T-h))$.

I use a weak prior, i.e., $v_0 = 0$, $N_0 = 0$, and arbitrary $S_{0,h}$ and $\bar{Q}_{0,h}$. This implies that the prior distribution is proportional to $\sigma^2_{\epsilon,h}$ and that $v_h = I \times (T-h)$, $S_h = \hat{\sigma}^2_{\epsilon,h}$, $\bar{Q}_h = \hat{Q}_h$, and $N_h = \sum_i X'_{i,h} X_{i,h}$. Due to the spatial and temporal correlations of the error term $u_{i,t+h}$, the likelihood function is misspecified which in turn requires that the residual variance estimate $\hat{\sigma}^2_{\epsilon,h}$ be appropriately modified so as to improve estimation precision (Müller (2013)). Toward this end, I apply a correction to $\hat{\sigma}^2_{\epsilon,h}$ based on Driscoll and Kraay (1998) which accounts for arbitrary spatial and temporal correlations of the error term and denote the corrected variance estimate by $\hat{\sigma}^2_{\epsilon,h,hac}$.[2]

We are now in position to lay out the posterior simulator for Q_h and $\sigma^2_{\epsilon,h}$, which accounts for uncertainty in the estimation of the credit supply shock series $\hat{u}_{1,t}$ and can be described as follows:

1. Do Steps 1-3 from the posterior simulator of the VAR given by System (7) and obtain $\hat{u}_{1,t}$ (whose standardized raw value is to be used as explanatory variables for the next two steps).

2. Draw $\sigma^2_{\epsilon,h}$ from an $IW_k(I \times (T-h+1)\hat{\sigma}^2_{\epsilon,h,hac}, I \times (T-h+1))$ distribution.

3. Draw Q_h from the conditional distribution $MN(\hat{Q}_h, \sigma^2_{\epsilon,h} \times \sum_i (X'_{i,h} X_{i,h})^{-1})$.

4. Repeat Steps 1-3 a large number of times and collect the drawn Q_h's and $\sigma^2_{\epsilon,h}$'s. (The Q_h's can then be used to construct the posterior distribution of firm-level real capital stock impulse responses and firm size category employment impulse responses, which in turn also facilitates forming the posterior distribution of the estimated capital-and labor-misallocation-induced TFP change from Decomposition (4) of the paper.)

[2] To facilitate the computation of this correction for the capital misallocation channel analysis, I apply it at the industry level ((based on SIC 4-digit classification code)).

Appendix B Robustness Checks: Top-Down Approach

This section examines the robustness of the baseline top-down results from the paper along eight dimensions.[3] 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. The fourth regards the robustness of the results to alternative credit supply shock identification approaches. The fifth and sixth consider estimations of a proxy-VAR and a time-varying parameter VAR. The seventh allows for sign-dependency in impulse responses and the eight considers CPI in levels in the VAR. In all of these exercises I find the baseline result of a weak and short-lived TFP response to credit supply shock to remain intact.

B.1 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 (6) from the paper, the observables ought to be capable of perfectly forecasting any unobserved 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

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

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.[4] 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 B.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 B.1 also reports the R^2s associated with each regression in line with the important message from Beaudry et al. (2019) 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. (2019) 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.

B.2 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 B.1a and B.1b, which correspond to Figures 1a and 1b from the paper except that now the sample starts in 1983:Q1, show the impulse responses and FEV contributions from this estimation. It is apparent that 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

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

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.

B.3 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 likely 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 B.2a and B.2b, which correspond to Figures 1a and 1b from the paper 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 baseline top-down analysis 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.

B.4 Alternative Credit Supply Shock Identification

I consider five alternative credit supply shock series relative to the baseline analysis. The first is obtained from a different ordering of the variables in the baseline VAR and the remaining four are all obtained as the reduced form VAR innovations in the following credit supply shock series from Mumtaz et al. (2018) (each replacing EBP in the baseline VAR and standardized to have zero mean and unit variance):[5] the measure of bank lending shocks (BCDZ) calculated by Bassett et al. (2014), covering 1992:Q1-2010:Q4; the innovations to the financial conditions index (JQ) calculated by Jermann and Quadrini (2012), covering 1984:Q2-2010Q2; the risk shock (CMR) from the DSGE model of Christiano et al. (2014), covering 1981:Q1-2010:Q1; and a textual measure of credit supply shocks (MPT) developed by Mumtaz et al. (2018) that is based on a search for the words "credit crunch" and "tight credit" using nine U.S. newspapers, covering 1980:Q1-2012:Q4.

Gilchrist and Zakrajšek (2012)'s Cholesky Ordering. As discussed in Footnote 10 from the paper, I ordered EBP first in my baseline VAR, rather than fifth (after output, consumption, investment, and inflation) as in Gilchrist and Zakrajšek (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 Zakrajšek (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 B.3a and B.3b, which correspond to Figures 1a and 1b from the paper except that now the Cholesky ordering from Gilchrist and Zakrajšek (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 from the baseline VAR is robust to using the alternative Cholesky ordering employed in Gilchrist and Zakrajšek (2012) for the identification of credit supply shocks.

Shocks to the BCDZ Series. The results from the VAR in which the BCDZ series replaces EBP are presented in Figures B.4a and B.4b, which correspond to Figures 1a and 1b from the paper except that now the identified credit supply shocks are innovations in the BCDZ Series rather

[5]Increases in all series except the JQ shock series can be interpreted as adverse credit supply shocks; the JQ series is multiplied by -1 so that an increase in this series can be interpreted as an adverse credit supply shock.

than EBP. While the BCDZ shock causes a significant decline in the real aggregates, its effect on TFP is insignificant at all horizons thereby continuing to support the main result from the baseline VAR.

Shocks to the JQ Series. The results from the VAR in which the JQ series replaces EBP are presented in Figures B.5a and B.5b, which correspond to Figures 1a and 1b from the paper except that now the identified credit supply shocks are innovations in the JQ Series rather than EBP.

The JQ shock induces a large decline in output which peaks at -0.41% after 4 quarters and corresponds to a peak FEV share contribution of 63% at the 2nd horizon. This may point to this shock possibly capturing other shocks on top of credit supply ones. This notwithstanding, the JQ shock produces a very short-lived significant effect on TFP which takes place contemporaneously with a -0.39% decline but thereafter this effects becomes insignificant. That the TFP decline is significant only for the impact quarter is consistent with the main result of the baseline VAR regarding the very initial and temporary decline in TFP following credit supply shocks.

Shocks to the CMR Series. The results from the VAR in which the CMR series replaces EBP are presented in Figures B.6a and B.6b, which correspond to Figures 1a and 1b from the paper except that now the identified credit supply shocks are innovations in the CMR Series rather than EBP. The results from the CMR shock are also consistent with the main message from the baseline VAR, with TFP responding insignificantly at all horizons.

Shocks to the MPT Series. The results from the VAR in which the MPT series replaces EBP are presented in Figures B.7a and B.7b, which correspond to Figures 1a and 1b from the paper except that now the identified credit supply shocks are innovations in the MPT Series rather than EBP. The only horizon at which TFP responds significantly to the credit supply shock is the last one, with a modest decline of -0.16%. The insignificant decline in TFP at business cycle frequencies continues to support the main claim of this paper of a weak TFP response to credit supply shocks.

B.5 Proxy SVAR

The discussion at the bottom of Page 7 and associated Footnote 7 from the paper make the case that my baseline specification is a more valid and robust identification approach than the proxy SVAR approach. Nevertheless, to further enhance the reliability of my baseline results, it is worthwhile to provide results from a proxy SVAR which uses EBP as an external instrument for credit supply shocks.[6]

The results from this exercise are presented in Figures B.8a and B.8b, which correspond to Figures 1a and 1b from the paper except that now a proxy SVAR is estimated with EBP serving as the proxy (instrument) for credit supply shocks. It is apparent that credit supply shocks continue to have a limited, very short-lived effect on TFP (there is a significant effect on TFP of -0.18% only in the second quarter), with correspondingly low contributions to the business cycle variation in TFP. Hence, we can infer from this exercise that the main result from the baseline VAR is robust to estimating a proxy SVAR.

B.6 Time-Varying Parameter VAR

Sections B.2 and B.3 demonstrated the robustness of the baseline results to sub-samples omitting pre-1983 and post-2007:Q3 observations, respectively, thus alleviating the concern that the baseline results are driven by sub-sample instability. Nevertheless, one can still argue that such instability may still be a problem if it is continuously present throughout the sample rather than at the discrete sample break points covered by the analysis from Sections B.2 and B.3. A specific concern is that credit supply shocks could induce effects that vary over the business cycle, i.e., being different across the different recessions and expansions covering my sample.

[6] Since the proxy SVAR model implies a reduced form block recursive framework in which the endogenous variables are functions of own lags and current lagged values of the proxy variables with the latter being exogenous (at most being each a function of its own lags), I implement this estimation exercise by applying 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. In my case, I only have two blocks, where the first consists of a single equation in which EBP depends on its own lags, and the second block contains a seven equation VAR for the remaining variables in which EBP 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.

To address this issue, this section provides results from estimating a time-varying parameter VAR (TVP-VAR) which allows for both time-varying coefficients and time-varying variance covariance matrix of reduced form innovations. I follow Primiceri (2005)'s specification and Bayesian estimation algorithm,[7] where the VAR's reduced form coefficients are modeled as random walks and the innovations' variance covariance matrix is modeled in a multivariate stochastic volatility framework. To facilitate estimation, I include three variables in the TVP-VAR: EBP, TFP, and output. The credit supply shock is identified as in the baseline approach, i.e., as the reduced form innovation of EBP, only that now both its standard deviation and its dynamic effects on the other variables are allowed to vary over time.

The results from this exercise are shown in Figures B.9a and B.9b, where median and 95% posterior bands of impulse responses to a one standard deviation credit supply shock are shown for expansions and recessions, respectively. Given my 10-year training sample and 4 lags included in the TVP-VAR (see Footnote 7), the first quarter I can estimate the impulse responses for is 1984:Q1. Hence, the expansionary quarters I consider are 1986:Q3, 1996:Q1, 2004:Q4, and 2013:Q3 whereas the recessionary quarters are 1990:Q4, 2001:Q3, and 2008:Q3. The expansionary quarters are chosen as the middle periods between the end of the recession preceding the corresponding expansion and the beginning of the subsequent recession while the recessionary quarters are chosen as the middle periods between the beginning and ending quarters of the recessions. (Expansion and recession dates are based on NBER dating.)

It is apparent from both figures that credit supply shocks have a weak effect on TFP with at all considered quarters. In fact, the effect on TFP is insignificant at all considered horizons for all considered time periods, including the 2008:Q3 period which corresponds to the Great Recession and for which the effect on output is the most significant. Hence, we can infer from this exercise that the main result from the baseline VAR is robust to estimating a TVP-VAR.

[7] I account for the corrigendum to this algorithm described in Del Negro and Primiceri (2015), using the codes from Dimitris Korobilis's webpage https://sites.google.com/site/dimitriskorobilis/matlab/code-for-vars. I specify the TVP-VAR with 4 lags and use 2000 posterior draws and a burn-in period of 500 for the estimation, with a training sample of ten years.

B.7 Accounting for Sign-Dependency of Impulse Responses

An additional concern regarding the baseline analysis is that the linearity assumption underlying it may mask meaningful asymmetry in the response of TFP to adverse versus favorable credit supply shocks. In other words, the weak TFP channel of credit supply shocks that the baseline analysis captures may be the *average* of a very strong TFP channel of adverse (favorable) credit shocks and a very weak or null channel of favorable (adverse) shocks. It is therefore worthwhile to estimate the sign-dependent impulse responses of TFP to credit supply shocks and account for potential asymmetry in the TFP channel of credit supply shocks.

Toward this end, I perform a Bayesian estimation procedure which proceeds in three steps. First, I regress EBP on lags of its raw values and squared values, lags of raw and squared values of the log-first difference of TFP, and all possible interactions of the lagged products of EBP and the log-first difference of TFP.[8] Second, I regress the residual from the first step on its squared value and take the standardized residual from this regression to be the credit supply shock series. The second estimation step is meant to ensure that any contemporaneous, exogenous sign-dependent mechanism (as reflected in terms of squared values of the true credit supply shock present in the EBP innovation) linking the credit supply shock and its associated fundamental (i.e., EBP) is not biasing my identified shock series.[9] Indeed, the coefficient from the regression of the second step

[8]The objective of the first step is to be as internally consistent as possible with this section's overall objective of identifying the sign-dependent effects of credit supply shocks, thus leading me to specify a second-order fully nonlinear EBP process in lagged EBP and TFP growth. The inclusion of TFP in levels in the baseline VAR accords with the baseline analysis' choice to estimate a levels VAR that is in turn robust to possible cointegration among the various non-stationary variables included in the baseline VAR (with such levels VARs well known to lead to good shock identification). However, here this cointegration issue does not play a role given the exclusion of all the other non-stationary variables from the specification as well as the stationarity of EBP which in turn dictates specifying TFP in stationary form. It is also noteworthy that my choice to only have two variables in the nonlinear specification stems from needing to preserve a reasonable number of degrees of freedom for the facilitation of estimation.

[9]A basic litmus test for the ability of the second step to truly capture the effect of the squared value of the true shock, as opposed to just erroneously pick up a potentially non-zero skewness of the true shock, is that the EBP response asymmetries from an estimation procedure that includes and excludes the second step are similar to one another. The reason for the validity of this litmus test is that an estimation that excludes the second step, while not able to identify the true shock series in the presence of true contemporaneous response asymmetry in EBP, is still able to identify the response asymmetry itself with this ability being robust to the distributional asymmetry of the true shock. Importantly, I have confirmed that such similarity is borne out by the data, indicating that the second estimation step is likely to do a good job of purging the residual from the first step and getting at the true shock as opposed to merely picking up a potentially non-zero skewness of the true shock.

is significantly positive, indicating that there appears to be such contemporaneous mechanism; in accordance with this, the contemporaneous response of EBP to a positive shock is significantly larger than the corresponding response to a negative shock. Third, I estimate local projection regressions á la Jorda (2005) of TFP[10] on current raw and squared values of the extracted shock series from the second step and construct impulse responses to positive and negative shocks from the first- and second-order polynomial coefficients.[11]

The econometric framework just described can be formally presented with the following three-equation system:

$$\begin{aligned} EBP_t &= C + \Gamma_1^{EBP} EBP_{t-1} + \Psi_1^{EBP} EBP_{t-1}^2 + ... + \Gamma_4^{EBP} FBP_{t-p} + \Psi_4^{EBP} EBP_{t-4}^2 + \quad \text{(B.1)} \\ &+ \Gamma_1^{TFP} \Delta TFP_{t-1} + \Psi_1^{TFP} \Delta TFP_{t-1}^2 + ... + \Gamma_4^{TFP} \Delta TFP_{t-1} + \Psi_4^{TFP} \Delta TFP_{t-1}^2 + \\ &+ \sum_{i=1}^{4} \sum_{j=1}^{4} \Omega_{i,j} EBP_{t-i} \Delta TFP_{t-j} + \epsilon_t, \end{aligned}$$

$$\hat{\epsilon}_t = \delta + \gamma \hat{\epsilon}_t^2 + \xi_t, \tag{B.2}$$

$$TFP_{t+h} - TFP_{t-1} = \alpha_h + \Xi_h \hat{\xi}_t + \Phi_h \hat{\xi}_t^2 + u_{t+h}, \tag{B.3}$$

where C is a constant; Γ_i^j and Ψ_i^j are scalar coefficients on raw and squared values of EBP and log-first-difference of TFP (with $j = EBP, TFP$); $\Omega_{i,j}$ is a scalar coefficient on the interaction (product) between EBP at lag i and log-first-difference of TFP at lag j; ϵ_t is the true residual from Equation (B.1) whose standard deviation is denoted by σ_1; $\hat{\epsilon}_t$ is the estimated residual from Equation (B.1) and ξ_t is the true residual (i.e., true credit supply shock) from Equation (B.2) whose standard deviation is denoted by σ_2, with δ the constant of this equation and γ the coefficient on the squared value of ϵ_t; the LHS of Equation (B.3) is the log-cumulative-difference of TFP from $t-1$ to $t+h$;[12] α_h is a constant; $\hat{\xi}_t$ is the estimated residual (credit supply shock) from Equation (B.2), normalized

[10] While TFP is my central variable of interest, for completeness I also consider the other seven variables from the baseline VAR.

[11] Ben Zeev (2020) has shown that this approach to estimating impulse response sign-dependency does a better job of identifying the true response asymmetry than dichotomously regressing the outcome variable on separate series of only positive and only negative credit supply shock realizations.

[12] Logged TFP is entered in cumulative differences so as to remove any potential stochastic trends and thus make the data stationary, which is necessary for validating the local projections estimation and inference approach undertaken here (also see Footnote 12 in the paper from the bottom-up estimation approach). For completeness, I also show results for the other seven variables from the baseline VAR of this paper, taking in raw form the incontrovertibly stationary EBP and inflation variables, while taking in cumulative difference form the other variables.

to have unit variance by dividing it by σ_2; Ξ_h and Φ_h are the first- and second-order effects of the credit supply shock, where $\Xi_h + \Phi_h$ and $\Xi_h - \Phi_h$ give the responses of the outcome variable at period h to a positive and negative one standard deviation credit supply shock at time t, respectively; and u_{t+h} is the residual of Equation (B.3) with standard deviation $\sigma_{3,h}$. For future reference, let the stacked 33x1 $B^1 = [\Gamma_1^{EBP}, \Psi_1^{EBP}, \Gamma_1^{TFP}, \Psi_1^{TFP}, ..., \Gamma_p^{FBP}, \Psi_p^{FBP}, \Gamma_p^{SP}, \Psi_p^{SP}, \Omega_{i,1}{}_{i=1}^4, ..., \Omega_{i,4}{}_{i=1}^4, C]'$ matrix and 2x1 $B^2 = [\gamma, \delta]'$ matrix represent the coefficient matrices from Equations (B.1) and (B.2), respectively, such that B^1 and σ_1 and B^2 and σ_2 correspond to the parameters to be estimated from these two equations.

I estimate Equations (B.1), (B.2), and (B.3) jointly by applying the Bayesian estimation algorithm for strong block-recursive structure put forward by Zha (1999) in the context of block-recursive VARs, where the likelihood function is broken into the different recursive blocks. In my case, I have only two blocks, where the first consists of Equation (B.1) and Equation (B.2) and can be estimated via a two-step procedure explained below on Page 13 and the second corresponds to Equation (B.3). As shown in Zha (1999), this kind of block separation along with the standard assumption of a normal-inverse Wishart conjugate prior structure leads to a normal-inverse Wishart posterior distribution for the block-recursive Equation parameters.

Specifically, considering that the number of RHS variables in Equation (B.3) is 3 (raw and squared shock and the constant), let the stacked 3x1 coefficient matrix $Q_h = [\Xi_h, \Phi_h, \alpha_h]'$ represent the coefficients from Equation (B.3). Moreover, let $\sigma_{3,h}$ represent the standard deviation of the residual from Equation (B.3) at each horizon h. Hence, the parameters to be estimated from Equation (B.3) can be summarized by the coefficient matrix Q_h and residual variance $\sigma_{3,h}$. I assume a diffuse normal-inverse Wishart prior distribution for both $[B^1, \sigma_1, B^2, \sigma_2]$ and $[Q_h, \sigma_{3,h}]$; this conjugate prior structure coupled with the assumption of a Gaussian likelihood for the data sample imply a posterior density of these parameters that is also distributed as a normal-inverse Wishart. Following the suggestion from Müller (2013) to increase estimation precision in the presence of a misspecified likelihood function (as in my setting owing to the temporal correlation in u_{t+h}), I apply a Newey-West correction to $\sigma_{3,h}$ which accounts for arbitrary temporal correlations of the error term.

Operationally, for each posterior draw of the coefficients from Equation (B.1), I collect the estimated residual from this equation ($\hat{\epsilon}_t$) and use its raw and squared values as the outcome and explanatory variables in Equation (B.2), respectively, to form a posterior distribution of δ and γ conditional on $\hat{\epsilon}_t$. I then take a posterior draw of δ and γ and obtain $\hat{\xi}_t$, subsequently using its raw and squared values (converting it to unit standard deviation units by dividing $\hat{\xi}_t$ by σ_2) in Equation (B.3) to form a posterior distribution for Ξ_h and Φ_h. I then take a posterior draw of these coefficients and estimate the sign-dependent response of each outcome variable (TFP as well as, for the sake of completeness, the other seven variables from the baseline VAR of this paper) at horizon h to positive and negative one standard deviation credit supply shocks as $\Xi_h + \Phi_h$ and $\Xi_h - \Phi_h$, respectively. I generate 2000 such posterior draws from which I am then able to estimate the median sign-dependent impulse responses to credit supply shocks along with their posterior confidence bands.

The results from the estimation of Equations (B.1)-(B.3) appear in Figures B.10a and B.10b, where each row of these figures shows each of the eight considered outcome variables' response to a positive and negative credit supply shock (both of one standard deviation size) as well as the difference between the positive shock's effect and the negative shock's effect.[13] Solid lines depict the median estimates of the responses while dashed line correspond to the 95% posterior confidence bands.

While the central variable of interest is TFP, it is noteworthy that the real aggregates do exhibit some asymmetry in their response to credit supply shocks in a way consistent with the view that adverse (positive) shocks drive most of the baseline linear impulse response results for these variables. This asymmetry is most pronounced for output, investment and hours, with adverse (positive) shocks lowering these variables more than the increase in these variables induced by favorable (negative) shocks (to see the actual change in the variables following a negative shock, simply multiply the second column of each Figure by -1). As discussed in Ben Zeev (2020), who looks at additional credit market variables relative to this paper's analysis, the response asymmetry in economic activity is likely also driven by asymmetry in the role of financial frictions in shock transmission and not only by the stronger response of EBP after a positive shock than its response

[13]Note that there is no need to multiply by -1 either the positive shock's effect or the negative shock's effect in Regression (B.3) for comparison purposes because the estimated responses already reflect effects that go in the same direction in the absence of asymmetry.

to a negative shock also observed here.[14]

Notwithstanding the asymmetry in real aggregates' responses, the TFP response difference across positive and negative shocks is insignificant at all horizons, with the point-wise estimate difference actually going in a direction which is opposite to that underlying the asymmetry in real aggregates' responses. In particular, adverse shocks actually *raise* TFP more at business cycle frequencies than the corresponding increase induced by favorable shocks. Be that as it may, the important result to take away from TFP's sign-dependent response for the purposes of this paper is that it is insignificant at all considered horizons for both positive and negative shocks. Therefore, we can conclude that the main result from the baseline VAR is robust to accounting for impulse response sign-dependency in that TFP does not seem to display a significant response to credit supply shocks regardless of their sign.

B.8 Including CPI in Levels in the VAR

My baseline VAR is a non-stationary VAR in the sense that it includes variables in levels form without first-differencing the non-stationary ones to obtain stationarity. The only exception is CPI, which is included in the VAR in log-first-difference form. The reason for this exception is that reduced-form solutions of DSGE models (which are in general *approximately* VARs) include the log-first-difference of CPI alongside logged real aggregates as the vector of endogenous variables that is being solved for. (And this accords with the presence of inflation, rather than the level of logged prices, in these models' structural equations.)

Nevertheless, it is worthwhile to confirm that results are robust to keeping CPI in levels in line with the keeping of the other variables in the VAR in their levels. Toward this end, I ran the estimation of the baseline VAR with logged CPI instead of with log-first-differenced CPI. The

[14] At first pass, this contemporaneous EBP response asymmetry result does not seem very sensible because EBP is the fundamental associated with credit supply shocks and we usually think of shocks as affecting their fundamental on impact in a symmetric way. This need not be necessarily the case, however, as there could be an exogenous sign-dependent mechanism by which U.S. credit markets get rattled by bad credit supply shocks more than they get frothy after good shocks of the same size. And this possibility is the reason for my including the second step in my estimation procedure involving regressing the residual from the first step on its squared value. It turns out that a significant relation is borne out by this regression, consistent with the significant contemporaneous difference between the EBP response to positive and negative credit supply shocks.

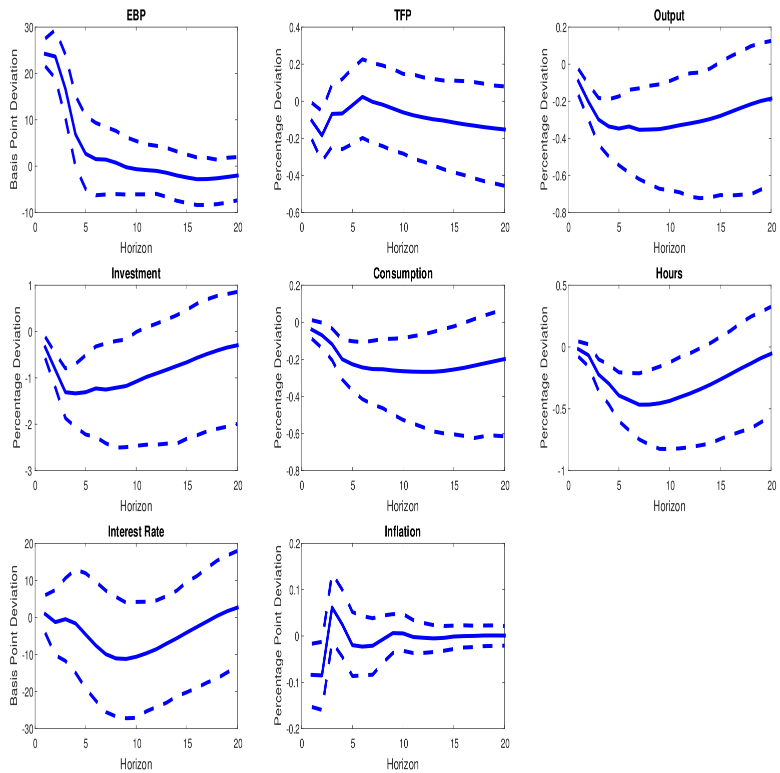
results from estimation appear in Figures B.11a and B.11b, which correspond to Figures 1a and 1b from the paper except that now as mentioned above CPI is included in log-levels form in the VAR. Clearly, the baseline results carry over to this estimation exercise, with TFP continuing to exhibit a weak and short-lived response to credit supply shocks. (And the drop in the level of prices is immediate and persistent, in accordance with the behavior of inflation in the baseline case.)

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

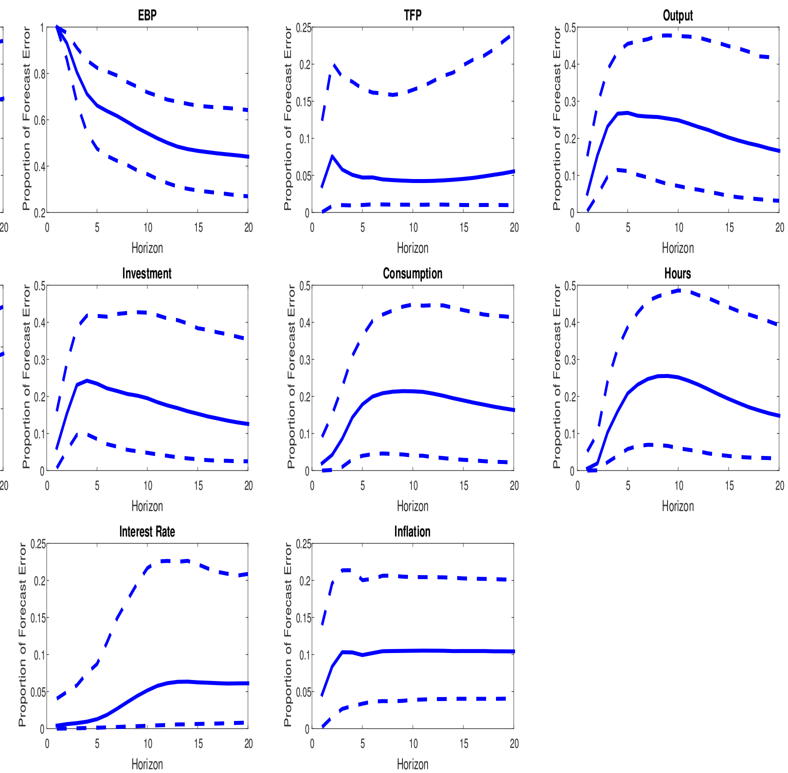
	Principal Components (from 1 to n)							
	1	2	3	4	5	6	7	8
P-Value	0.95	0.21	0.41	0.47	0.13	0.15	0.14	0.24
R^2	0	0.05	0.06	0.07	0.13	0.12	0.17	0.17

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 B.1: **Post-1982 VAR: (a) Impulse Responses; (b) Contribution to FEV**.



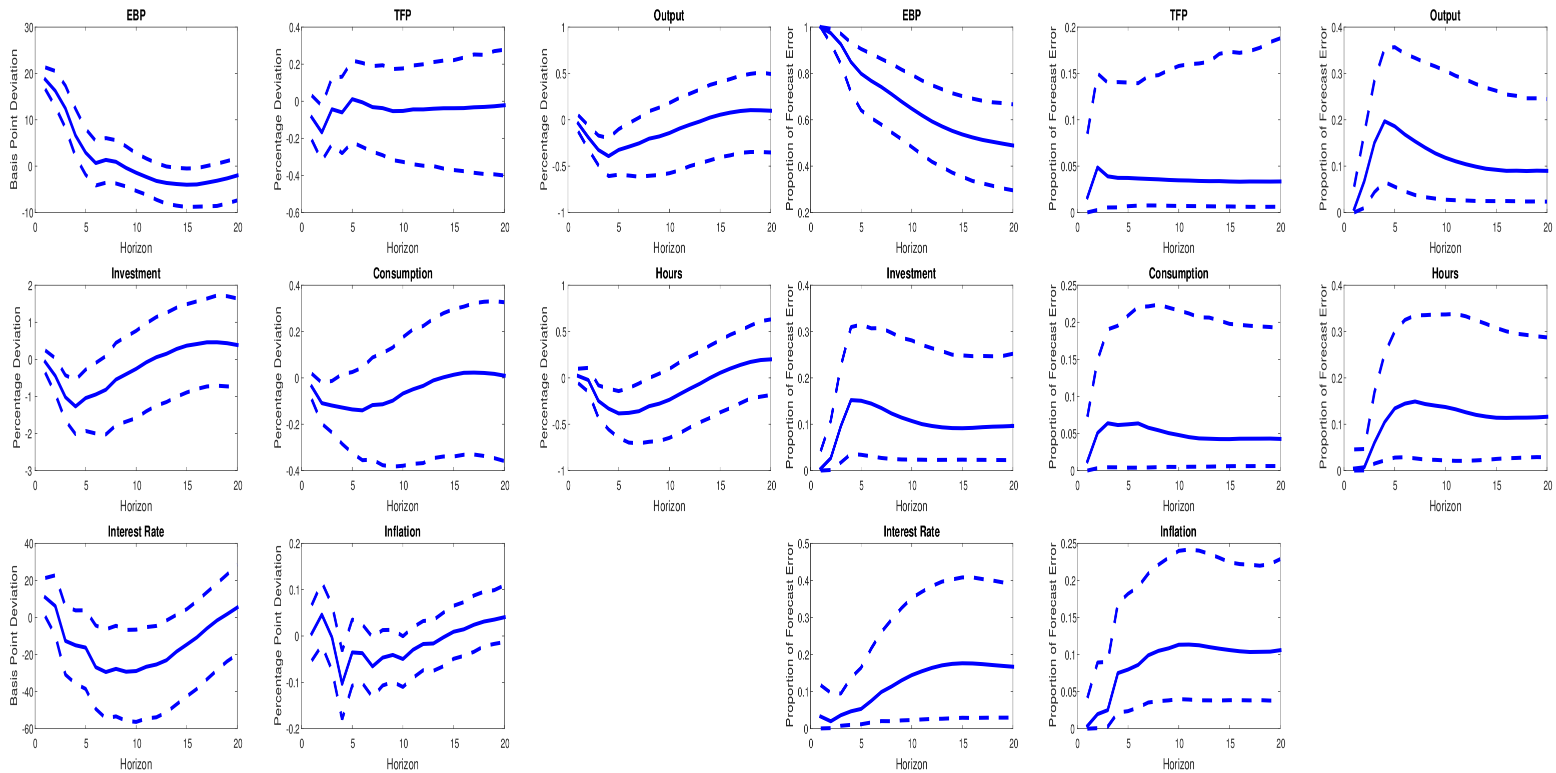
(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock.



(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shocks 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 post-1982 VAR. Responses are in terms of deviations from pre-shock values (in basis point deviation for EBP and interest rate, percentage point deviation for inflation, and percentage deviation for all other variables). Horizon is in quarters. 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. Horizon is in quarters.

Figure B.2: **Excluding the Great Recession and ZLB Periods: (a) Impulse Responses; (b) Contribution to FEV**.

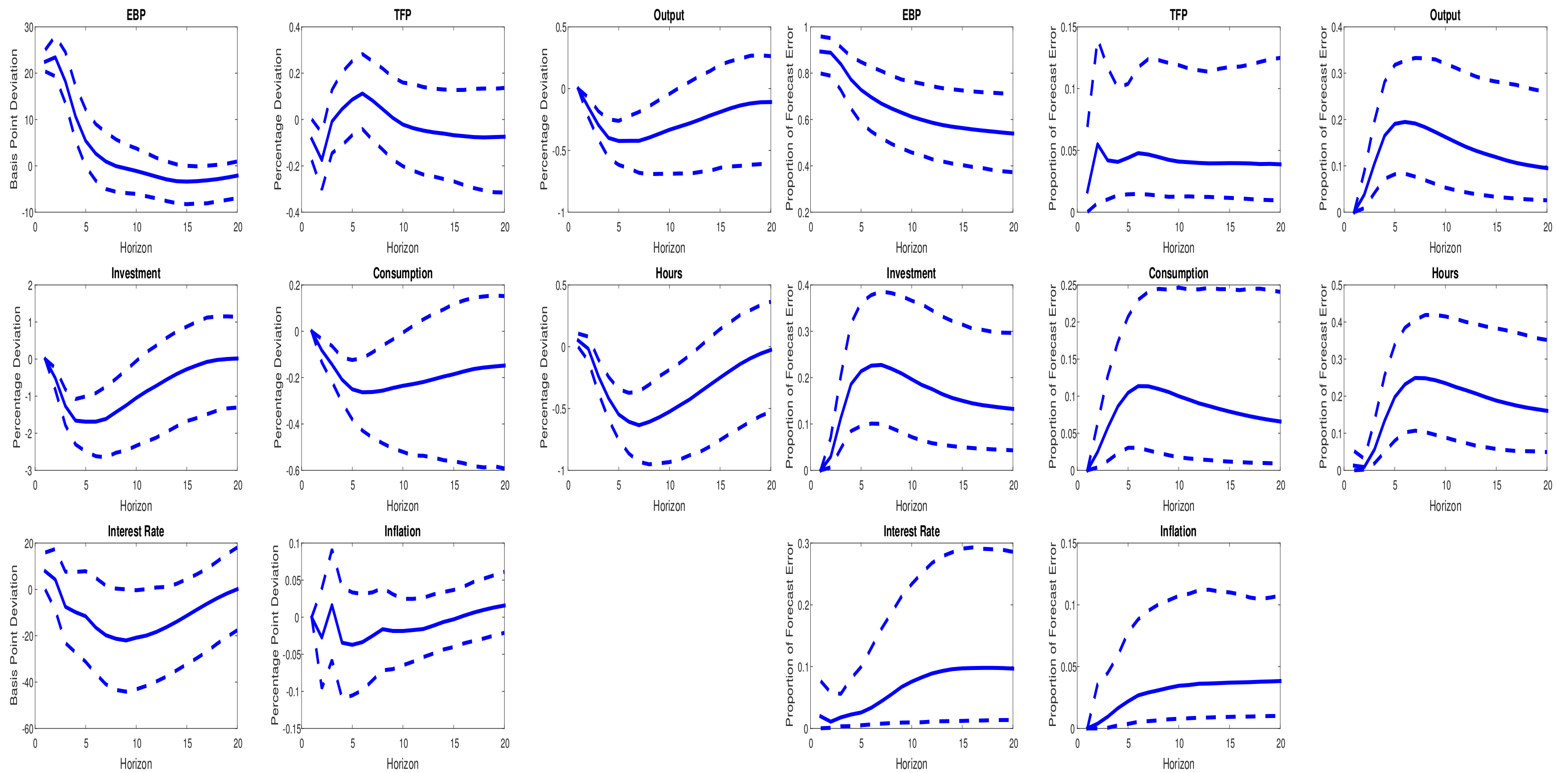


(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock.

(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. Responses are in terms of deviations from pre-shock values (in basis point deviation for EBP and interest rate, percentage point deviation for inflation, and percentage deviation for all other variables). Horizon is in quarters. 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. Horizon is in quarters.

Figure B.3: **Using the Choleky Ordering from Gilchrist and Zakrajšek (2012): (a) Impulse Responses; (b) Contribution to FEV**.

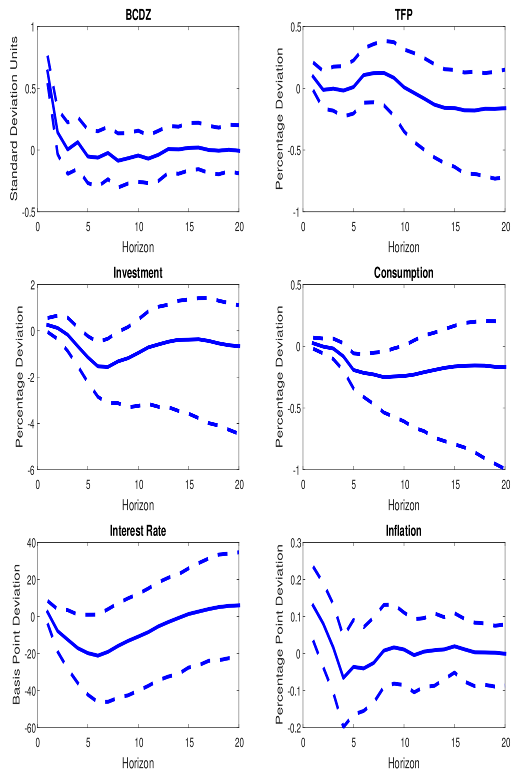


(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock.

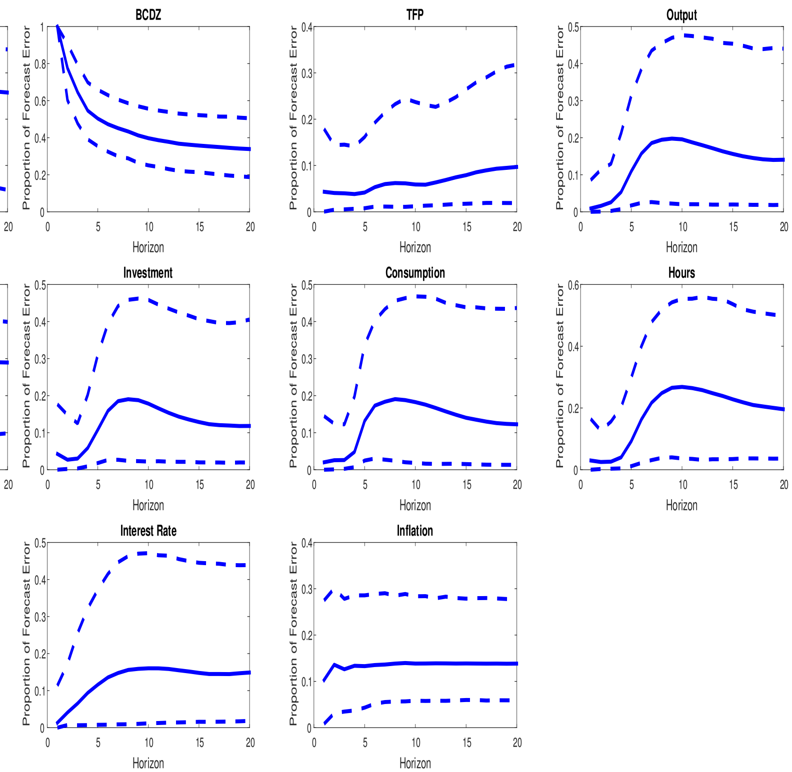
(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shocks to the Forecast Error Variance of the Variables.

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 as in Gilchrist and Zakrajšek (2012). Responses are in terms of deviations from pre-shock values (in basis point deviation for EBP and interest rate, percentage point deviation for inflation, and percentage deviation for all other variables). Horizon is in quarters. 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 as in Gilchrist and Zakrajšek (2012). Horizon is in quarters.

Figure B.4: **Credit Supply Shock from Bassett et al. (2014): (a) Impulse Responses; (b) Contribution to FEV**.



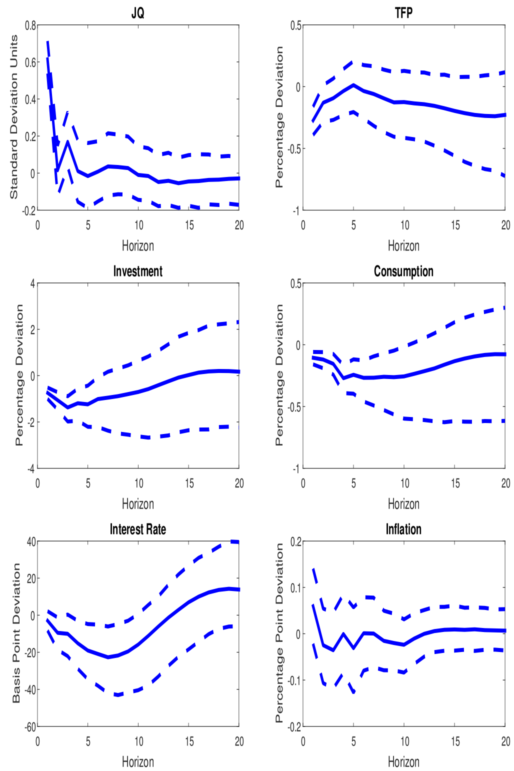
(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock.



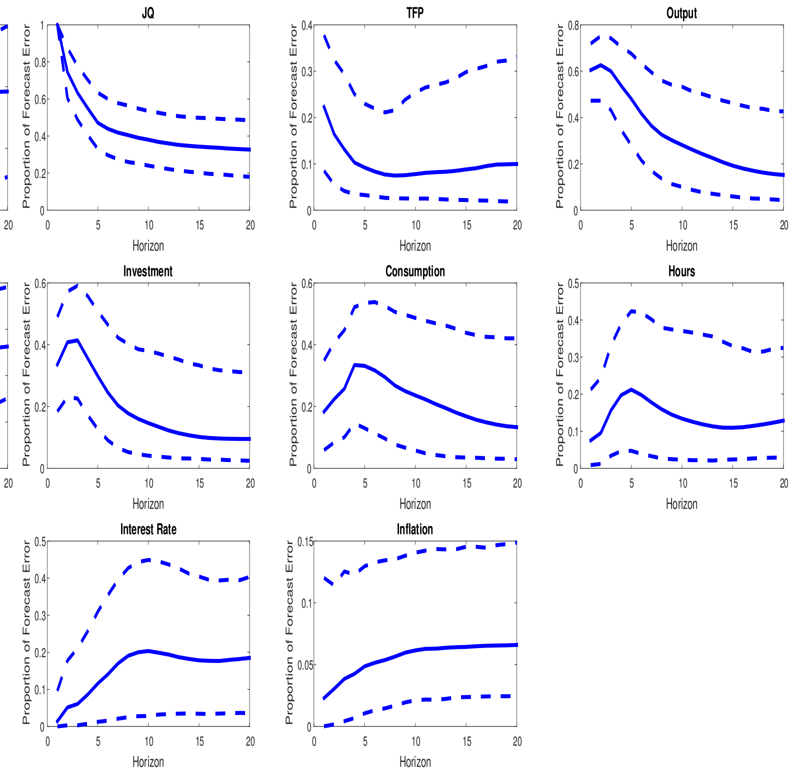
(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shocks to the Forecast Error Variance of the Variables.

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 in which EBP is replaced by the standardized measure of bank lending shocks (BCDZ) calculated by Bassett et al. (2014). Responses are in terms of deviations from pre-shock values (in standard deviation unit deviation for BCDZ, basis point deviation for interest rate, percentage point deviation for inflation, and percentage deviation for all other variables). Horizon is in quarters. 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 in which EBP is replaced by the standardized measure of bank lending shocks (BCDZ) calculated by Bassett et al. (2014). Horizon is in quarters.

Figure B.5: **Credit Supply Shock from Jermann and Quadrini (2012): (a) Impulse Responses; (b) Contribution to FEV**.



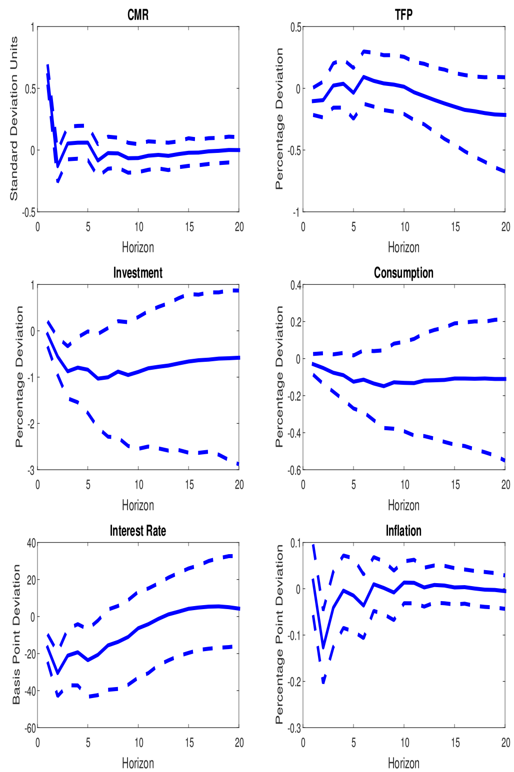
(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock.



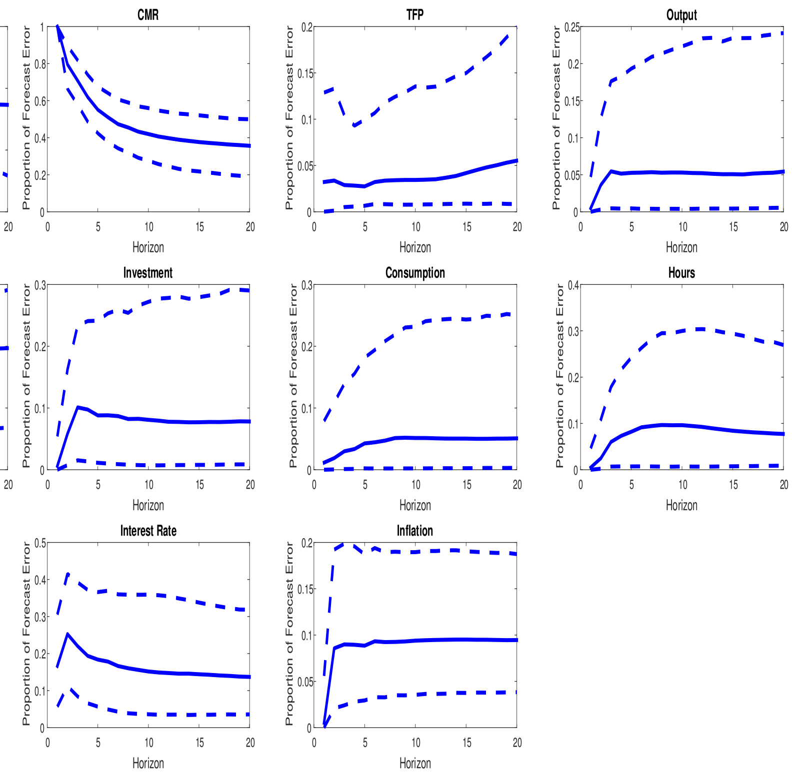
(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shocks to the Forecast Error Variance of the Variables.

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 in which EBP is replaced by the standardized innovations to the financial conditions index (JQ) calculated by Jermann and Quadrini (2012). Responses are in terms of deviations from pre-shock values (in standard deviation unit deviation for JQ, basis point deviation for interest rate, percentage point deviation for inflation, and percentage deviation for all other variables). Horizon is in quarters. 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 in which EBP is replaced by the standardized innovations to the financial conditions index (JQ) calculated by Jermann and Quadrini (2012). Horizon is in quarters.

Figure B.6: **Credit Supply Shock from Christiano et al. (2014): (a) Impulse Responses; (b) Contribution to FEV**.



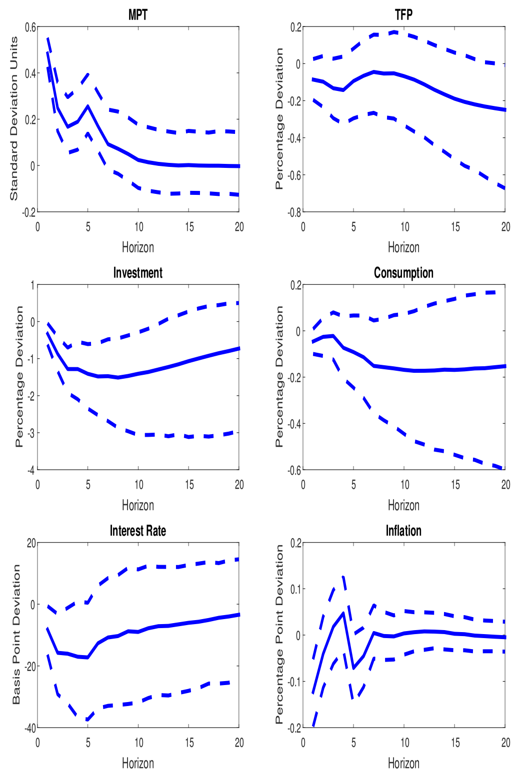
(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock.



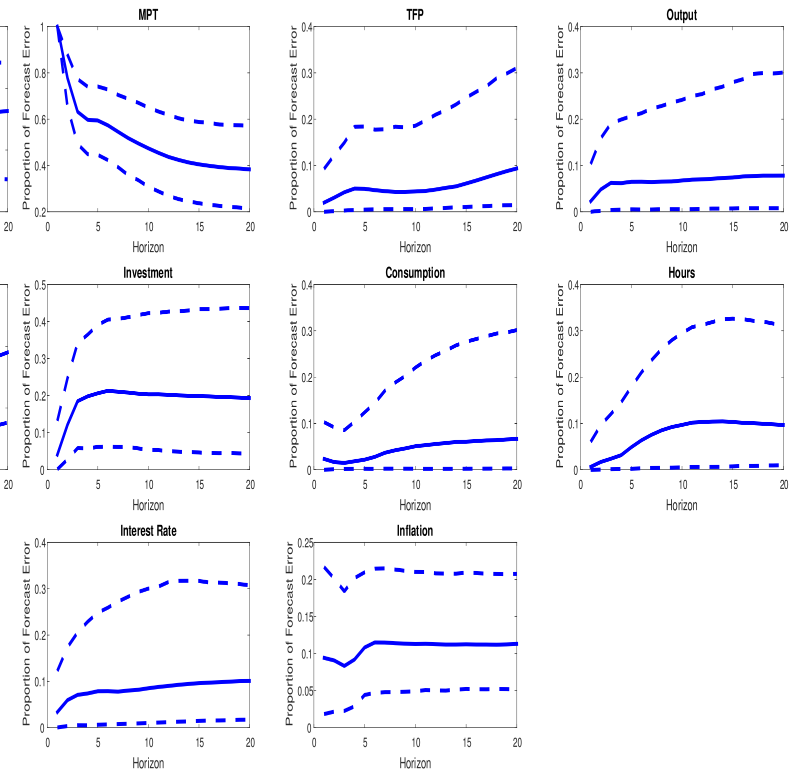
(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shocks to the Forecast Error Variance of the Variables.

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 in which EBP is replaced by the standardized risk shock (CMR) from the DSGE model of Christiano et al. (2014). Responses are in terms of deviations from pre-shock values (in standard deviation unit deviation for CMR, basis point deviation for interest rate, percentage point deviation for inflation, and percentage deviation for all other variables). Horizon is in quarters. 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 in which EBP is replaced by the standardized risk shock (CMR) from the DSGE model of Christiano et al. (2014). Horizon is in quarters.

Figure B.7: **Credit Supply Shock from Mumtaz et al. (2018): (a) Impulse Responses; (b) Contribution to FEV**.



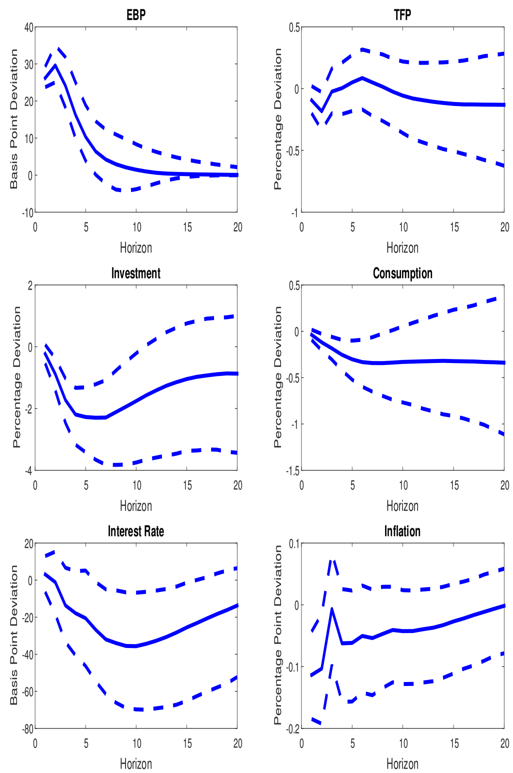
(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock.



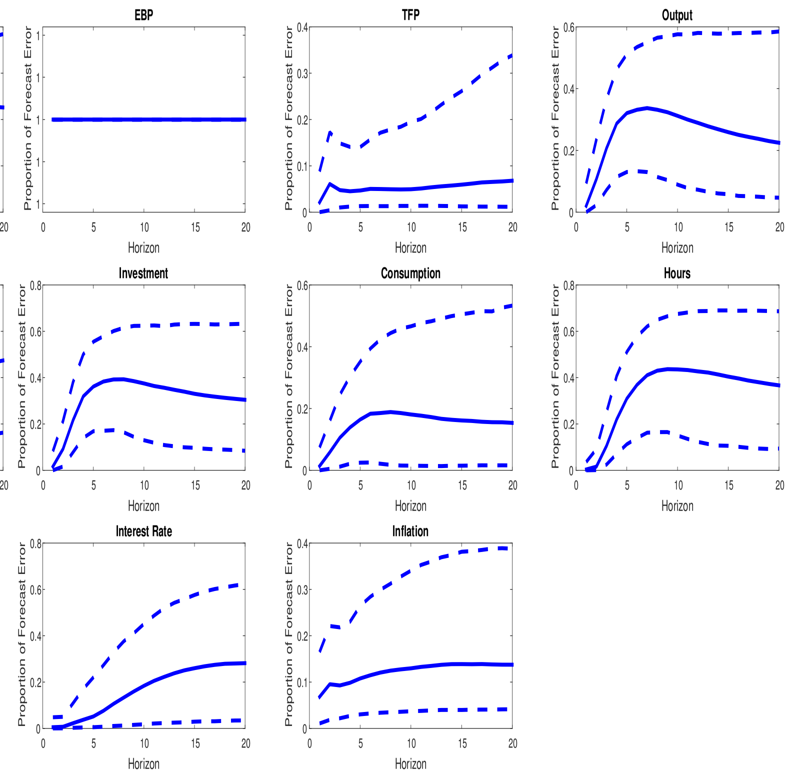
(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shocks to the Forecast Error Variance of the Variables.

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 in which EBP is replaced by the standardized textual measure of credit supply shocks (MPT) developed by Mumtaz et al. (2018). Responses are in terms of deviations from pre-shock values (in standard deviation unit deviation for MPT, basis point deviation for interest rate, percentage point deviation for inflation, and percentage deviation for all other variables). Horizon is in quarters. 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 in which EBP is replaced by the standardized textual measure of credit supply shocks (MPT) developed by Mumtaz et al. (2018). Horizon is in quarters.

Figure B.8: **Proxy SVAR: (a) Impulse Responses; (b) Contribution to FEV**.



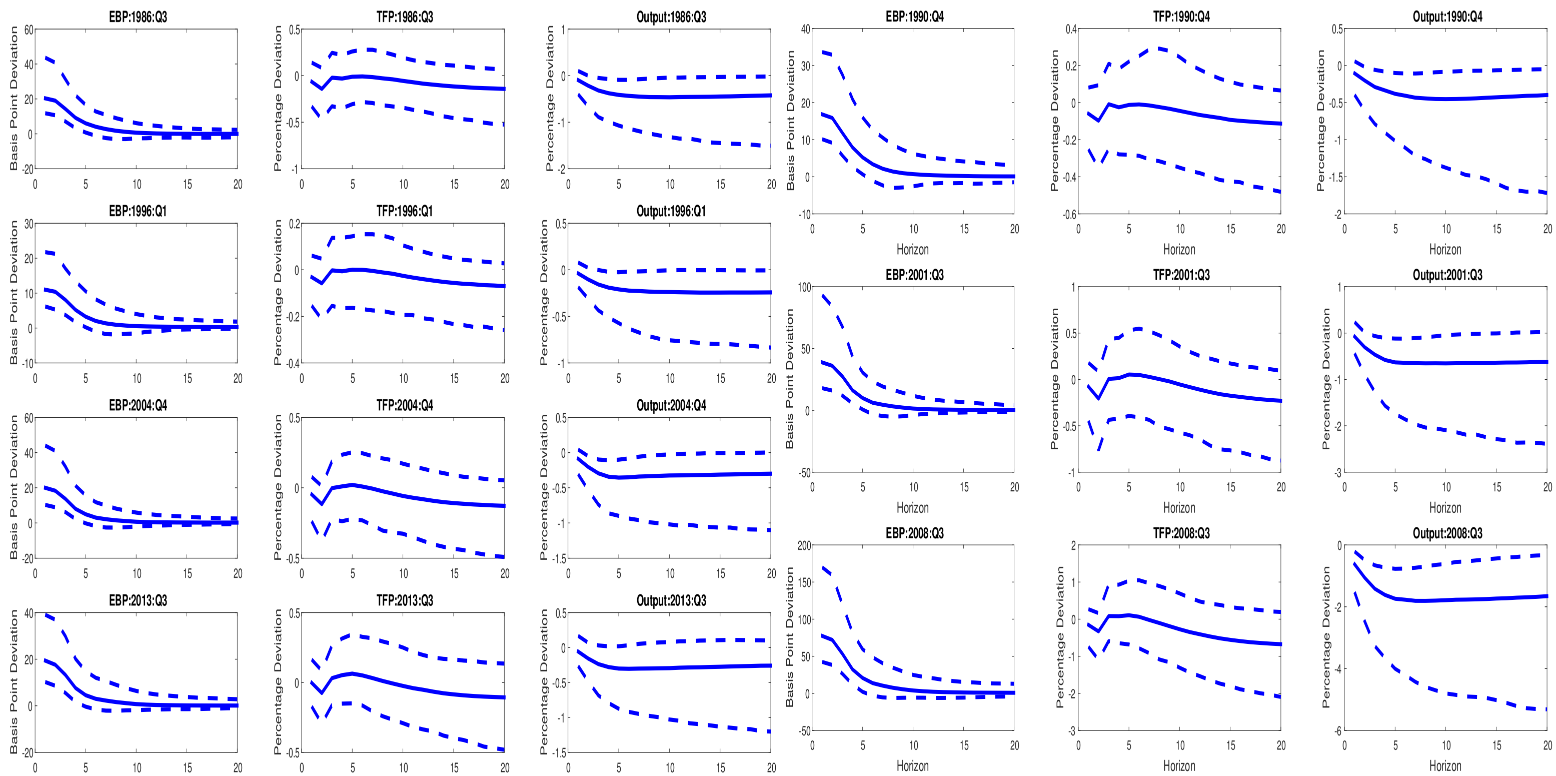
(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock.



(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shocks 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 which uses EBP as an external instrument for credit supply shocks. Responses are in terms of deviations from pre-shock values (in basis point deviation for EBP and interest rate, percentage point deviation for inflation, and percentage deviation for all other variables). Horizon is in quarters. 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 which uses EBP as an external instrument for credit supply shocks. Horizon is in quarters.

Figure B.9: **Time-Varying Parameter VAR: (a) Impulse Responses for Expansions; (b) Impulse Responses for Recessions**.

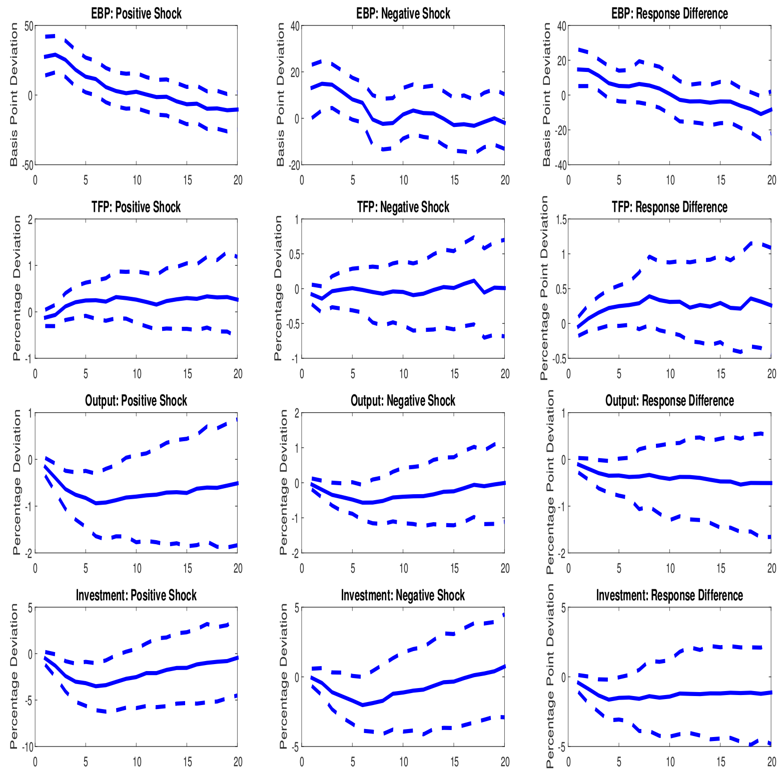


(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock for NBER-Determined Expansions.

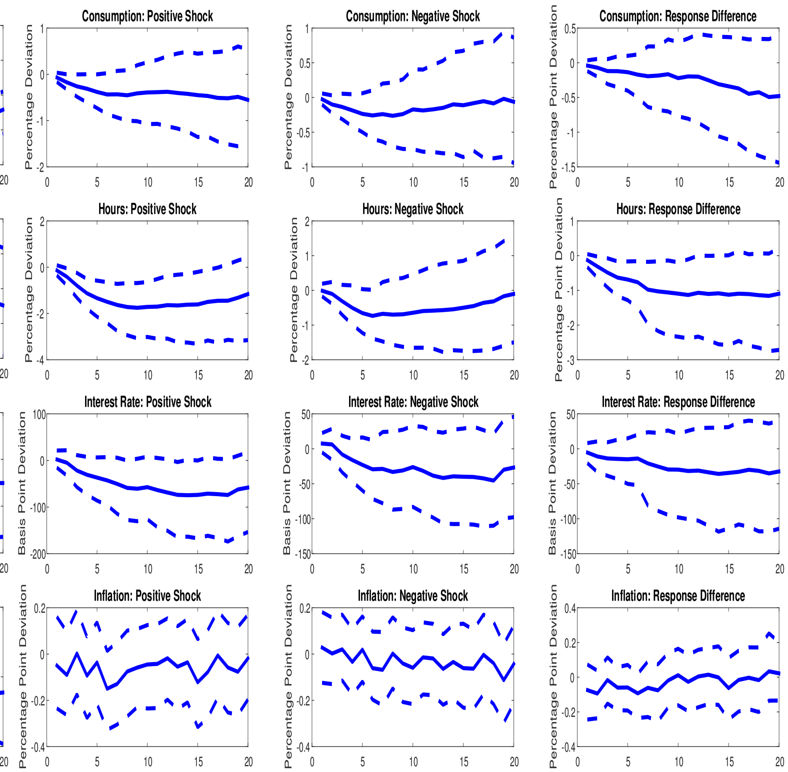
(b) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock for NBER-Determined Recessions.

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 time-varying parameter VAR (TVP-VAR) for NBER-determined *expansions*. The TVP-VAR consists of the following three variables: EBP, TFP, and output. Responses are in terms of deviations from pre-shock values (in basis point deviation for EBP and percentage deviation for TFP and output). Horizon is in quarters. Panel (b): 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 time-varying parameter VAR (TVP-VAR) for NBER-determined *recessions*. The TVP-VAR consists of the following three variables: EBP, TFP, and output. Responses are in terms of deviations from pre-shock values (in basis point deviation for EBP and percentage deviation for TFP and output). Horizon is in quarters.

Figure B.10: **Sign-Dependent Impulse Responses: (a) Sign-Dependent Impulse Responses of EBP, TFP, Output, and Investment; (b) Sign-Dependent Impulse Responses of Consumption, Hours, Interest Rate, and Inflation**.



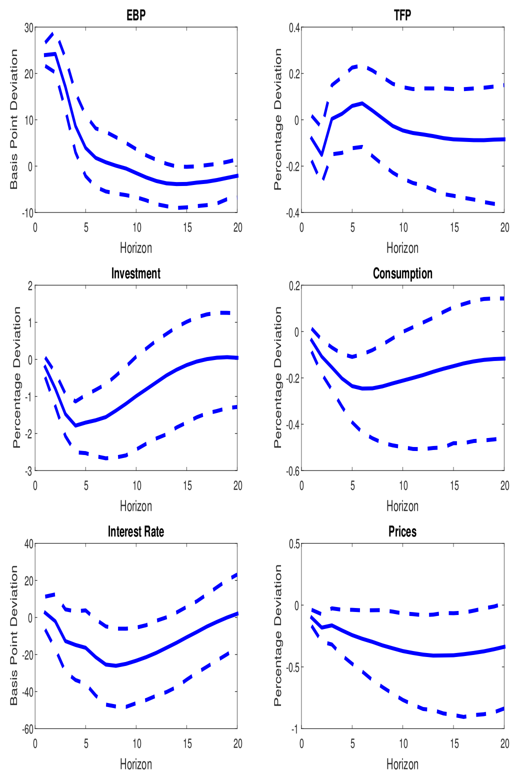
(a) The Median and 97.5th and 2.5th percentiles of the Sign-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock of EBP, TFP, Output, and Investment.



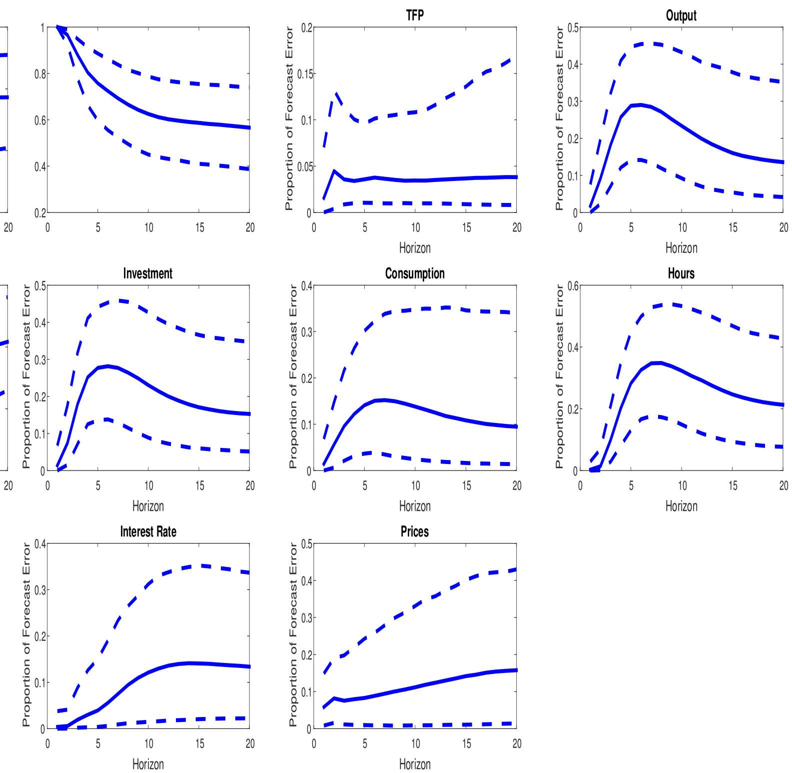
(b) The Median and 97.5th and 2.5th percentiles of the Sign-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock of Consumption, Hours, Interest Rate, and Inflation.

Notes: Panel (a): The solid line is the median sign-dependent impulse response and the dashed lines are the 97.5th and 2.5th percentiles of the posterior distributions of sign-dependent impulse responses from estimation of Equations (B.1), (B.2), and (B.3) for the following outcome variables: EBP, TFP, output, and investment. The first column of the figure corresponds to the positive shock; the second column corresponds to the negative shock; and the last column corresponds to the difference between the positive shock's effect and the negative shock's effect. Responses are in terms of deviations from pre-shock values (in basis point deviation for EBP and percentage deviation for all other variables). Horizon is in quarters. Panel (b): The solid line is the median sign-dependent impulse response and the dashed lines are the 97.5th and 2.5th percentiles of the posterior distributions of sign-dependent impulse responses from estimation of Equations (B.1), (B.2), and (B.3) for the following outcome variables: consumption, hours, interest rate, and inflation. The first column of the figure corresponds to the positive shock; the second column corresponds to the negative shock; and the last column corresponds to the difference between the positive shock's effect and the negative shock's effect. Responses are in terms of deviations from pre-shock values (in basis point deviation for interest rate, percentage point deviation for inflation, and percentage deviation for consumption and hours). Horizon is in quarters.

Figure B.11: **CPI in Levels: (a) Impulse Responses; (b) Contribution to FEV**.



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



(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shocks 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 in which CPI is included in levels. Responses are in terms of deviations from pre-shock values (in basis point deviation for EBP and interest rate and percentage deviation for all other variables). Horizon is in quarters. 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 in which CPI is included in levels.. Horizon is in quarters.

Appendix C Robustness Checks: Bottom-Up Approach: Capital Misallocation Channel

This section presents results from sixteen additional exercises that are based on alterations of the baseline bottom-up analysis of the capital misallocation channel and are meant to achieve the goal of bolstering the confidence in the message from the baseline results.

C.1 Accounting for Non-Zero Pure Profits

My measurement of firms' capital shares in the baseline capital misallocation analysis as their shares of operating income in sales relies on the assumption of zero pure profits so that operating income represents the share of income that is completely attributable to capital. However, this measurement can be biased if pure profits are non-zero, which could be the case in the presence of positive markups or decreasing returns to scale. And this bias, if present, can also lead to a bias in the measurement of firms' MPKs as these are a function of measured capital shares. It is therefore of value to examine the sensitivity of the baseline results to accounting for the possibility of non-zero pure profits.

Toward this end, I define firms' capital shares as the share of the difference between operating income and net income (Compustat item NI) in sales, with net income representing the firms' pure profit, i.e., the residual income left for firms to either keep internally or distribute as dividend after making all their payments. (And MPK is accordingly computed as the product of this capital share measure and the sales-to-capital ratio.) As such, this refined measure of capital share is capable of capturing the true share of capital in production that is purged of elements related to non-zero markups or decreasing returns to scale. The resulting sample based on these refined capital share and MPK measures includes 2185 firms and a total of 207,276 observations, which are slightly higher than the baseline numbers due to the fact that the modified mean firm-level capital shares and MPKs are less frequently negative than the baseline case.

Figures C.1a and C.1b (which share the same exposition structure as in Figures 4a and 4b from the paper) show the results from the bottom-up estimation procedure for the above-discussed revised measure of capital shares (and the resulting modified MPK measure). It is apparent that the main message from the baseline model remains unchanged, with the capital-misallocation-induced TFP response being insignificant and negligible following a positive credit supply shock. Moreover, as in the baseline specification, there does not seem to be meaningful heterogeneity in the way that capital of firms with different weight sub-components responds to credit supply shocks.

C.2 Gross Versus Value Added Output Based Aggregation

The conceptual framework from Section 3 of the paper defines aggregate output as the sum of firms' gross outputs rather than value added outputs (i.e., gross output minus materials purchases). Defining aggregate output this alternative way would require data on firms' materials purchases. The reason for this is that the firm size and capital share terms in Decomposition (4) from the paper would now correspond to firms' shares of value added in aggregate value added and their capital shares of their value added outputs, respectively, rather than the baseline measures of shares of gross outputs in aggregate gross output and their capital shares of their gross outputs.

Unfortunately, Compustat data does not include firms' materials purchases as a separate item, which is the main factor behind my choosing to use a gross output based framework. Nevertheless, to try to address the concern that the baseline results are driven by basing my aggregation framework on gross output rather than value added output, one may argue that it may be of value to use a measure of materials purchases that although imperfect still possess some information about materials purchases. Toward this end, I make use of Compustat's cost of goods sold item (COGS) to compute measures of firms' value added outputs (sales minus cost of goods sold), on the basis of which the measurement of the firm size and capital share components from Decomposition (4) from the paper are modified accordingly. While COGS includes not only materials purchases but also all other expenses directly allocated by the firm to production such as labor and overhead, I still view doing an estimation exercise that is based on this imperfect value added measure as a worthwhile sensitivity check which can attest to the robustness of the results to an alternative reasonable aggregation framework. The sample for this exercise includes 1821 firms and a total of 173,525 observations, which are lower than the baseline numbers due to the lesser availability of the COGS Compustat item.

Figures C.2a and C.2b (which share the same exposition structure as in Figures C.1a and C.1b) show the results from the bottom-up estimation procedure for the above-discussed value added based aggregation framework. The capital-misallocation-induced TFP response continues to be quantitatively negligible and statistically insignificant at all horizons. Moreover, as in the baseline specification, there does not seem to be meaningful heterogeneity in the way that capital of firms with different weight sub-components responds to credit supply shocks. Hence, it is apparent that the main message from the baseline model regarding the negligible quantitative role of the capital misallocation channel is robust to using an alternative aggregation framework that is based on value added output.

C.3 Removing Service Industries

As discussed on Page 22 in the paper, the vast majority (91%) of the firms in the baseline sample have MPKs that are higher than the aggregate MPK (which is equal to 7.7% in the baseline sample), with these firms having a median MPK that is 51.8% lower than the median MPK of the remaining 20% share of the firms. This extremely right-skewed distribution is driven to a large extent by the presence of many small firms in service industries possessing very high MPKs, as exemplified by the fact that removing all service industries firms results in a reasonable 57% share of the firms having higher MPKs than the aggregate MPK (which is equal to 14.6% now) with the median MPK of these firms being actually even slightly lower (by 7.1%) than that of the remaining firms.

Hence, to address the concern that the baseline results are driven by the strong right skewness of the MPK distribution with respect to aggregate MPK, I repeated the bottom-up estimation procedure for only firms that belong to non-service industries. This sample modification results in a total of 842 firms and 89,548 observations. The results from this exercise appear in Figures C.3a and C.3b (which share the same exposition structure as in Figures C.1a and C.1b). Importantly, the main message of the baseline bottom-up capital misallocation channel analysis remains intact also for this reduced sample, with the capital-misallocation-induced TFP response being insignificant and negligible at all horizons and firm-level responses still appearing to be rather homogenous across the different considered firm characteristics.

C.4 Accounting for Heterogeneity in Output-Capital Price Ratio

The way I measure firm-level MPKs in my baseline capital misallocation channel analysis can lead to a bias in my estimation of capital misallocation if there is heterogeneity in the ratio of output price to capital prices across firms. If this were the case, then part of what I measure as MPK heterogeneity would actually represent differences across firms in their output-capital price ratio and would therefore potentially bias my interpretation of the results.

To address this issue, I consider a robustness exercise where I restrict myself to a much smaller sample of firms for which I can collect SIC 4-digit industry-specific output and investment deflators data from the NBER-CES Manufacturing Industry Database. While these data are annual, I only use them for the construction of firms' MPKs which are in steady state (or average) terms, thus making the annual frequency less detrimental for the purposes of this exercise. (I.e., I measure firm-level quarterly real capital stocks for the estimation of Equation (B.3) as in the baseline case.) I assume equal values of these deflators within each year (with this data going up to 2011) and convert investment deflators into capital deflators via the perpetual inventory method where capital price is defined as the ratio of the nominal capital stock to real capital stock (whose construction is based on industry-specific investment deflators).

Since such industry-specific deflators are only available for manufacturing industries, the resulting modified sample results in a total of 482 firms and 51,009 observations. Note that this number of manufacturing firms is smaller than the total number of manufacturing firms in my baseline sample (718). The reason for this is that only 482 firms out of these 718 manufacturing firms belong to industries covered by the NBER-CES Manufacturing Industry Database. (These 482 firms correspond to a total of 108 such industries.)

The results from doing the bottom-up estimation for this reduced sample appear in Figures C.4a and C.4b (which share the same exposition structure as in Figures C.1a and C.1b). While significance of the real capital stock response for the 'median firm' does diminish somewhat for this exercise's reduced sample relative to the baseline case, it is still negative in terms of statistical significance in the 7th, 8th, and 12th-14th horizons (being negative in terms of its point-wise estimate for all horizons). More important, however, is the fact that the main message of the baseline bottom-up capital misallocation channel analysis is robust to accounting for heterogeneity in output-capital price ratios across firms as the capital-misallocation-induced TFP response continues to be insignificant and negligible and firm-level responses still appear to be broadly homogenous across the different considered firm characteristics.

C.5 Accounting for Markups-Induced Capital Misallocation

The seminal work by Basu and Fernald (2002) develops a general decomposition of aggregate TFP growth as the sum of technological growth and various misallocation terms, including capital and labor misallocation terms as well as misallocation terms related to markups. Building on the insight that firms' first-order cost minimization conditions imply that $MPK_i = \mu_i P_{i,K}$, where μ_i is firm i's steady state markup and $P_{i,K}$ is its real shadow rental cost of capital (deflated by its output price) in steady state, Basu and Fernald (2002) are able to construct a capital misallocation term that is similar to mine except that $P_{i,K}$ replaces MPK_i (see the fifth term in their Decomposition given by Equation (26)).

Importantly, the relation $MPK_i = \mu_i P_{i,K}$ stresses a potential concern arising from my baseline analysis: is the capital-misallocation-induced TFP change I am measuring stemming from heterogeneity in capital markets' frictions facing firms (i.e., heterogeneity in $P_{i,K}$) or is it stemming from heterogeneity in output markets' markups (i.e., heterogeneity in μ_i)? Given that the literature on the TFP channel of credit supply shocks has mainly focused on the former as candidate frictions for producing a meaningful such channel, it would be of value to show that the baseline results are robust to an exercise which is reasonably capable of picking up only the role of credit markets' frictions heterogeneity.

Toward this end, as in Crouzet and Eberly (2018) and Anderson et al. (2018), I measure firm-level markups in each period ($\mu_{i,t}$) as their ratio of sales to cost of goods sold (Compustat item COGS, which was also used in Section C.2) and then compute the unobserved steady state real shadow rental cost of capital ($P_{i,K}$) as the time-series average of $P_{i,K} = \frac{MPK_{i,t}}{\mu_{i,t}}$. I then feed my measured $P_{i,K}$ into the second term from Decomposition (4) from the paper instead of MPK_i with $P_K = \sum_{i=1}^{N} \frac{P_{i,K} K_i}{K}$ replacing MPK.

The results from the bottom-up approach estimation for this refined aggregation framework appear in Figures C.5a and C.5b (which share the same exposition structure as in Figures C.1a and C.1b). The sample for this exercise includes 1990 firms and a total of 193,468 observations, which are lower than the baseline numbers due to the lesser availability of the COGS Compustat item.[15] Notably, the baseline takeaway does not change also when the baseline estimated capital-misallocation-induced TFP change is purged of markup effects: the capital-misallocation-induced TFP response is insignificant and negligible at all horizons, supporting the notion that credit supply shocks do not seem to produce a meaningful fall in TFP that is rooted in heterogeneity related to capital markets frictions.

C.6 Accounting for Sign-Dependency of Impulse Responses

This section's exercise complements that from Section B.7, where I demonstrated that the baseline top-down results are robust to accounting for potential sign-dependency in credit supply shocks' effects. In this section I follow the three-step estimation procedure from Equations (B.1), (B.2), and (B.3), only that Equation (B.3) is now replaced by an equation which uses the cumulative change in logged firm-level capital as a function of raw and squared values of credit supply shocks. For convenience and completeness, I present here the precise three-equation system I estimate for the purposes of this section:

$$\begin{aligned} EBP_t &= C + \Gamma_1^{EBP} EBP_{t-1} + \Psi_1^{EBP} EBP_{t-1}^2 + ... + \Gamma_4^{EBP} FBP_{t-p} + \Psi_4^{EBP} EBP_{t-4}^2 + \quad \text{(C.1)} \\ &+ \Gamma_1^{TFP} \Delta TFP_{t-1} + \Psi_1^{TFP} \Delta TFP_{t-1}^2 + ... + \Gamma_4^{TFP} \Delta TFP_{t-1} + \Psi_4^{TFP} \Delta TFP_{t-1}^2 + \\ &+ \sum_{i=1}^{4}\sum_{j=1}^{4} \Omega_{i,j} EBP_{t-i} \Delta TFP_{t-j} + \epsilon_t, \\ \hat{\epsilon}_t &= \delta + \gamma \hat{\epsilon}_t^2 + \xi_t, \qquad \text{(C.2)} \\ k_{i,t+h} - k_{i,t-1} &= \alpha_{i,h} + \Xi_{i,h} \hat{\xi}_t + \Phi_{i,h} \hat{\xi}_t^2 + u_{i,t+h}, \qquad \text{(C.3)} \end{aligned}$$

where the estimation and associated terminology related to this system corresponds to those from Equations (B.1), (B.2), and (B.3), only that Equation (C.3) differs from Equation (B.3) in that i indexes firms with $i = 1, 2, ..., I$; $k_{i,t+h}$ is the log of firm i's real capital stock $K_{i,t}$; $\alpha_{i,h}$ is the firm fixed

[15] Note that the resulting sample here is larger than the one from Section C.2 which also made use of COGS; the reason for this is that Section C.2 made use of COGS more extensively, using it for both the MPK and capital share measures, thus leading to more observations being removed in the cleaning procedure described in Section 6.1.1 from the paper.

effect at horizon h; and $\Xi_{i,h}$ and $\Phi_{i,h}$ are the first- and second-order effects of the credit supply shock, where $\Xi_{i,h} + \Phi_{i,h}$ and $\Xi_{i,h} - \Phi_{i,h}$ give the responses of logged firm-level real capital stock at period h to a positive and negative one standard deviation credit supply shock, respectively.

The results from this exercise are summarized and presented in Figures C.6a-C.8b, where the exposition structure of each figure pair follows that of baseline Figures C.1a and C.1b with Figures C.6a and C.6b corresponding to a positive credit supply shock; Figures C.7a and C.7b corresponding to a negative credit supply shock; and Figures C.8a and C.8b corresponding to the difference between the effects of a positive and negative credit supply shocks.

While positive credit supply shocks induce a significantly stronger effect on the median firm's real capital stock than the corresponding effect of negative shocks (simply multiply Figure C.6a by -1 to get the actual change in real capital stock following the negative credit supply shock), the capital-misallocation-induced TFP response is negligible for both the positive and the negative shock as is the asymmetry in this response. Moreover, the firm-level responses continue to be quite homogenous regardless of the shock sign. Hence, we can conclude that the main message of the baseline bottom-up capital misallocation channel analysis is robust to allowing and accounting for sign-dependency in impulse responses.

I end this section with a discussion on how this section's results connect with those from Eisfeldt and Rampini (2006), who provide unconditional evidence that reallocation of existing capital is procyclical. The evidence I provide in this section suggests that the capital misallocation that results from a recession-inducing adverse credit supply shock is not meaningful but that firm-level real capital stock responses to such a shock are much greater than those generated by a boom-inducing favorable credit supply shock. Since the firm-level real capital stock response I estimate includes both existing and new capital related changes, viewing this section's results through the lens of the unconditional evidence on procyclical existing capital reallocation from Eisfeldt and Rampini (2006) seems to suggest that *new* capital reallocation is likely to be the dominant driver behind the strong sign-dependency in the firm-level capital responses. Be that as it may, this section's results show that this strong sign-dependency does not lead to meaningful sign-dependency in the capital-misallocation-induced TFP response.

C.7 Near-VAR Instead of Local Projections

My baseline specification for the bottom-up approach takes the credit supply shock from the baseline VAR and runs firm-level local projection regressions of real capital stock on this shock. An alternative specification worth considering as an additional robustness check is a procedure that runs a total of I near-VARs (with I being the cross-sectional dimension of the sample) containing the eight variables from the baseline VAR and an additional ninth variable corresponding to $k_{i,t}$ (logged firm-level real capital stock) which is restricted to have no effect on the other variables while being allowed to respond to both their contemporaneous as well as lagged values. Such a nine-variable VAR is not only a *near*-VAR because of its block-recursive structure but also because the sample corresponding to its eight-variable block is generally larger than that corresponding to the firm-level real capital stock block. In my estimations I explicitly account for these unequal samples by assigning the relevant degrees of freedom in the Bayesian estimation procedure of the two blocks.[16]

I assume 4 lags in both blocks and, to facilitate estimation with a reasonable number of degrees of freedom, I only keep firms that have at least 20 years of consecutive observations. This more stringent requirement relative to the baseline estimation which requires only 10 years of consecutive observations speaks to an important advantage of the baseline estimation procedure relative to the near-VAR based one related to degrees of freedom availability. Specifically, the two-step estimation procedure of the baseline bottom-up approach conserves on degrees of freedom in the joint estimation of the 2037×20 firm-level real capital stock local projection regressions by only including in them one explanatory variable, i.e., the credit supply shock estimated from the baseline VAR (which is the first step of the estimation procedure). This conservation on degrees of freedom allows the quite low 10-year threshold of consecutive number of observations in the baseline case. But using the near-VAR estimation approach requires a higher threshold because the effective estimation of the responses of firm-level real capital stocks is applied to a regression involving 4 lags

[16] I use the Bayesian estimation algorithm for strong block-recursive structure put forward by Zha (1999) in the context of block-recursive VARs, where the likelihood function is broken into the different recursive blocks. In my case, I have only two blocks, where the first consists of the VAR from (B.2) and the second corresponds to the firm-level real capital stock regression. As shown in Zha (1999), this kind of block separation along with the standard assumption of a normal-inverse Wishart conjugate prior structure leads to a normal-inverse Wishart posterior distribution for the block-recursive Equation parameters.

of nine variables and a constant (i.e., 37 estimated parameters). (The 20-year threshold reduces the baseline sample to 1171 firms from 2037 firms, i.e., $I = 1171$.)

The results from this estimation exercise appear in Figures C.9a and C.9b (which share the same exposition structure as in Figures C.1a and C.1b). The median firm's real capital stock response is less persistent than the baseline case, exhibiting a hump-shaped nature with a statistically significant decline that troughs at 0.02% after 3 years. The small magnitude of this decline as well as the small magnitude of the response differences across firms result in a negligible capital-misallocation-induced TFP response for all horizons, implying that the main message of the baseline bottom-up capital misallocation channel analysis is robust to using a near-VAR estimation approach.

C.8 One-Step Procedure Instead of Two-Step Procedure

The baseline specification for the bottom-up approach is effectively a two-step estimation procedure which in the first step estimates the baseline VAR and then in the second step estimates local projection regressions of firm-level real capital stocks on the credit supply shock obtained from the first step. An alternative to this estimation approach is to do a one-step estimation procedure where all the VAR variables are included in lagged form as control variables in the local projection regression except for EBP which is also included in current form. In this specification the coefficient on the current value of EBP is the coefficient of interest and captures the dynamic effect of credit supply shocks on firm-level real capital stocks.

It is noteworthy here too, in similar fashion to the discussion in the previous section, that doing the estimation in a one-step procedure is much less efficient in terms of degrees of freedom conservation relative to the baseline two-step case. The one-step estimation procedure adds 33 estimated parameters to the firm-level local projection regressions from which the identification of the role of the capital misallocation channel is obtained. This much smaller resultant number of degrees of freedom necessitates me to only keep firms that have at least 20 years of consecutive observations (as in the previous section concerning the near-VAR estimation approach, resulting in a reduced sample of 1171 firms relative to 2037 firms in the baseline case).

The results from this estimation exercise appear in Figures C.10a and C.10b (which share the same exposition structure as in Figures C.1a and C.1b). It is apparent that the main message of the baseline capital misallocation channel analysis is robust to using a one-step estimation procedure, with the capital-misallocation-induced TFP response continuing to be negligible and the firm-level responses continuing to maintain their homogeneity.

C.9 Adding Firm-Specific Control Variables in Local Projection Regressions

While the assumed exogeneity of credit supply shocks to firm-level real capital stocks warrants putting only the latter shocks in the local projection regressions, it is still worthwhile showing that my baseline results are not altered when time-variant firm-specific control variables are included in these regressions (on top of the time-invariant fixed effects). Toward this end, I consider a specification which adds to the baseline one 4 lagged values of firm-level leverage (defined as the ratio of total liabilities to total assets) and log-first-differences of sales. The controlling for the leverage variable accounts for firm-specific variation in indebtedness and its associated risks whereas that for sales accounts for firm-specific fluctuations in economic activity.[17]

The results from this estimation exercise appear in Figures C.11a and C.11b (which share the same exposition structure as in Figures C.1a and C.1b). Controlling for lagged leverage and sales growth yields results that are both quantitatively and qualitatively similar to the baseline ones, with the firm-level responses remaining quite homogeneous and the capital-misallocation-induced TFP response continuing to insignificant and negligible.

C.10 Using Lagged Value Rather Than Time-Series Average of MPK_i

In estimating the capital misallocation term from Decomposition (4) from the paper, I have used time-series averages of MPK_i for the baseline results. While this conceptually accords with the fact that this decomposition and associated capital misallocation term were obtained from approximating aggregate TFP about its steady state as well as the steady state values of $A_{i,t}$ and $K_{i,t}$

[17]In accordance with the baseline requirement from firm-level real capital stock and sales to have at least 10 years of consecutive observations, I have omitted firms whose leverage series had less than 10 years of consecutive observations. This omission resulted in a sample of 2035 firms, i.e., one that is nearly identical to the baseline sample of 2037 firms.

for all i, in practice such a time-series average may be prone to measurement error or unobserved heterogeneity in technology $A_{i,t}$. To ensure that results are not driven by this measurement issue, it is worthwhile to also consider constructing the capital-misallocation-induced TFP response to credit supply shocks on the basis of $MPK_{i,t-4}$, i.e., using the four-lagged value of MPK in the construction of capital misallocation term instead of MPK's time-series average.[18] (For internal consistency, I also insert $\alpha_{i,K}$ and $\frac{Y_i}{Y}$ in terms of their four-lagged values into Decomposition (4) from the paper instead of in terms of their time-series averages.)

Using one-year lagged values instead of time-series averages when constructing the firm-level weights multiplying the log-deviation of capital from Decomposition (4) from the paper results in time-varying weights in the capital misallocation term. Specifically, the baseline firm-level weights $\alpha_{i,K}\frac{Y_i}{Y}\frac{MPK_i-MPK}{MPK_i}$ from Decomposition (4) from the paper are now $\alpha_{i,K,t-4}\frac{Y_{i,t-4}}{Y_{t-4}}\frac{MPK_{i,t-4}-MPK_{t-4}}{MPK_{i,t-4}}$, thus resulting in capital misallocation being allowed to vary over time. In other words, conditional on a credit supply shock and the *time-invariant* firm-level real capital stock response to this shock, the initial distribution of capital shares, size, and MPK will now be allowed to vary over time resulting in a time-varying capital-misallocation-induced TFP response. In addition to providing an estimation that is robust to the possible measurement error and bias that may result from using time-series averages, I will use the estimation exercise of this section also to exploit its associated time-varying nature for studying the potential dependence of capital-misallocation on the state of the business cycle.

The results from this estimation exercise appear in Figures C.12a and C.12b, where median and 95% posterior bands of the capital-misallocation-induced TFP responses to a one standard deviation credit supply shock are shown for expansions and recessions, respectively. Given my sample, the expansionary quarters I consider are 1977:Q3, 1981:Q1, 1986:Q3, 1996:Q1, 2004:Q4, and 2013:Q3 whereas the recessionary quarters are 1974:Q3, 1980:Q2, 1982:Q1, 1990:Q4, 2001:Q3, and 2008:Q3. The expansionary quarters are chosen as the middle periods between the end of the recession preceding the corresponding expansion and the beginning of the subsequent recession while the recessionary quarters are chosen as the middle periods between the beginning and ending quarters of the recessions. (Expansion and recession dates are based on NBER dating.)

[18] Results are also robust to using shorter lags of MPK.

Note that, given my use of four-lagged values in constructing the firm-level weights, the capital-misallocation-induced TFP response at each of the previously mentioned expansionary and recessionary quarters is computed from the product of the estimated (time-invariant) firm-level real capital stock responses and the firm-level weights at a one-year lag relative to each expansionary and recessionary quarter.

It is apparent from Figures C.12a and C.12b that the capital-misallocation-induced TFP response, albeit generally negative point-wise, is both statistically and economically insignificant for all considered quarters and their associated response horizons. Hence, we can conclude from these results that the main message of this paper is robust to measuring firm-level weights with lagged values of their underlying objects (i.e., MPK, capital share, and size).

C.11 Using $MPK_{i,j} - MPK_j$ Instead of $MPK_i - MPK$

An additional alternative to the way $MPK_i - MPK$ is computed in Decomposition (4) from the paper is to consider it in terms of deviations from the industry-average and not the economy-wide average (as is done in the baseline case). The 2037 firms in my sample belong to 352 unique industries (based on SIC 4-digit classification code). Hence, to construct the capital-misallocation-induced TFP response on the basis of industry-average MPK deviations, I compute the time-series average of MPK for each of the 352 firm sub-groups corresponding to their unique industries and then take the difference between each firm's time-series averaged MPK and its associated industry's MPK.

The results from this estimation exercise appear in Figure C.13, where median and 95% posterior bands of the capital-misallocation-induced TFP responses to a one standard deviation credit supply shock are shown. It is apparent that the main message of the baseline capital misallocation channel analysis is robust to considering firm-level MPK deviations from industry-averages rather than economy-wide averages, with the capital-misallocation-induced TFP response being negligible at all horizons. (While this response is significantly negative for the 2nd, 4th, 7th, and 8th horizons, it has an average of -0.016% over the considered 20 horizons and it is always below -0.023% in absolute terms. In particular, for the four above-mentioned horizons at which it obtains significance, this response stands at the negligible values of -0.008%, -0.014%, -0.022%, and

-0.021%, respectively.)

C.12 Adding Industry Time Fixed Effects

While firm-level fixed effects are included in the baseline local projection regressions, it still may be the case that the presence of unobserved heterogeneity at the industry level which varies over time (e.g., certain industries having different sensitivities to credit supply shocks in a time-varying way) is at work thereby potentially biasing the results. One way to examine if the estimated homogeneity across firm-level responses found in my baseline analysis is driven by time-varying unobserved heterogeneity in firm-level behavior simply offsetting true differences across firm-level responses is to include time fixed effects at the industry level as it can prove useful in helping us learn about the validity of the latter offsetting mechanism in driving my estimated homogeneity from the baseline analysis.

The results from an estimation exercise which includes industry time fixed effects (based on SIC 4-digit classification code) appear in Figures C.14a and C.14b (which share the same exposition structure as in Figures C.1a and C.1b). The important element to look at in these figures is the differences between the responses of the various sub-groups of firms (i.e., large vs. small weight, high vs. low MPK, large vs. small size, and high vs. low capital share). Clearly, even after controlling for unobserved time-varying heterogeneity, these differences remain negligible thereby negating the concern that estimated homogeneity from the baseline analysis is an artifact of unobserved time-varying heterogeneity at the industry level. (The significance of the median firm's real capital stock response is actually mostly maintained relative to the baseline case, indicating that the industry time fixed effects are capturing unobserved industry-level time-varying heterogeneity that is largely unrelated to the aggregate credit supply shock.)

C.13 Alternative Credit Supply Shock Identification

In Section B.4 I considered five alternative credit supply shock series relative to the baseline top-down analysis. I repeat the baseline bottom-up analysis for the capital misallocation analysis for all of these five alternative identification schemes. For convenience, I describe these alternative series again followed by a summary of the results obtained from them.

The first alternative series is obtained from a different ordering of the variables in the VAR, ordering EBP fifth in the VAR (after output, consumption, investment, and inflation) as in Gilchrist and Zakrajšek (2012) (the results for this credit supply shock are shown in Figures C.15a and C.15b). The remaining four are all obtained as the reduced form VAR innovations in the following credit supply shock series from Mumtaz et al. (2018) (each replacing EBP in the baseline VAR): the measure of bank lending shocks (BCDZ) calculated by Bassett et al. (2014), covering 1992:Q1-2010:Q4 (the results for this credit supply shock are shown in Figures C.16a and C.16b); the innovations to the financial conditions index (JQ) calculated by Jermann and Quadrini (2012), covering 1984:Q2-2010Q2 (the results for this credit supply shock are shown in Figures C.17a and C.17b); the risk shock (CMR) from the DSGE model of Christiano et al. (2014), covering 1981:Q1-2010:Q2 (the results for this credit supply shock are shown in Figures C.18a and C.18b); and a textual measure of credit supply shocks (MPT) developed by Mumtaz et al. (2018) that is based on a search for the words "credit crunch" and "tight credit" using nine U.S. newspapers, covering 1980:Q1-2012:Q4 (the results for this credit supply shock are shown in Figures C.19a and C.19b).

There are two main takeaways from all of the results for these alternative credit supply shock series. First, the homogeneity in firm-level real capital stock responses observed for the baseline case continues to hold for all of the considered alternative shock series. And, second, the capital-misallocation-induced TFP response continues to be negligible at all horizons for all considered shock series. Hence, we can deduce that the main message from the baseline capital misallocation channel analysis is robust to considering alternative credit supply shock series from the literature. (While all five considered shock series produce generally negative point-wise real capital stock responses for the median firm, these responses are statistically significant only for the EBP based shock from Gilchrist and Zakrajšek (2012).)

C.14 Including Cross-Sectional MPK dispersion in the Baseline VAR

As an alternative to the two-step firm-level based regression estimation procedure of the bottom-up capital misallocation channel analysis, one can rely on a common measure of MPK dispersion given by the cross-sectional variance of MPK by developing a mapping between this measure and capital misallocation (see, e.g., Hsieh and Klenow (2009) and Gilchrist et al. (2013)) that builds on a log-normal second order approximation of aggregate TFP. In Gilchrist et al. (2013), e.g., such a mapping builds on a log-normal second order approximation of an equation relating logged aggregate TFP to firm-specific technologies and capital and labor wedges, with these wedges being functions of marginal products of their respective inputs and defined as the gap between input choices embodying efficient allocation and input choices distorted by firm-specific borrowing costs used to finance both capital and labor.

I preferred to use Decomposition (4) from the paper as the basis for my baseline quantification of the capital misallocation channel due to two reasons. First, it is more general in not relying on the log-normality assumption. And, second, it explicitly allows for a role of first-order fluctuations in firm-level capital in generating capital-misallocation-induced TFP changes by directly approximating around deviations from steady state capital rather than around deviations from steady state MPK or some function of MPK. This way of approximation provides a natural bridge to the examination of the capital misallocation channel through the lens of firm-specific economic fluctuations in *capital*, rather than its marginal product, caused by credit supply shocks. As such, it speaks to a more intuitive way of how capital misallocation can arise conditional on a shock, i.e., through shock-induced changes in capital of firms with different pre-shock MPKs.

Notwithstanding this preference for my baseline choice, it is still worthwhile to make sure that the cross-sectional dispersion of MPK is not meaningfully sensitive to credit supply shocks. Toward this end, I add the time series of the cross-sectional standard deviation of $MPK_{i,t}$ to the baseline VAR from the top-down analysis and estimate its response to a one standard deviation credit supply shock. The results from this exercise are presented in Figures C.20a and C.20b, which correspond to Figures 1a and 1b from the paper except that now the baseline VAR also includes the cross-sectional standard deviation of $MPK_{i,t}$.

The results from this exercise can be summarized as follows. First, it is apparent that TFP continues to respond in a weak and short-lived manner also in this extended VAR. Second, while MPK dispersion actually falls - implying that capital misallocation is reduced following the credit supply shock (in contrast to what most theoretical models would usually suggest) - this decline in MPK dispersion is only significant for the 5th quarter. This rather short-lived and broadly insignificant nature of the response of MPK dispersion accords with the main conclusion of this paper regarding the unimportant role of the TFP channel in the transmission of credit supply shocks.

C.15 Considering Sub-Samples Based on Size and Rollover Risk

One may argue that estimating the capital-misallocation-induced TFP response from the entire baseline sample of firms is quite crude as it might mask potentially important misallocation arising in specific subsets of this sample. Specifically, it can be worthwhile to estimate the capital-misallocation-induced TFP response from sub-samples of firms which are arguably more susceptible to financial frictions. Two such sub-samples correspond to relatively smaller firms within the baseline sample and to firms which rely relatively heavily on short-term debt, i.e., have relatively high rollover risk.

To construct the size based sub-sample, I take the part of my baseline sample that includes firms whose size is less than the median size. For the rollover risk based sub-sample, I follow Gopalan et al. (2014) and measure rollover risk by the ratio of short-term debt (i.e., having maturities of less than one year) to total debt. This measure is computed from dividing Compustat item DLCQ by the sum of DLCQ and Compustat item DLTTQ (i.e., long-term debt), which results in a sub-sample of 590 firms. I then cut this sample in half by only considering firms whose rollover risk measure is higher than its median value of 16.2%.

The results for the size based sub-sample appear in Figures C.21a and C.21b while those for the rollover risk based sub-sample are shown in Figures C.22a and C.22b. Both these figure pairs' exposition structure corresponds to that of Figures C.1a and C.1b. It is clear that the concern that misallocation in these two sub-samples is present and being masked by the baseline sample containing various other sub-samples on top of these two is unwarranted. The capital-misallocation-induced TFP response continues to be negligible and the firm-level real capital stock responses seem rather homogenous also for these two sub-samples. (While for the size based sub-sample exercise the capital-misallocation-induced TFP response is significantly negative for the 6th, 8th, and 10th-15th horizons, the point estimate of this response is always below -0.03% and has an average of -0.018% over the 20 considered horizons. Hence, the trifling magnitude of this response from the baseline case clearly holds firm also for the size based sub-sample.)

C.16 Sorting Firms Along the Whited and Wu (2006) Financial Constraints Index

In the baseline bottom-up analysis I look at the heterogenous response of firm-level real capital stock sorted along the size, capital share, and MPK dimensions. I use this sorting and the largely homogenous responses along these dimensions to explain the small estimated capital-misallocation-induced TFP response to credit supply shocks. However, an additional dimension along which it is worthwhile to examine the potentially heterogenous response of firms' capital is their level of financial constraints intensity. This dimension is important to look at due to the important theoretical role heterogenous financial frictions receive by the literature as a channel of capital misallocation in the presence of credit supply shocks. Hence, showing that firm-level capital responses are largely homogenous even when sorted by the level of financial constraints facing them would further enhance the claim that the capital misallocation channel is weak.

Toward this end, I use the Whited and Wu (2006) financial constraints index (WW) to construct measures of financially unconstrained firms (defined as belonging to the lower quartile of the WW distribution) and financially constrained firms (defined as belonging to the upper quartile of the WW distribution). Whited and Wu (2006) constructed their index via generalized method of moments (GMM) estimation of an investment Euler equation and this index is given by Equation (13) of their paper:

$$\begin{aligned} WW_{i,t} &= -0.091CF_{i,t} - 0.062DIVPOS_{i,t} + 0.021TLTD_{i,t} \\ &- 0.044LNTA_{i,t} + 0.102ISG_{i,t} - 0.035SG_{i,t}, \end{aligned} \tag{C.4}$$

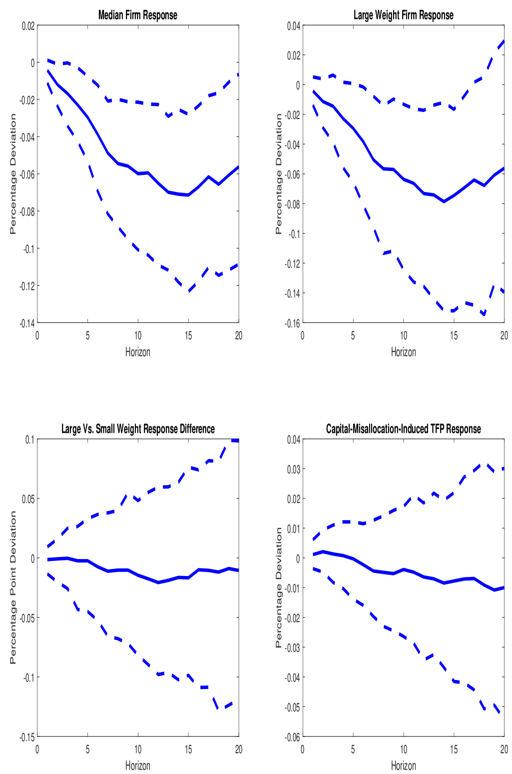
where CF is the ratio of cash flow to total assets;[19] DIVPOS is an indicator that takes the value of one if the firm pays cash dividends; TLTD is the ratio of the long-term debt to total assets; LNTA is the natural log of total assets; ISG is the firm's three-digit industry sales growth; and SG is firm sales growth. A higher value of WW implies greater financial constraints. For the calculation of the WW index, I make the baseline requirement that only firms that have at least 10 years of consecutive observations are kept in the sample, resulting in a sample of 480 firms. For each firm

[19]Cash flow is measured as the sum of net income (Compustat item NIQ) and depreciation and amortization (Compustat item DPQ).

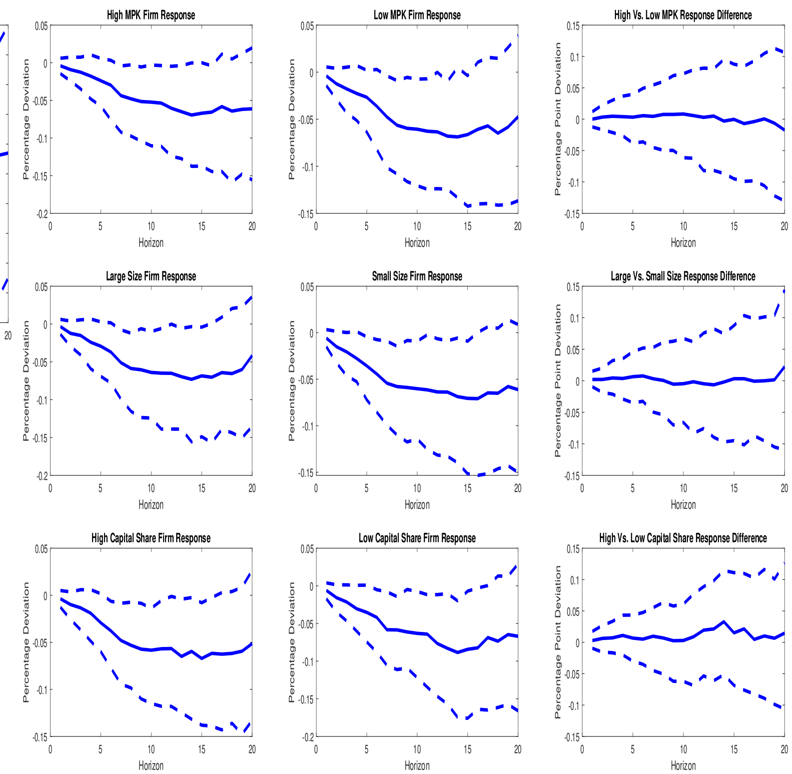
I compute its average WW index value and then sort the firms along their average WW index values for the estimation exercise.

The results from this estimation exercise are shown in Figure C.23, whose sub-figures contain the response of the high WW firm (financially constrained), the low WW firm (financially unconstrained), along with the response differences between each WW pair. The median and 95% posterior bands for each WW category firm response are obtained from computing the 2.5th, 50th, and 97.5th percentiles of the distribution of the median response across firms in each WW category. For completeness, the figure also shows the capital-misallocation-induced TFP response and the response of the median firm (constructed as in the baseline case). It is evident that high WW firms respond both quantitatively and qualitatively similar to low WW firms, with the capital-misallocation-induced TFP response continuing to be weak. (While this response is significantly negative from the impact through the 10th horizon, it lacks economic significance for all horizons having an average value of -0.019%.) Hence, we can interpret these findings as further evidence that a financial-frictions-based misallocation mechanism does not appear to be meaningfully present in my considered firm-level Compustat sample.

Figure C.1: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Accounting for Non-Zero Pure Profits: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



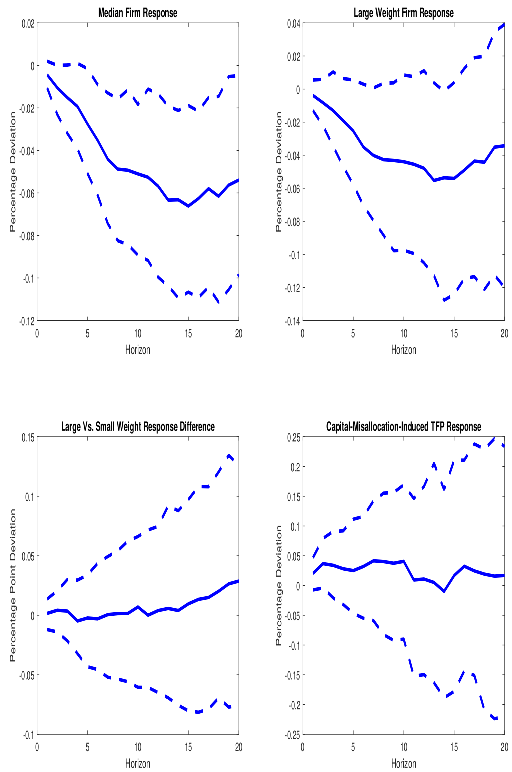
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



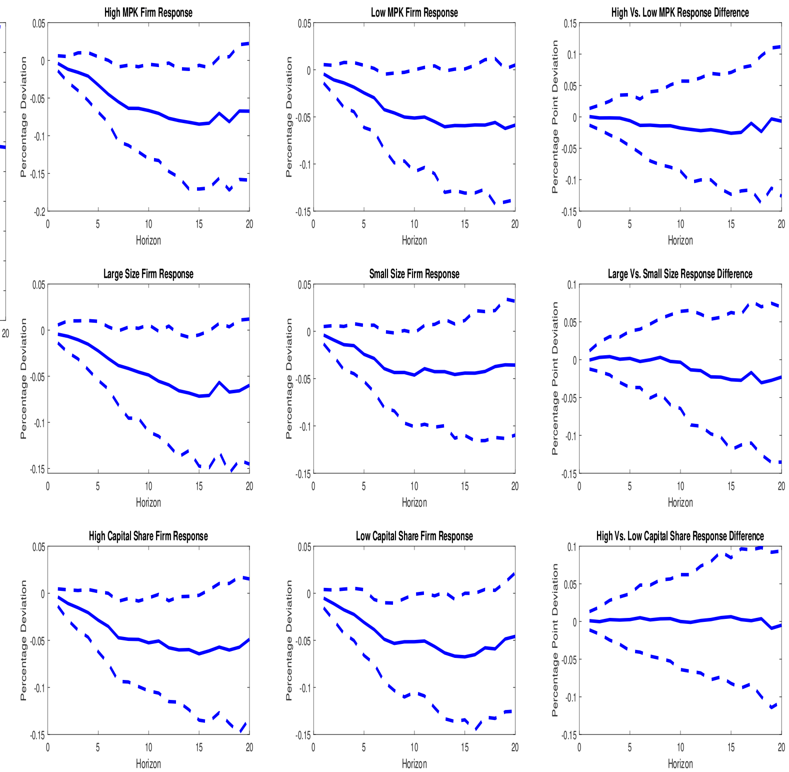
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from measuring capital shares as the difference between operating and net income as percentage of sales. Panel (a): The first sub-figure shows the median (solid line) and 95% confidence bands (dashed lines) of the real capital stock response to a one standard deviation credit supply shock for the 'median firm', i.e., from taking the median of the posterior distribution of firm-level responses. The second and third sub-figures present the responses from taking the median of the upper and lower quartile ranges of the firm-level weights from Decomposition (4) from the paper (i.e., 'large weight firm' and 'small weight firm' responses), respectively, while the fourth sub-figure shows the response difference between the responses from the second and third sub-figures. The fifth sub-figure presents the capital-misallocation-induced TFP response computed from the second term from Decomposition (4). Responses are in terms of percentage deviations from pre-shock values (with response differences accordingly in percentage point deviation terms). Horizon is in quarters. Panel (b): The sub-figures' exposition in this panel follows the structure from sub-figures 2-4 of Figure C.1a only that instead of distinguishing between firms on the basis of total weight, I make a distinction based on the three components comprising this total weight: capital share ($\alpha_{i,K}$), size ($\frac{Y_i}{Y}$), and MPK-related component ($\frac{MPK_i - MPK}{MPK_i}$). Horizon is in quarters.

Figure C.2: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Value Added Based Aggregation Framework: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



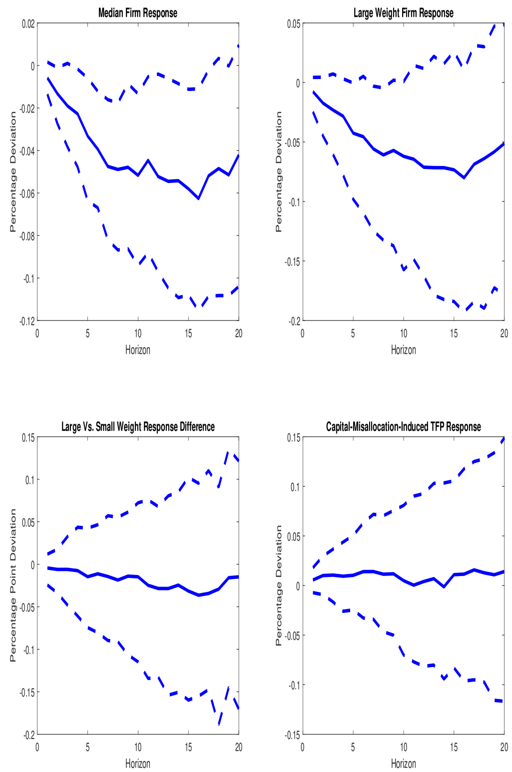
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



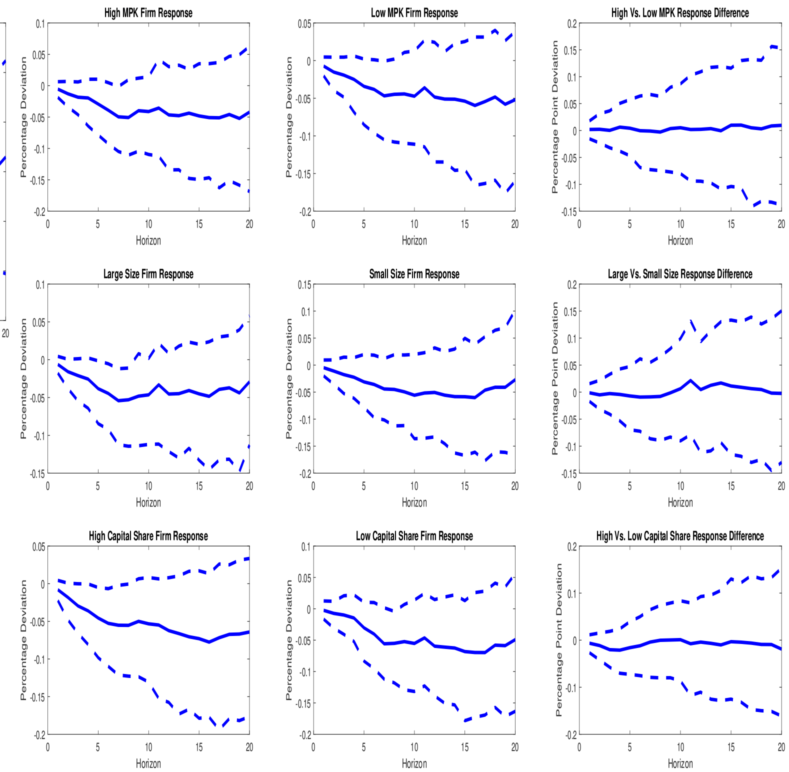
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from measuring capital shares as operating income as percentage of the difference between sales and cost of goods sold (i.e., value added) and firm size as value added as percentage of aggregate value added. The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.3: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Removing Service Industries Firms: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



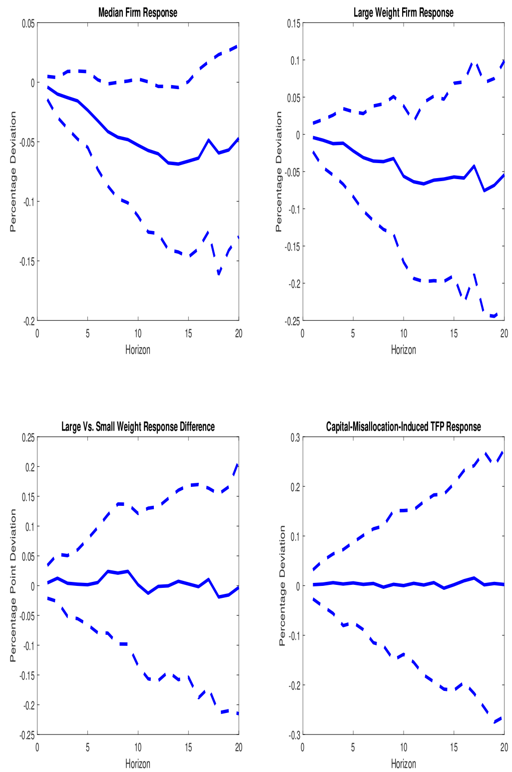
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



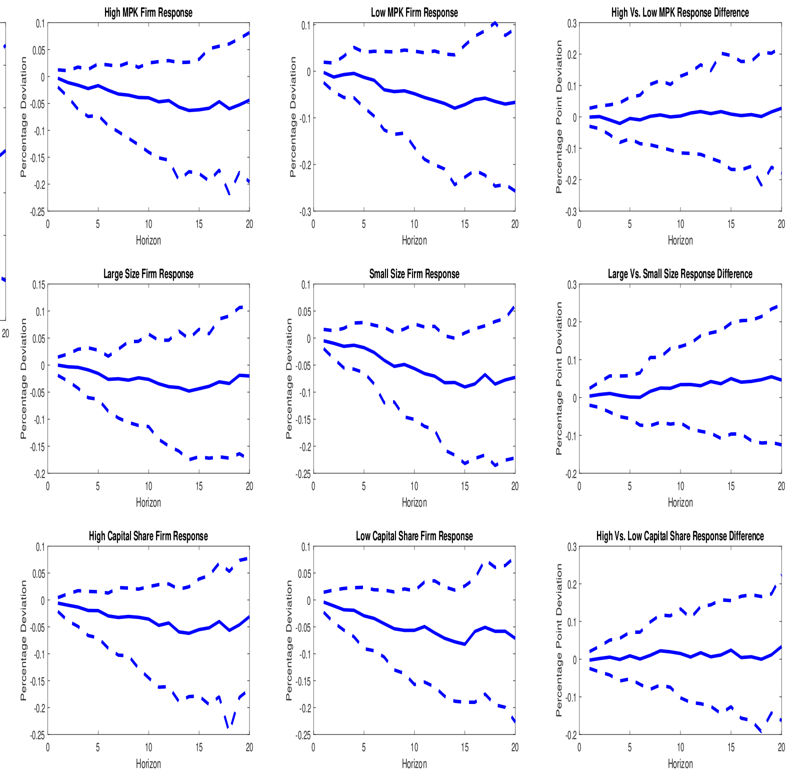
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from removing service industries firms from the baseline sample. The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.4: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Accounting for Heterogeneity in Output-Capital Price Ratio: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



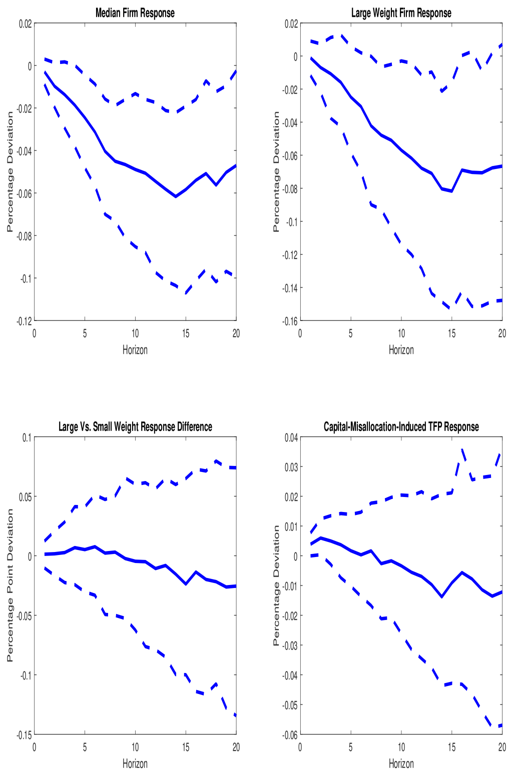
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



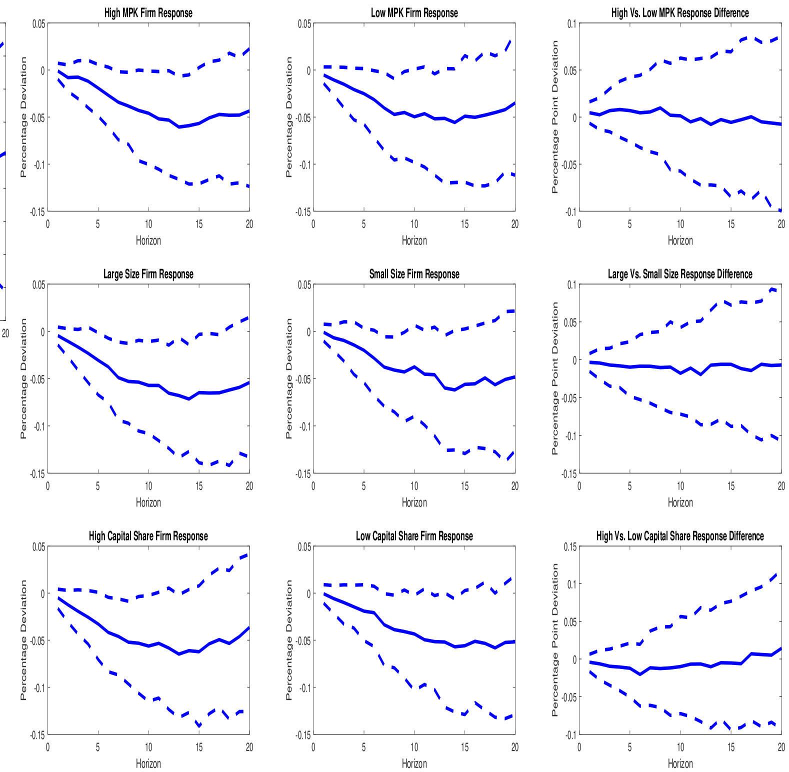
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from a reduced sample of firms with corresponding industry-specific output and investment deflators which are used to compute sales-to-capital ratio in real terms. The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.5: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Accounting for Markups-Induced Capital Misallocation: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**



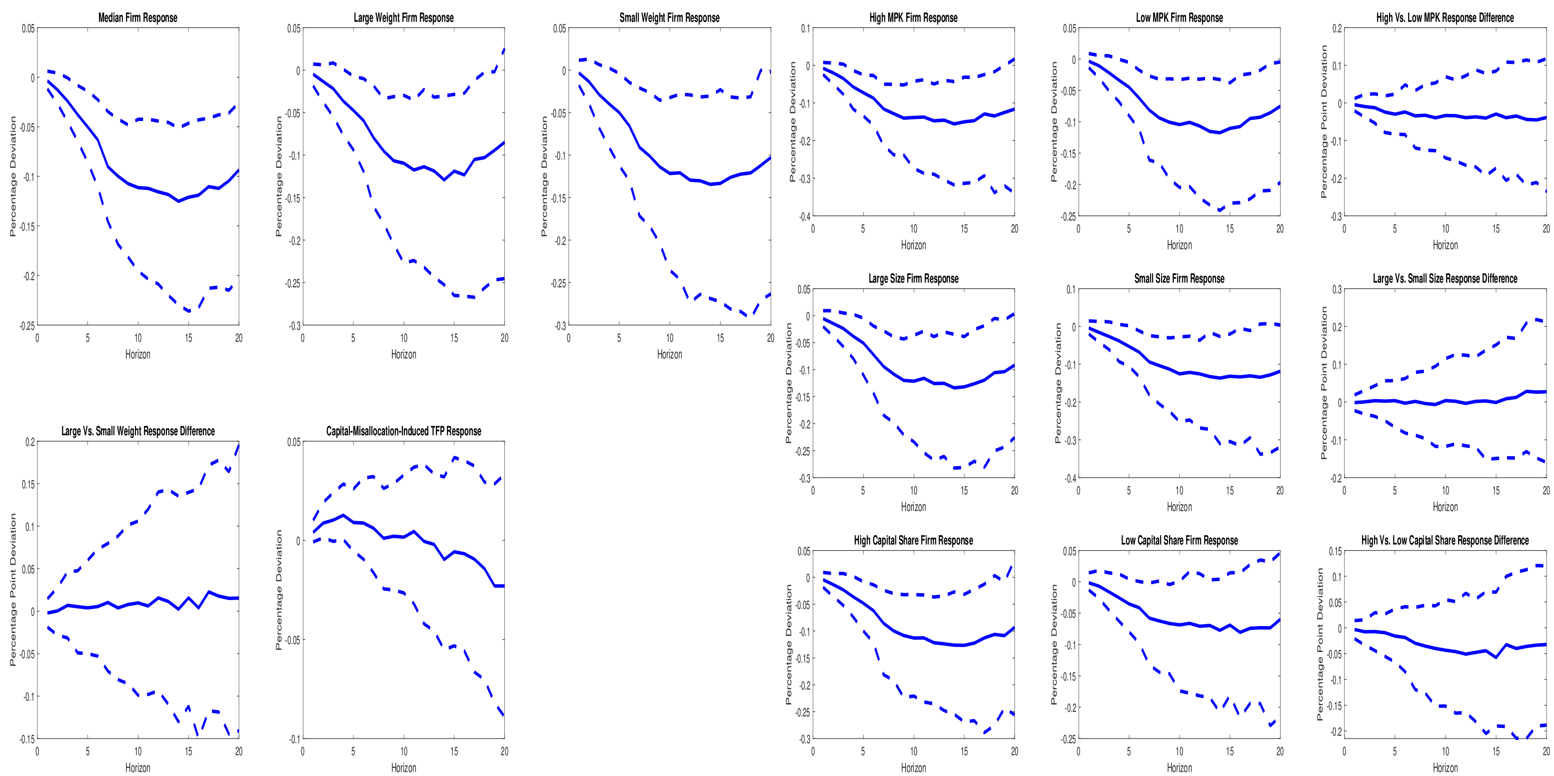
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from purging my firm-level MPK measure of markup effects by dividing the baseline MPK measure by the ratio of sales to cost of goods sold. The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.6: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Impulse Responses to Positive Shock: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.

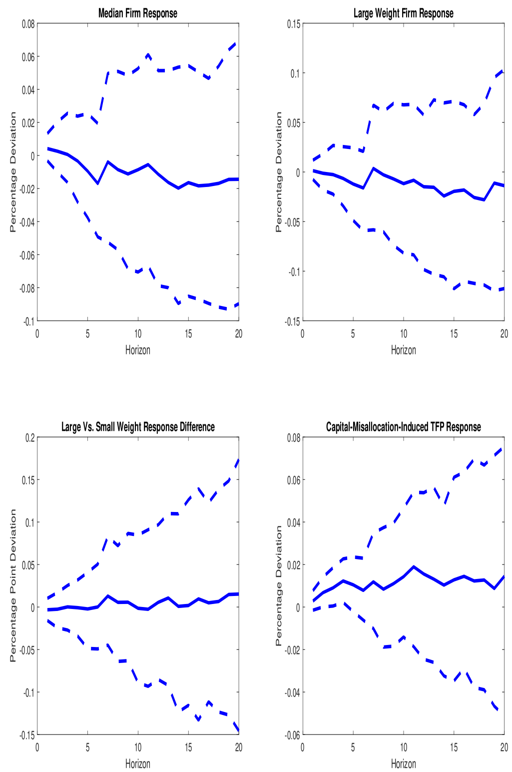


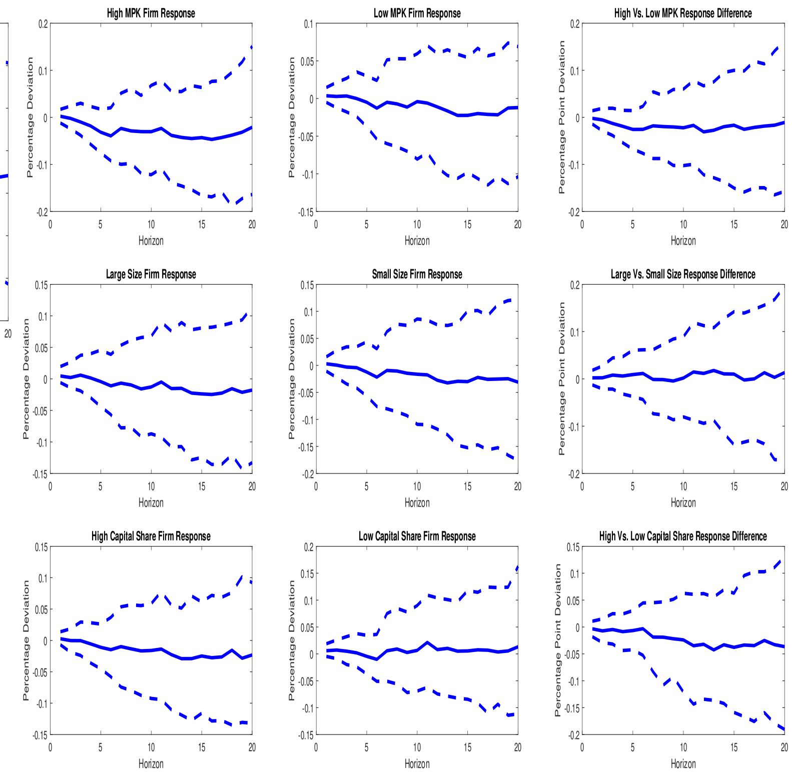
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.

(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for a *positive* credit supply shock from estimation of System (C.1)-(C.3). The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.7: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Impulse Responses to Negative Shock: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.

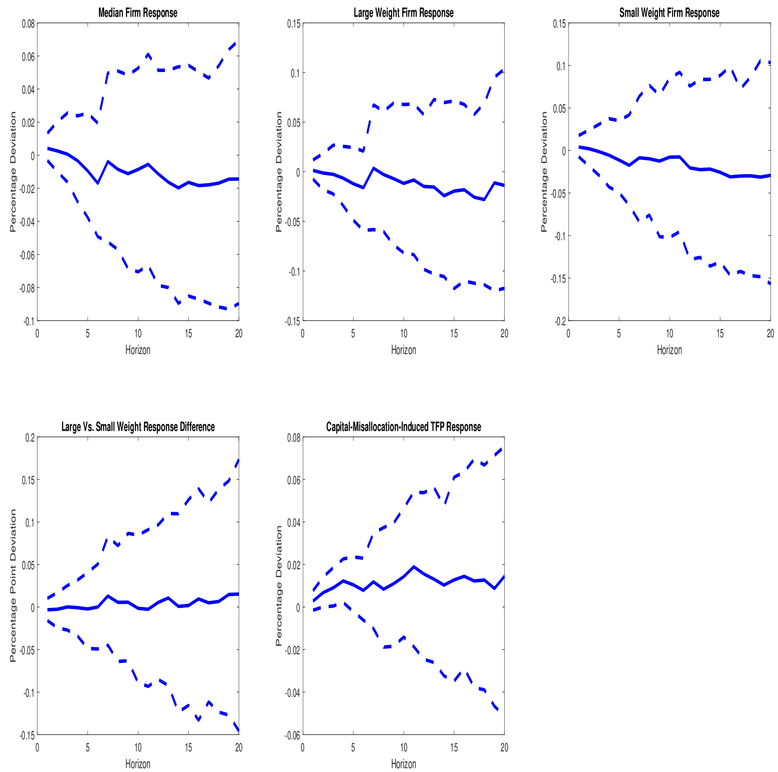




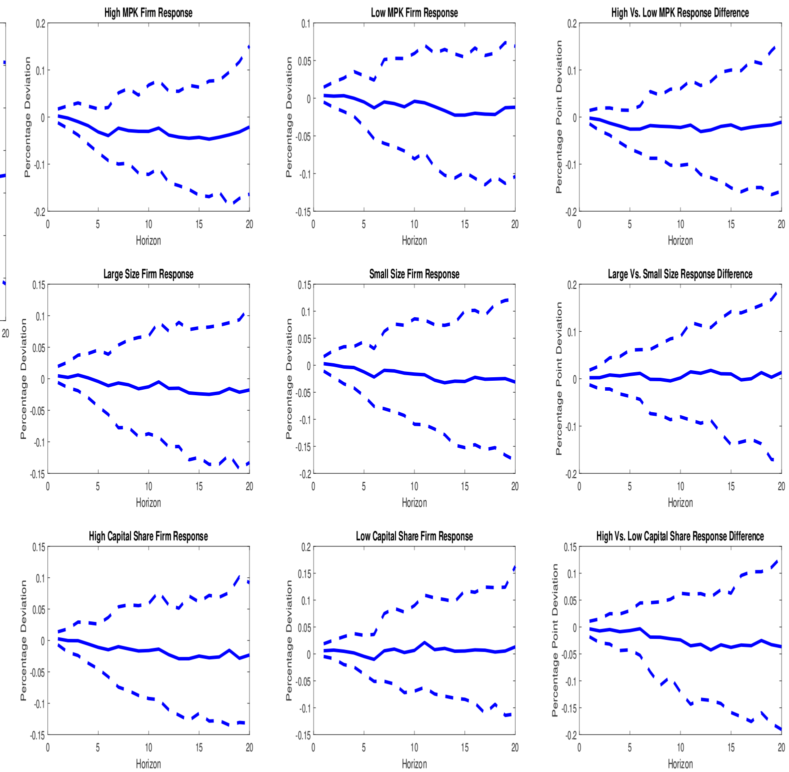
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response. **(b) Firm-Level Impulse Responses by Firm Characteristics.**

Notes: This figure presents the results for a *negative* credit supply shock from estimation of System (C.1)-(C.3). The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.8: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Impulse Response Asymmetry: (a) 'Median Firm' Capital Response Asymmetry and Capital-Misallocation-Induced TFP Response Asymmetry; (b) Firm-Level Impulse Response Asymmetry by Firm Characteristics**.



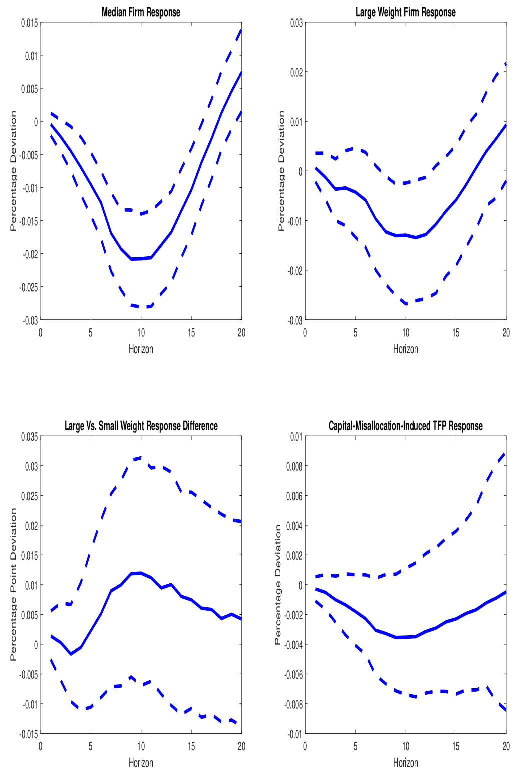
(a) 'Median Firm' Capital Response Asymmetry and Capital-Misallocation-Induced TFP Response Asymmetry.



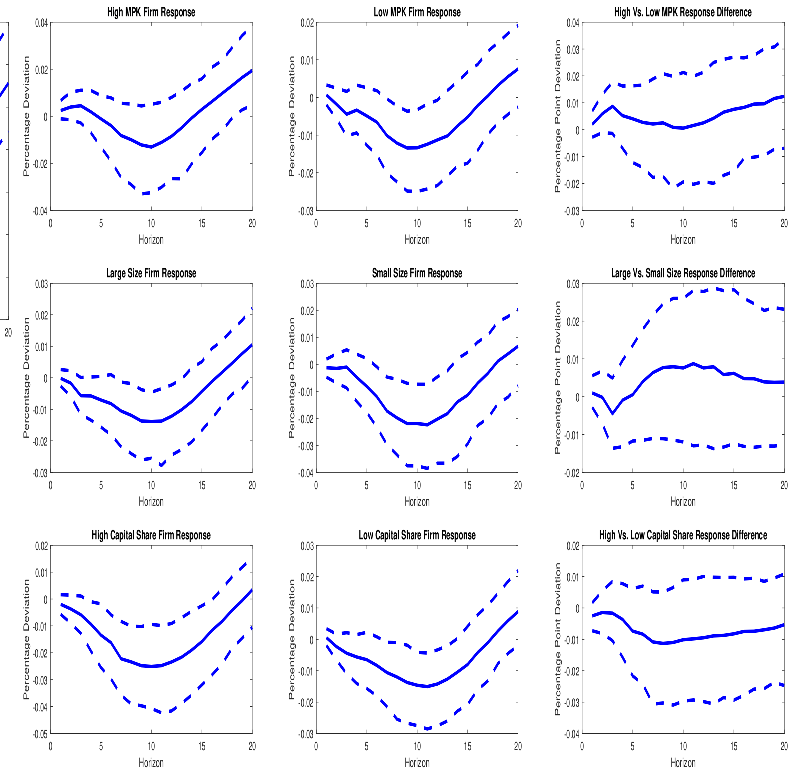
(b) Firm-Level Impulse Response Asymmetry by Firm Characteristics.

Notes: This figure presents the results for response asymmetry, calculated as the difference between positive and negative shocks' effects, from estimation of System (C.1)-(C.3). The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.9: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Near-VAR: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



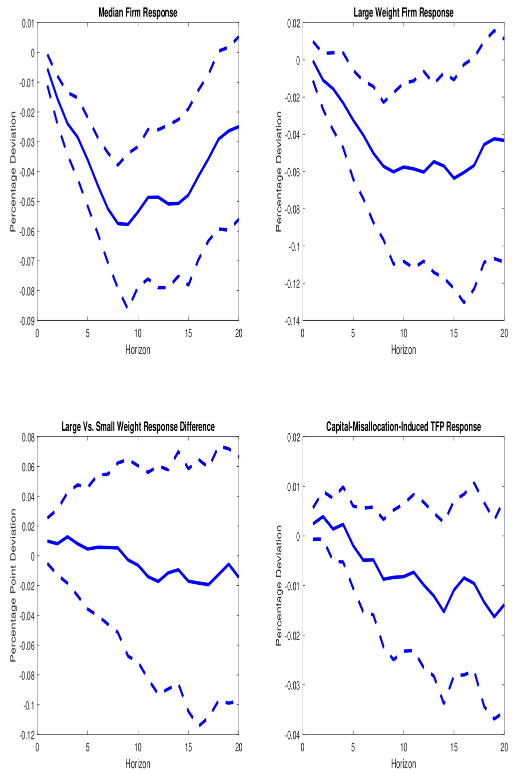
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



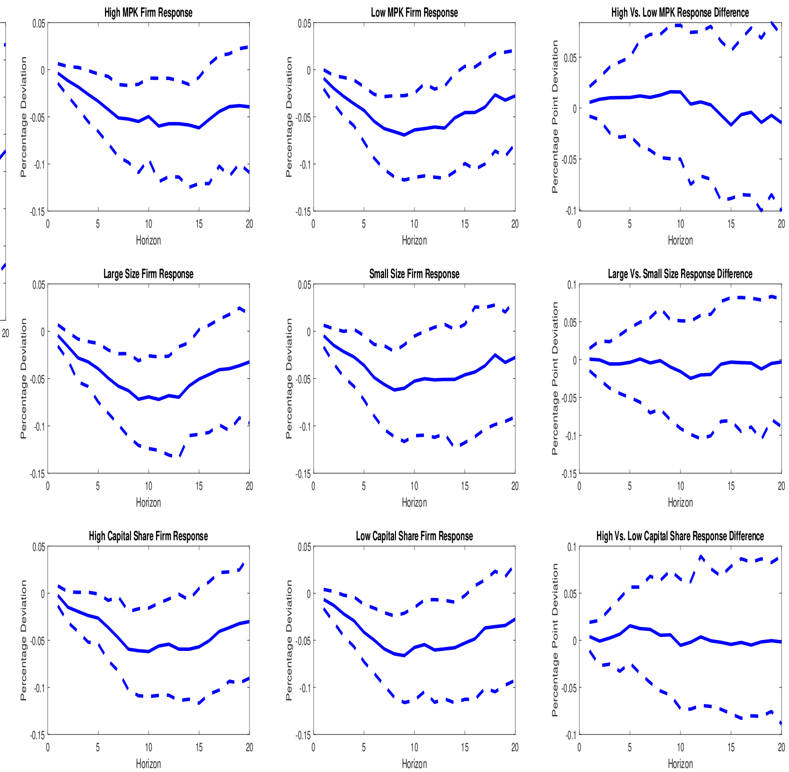
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from estimation of a near-VAR model, i.e., a procedure that runs a total of I near-VARs (with I being the cross-sectional dimension of the sample) containing the eight variables from the baseline VAR and an additional ninth variable corresponding to $k_{i,t}$ (logged firm-level real capital stock) which is restricted to have no effect on the other variables while being allowed to respond to both their contemporaneous as well as lagged values. Moreover, the difference in sample sizes covered by the aggregate variables and the firm-specific real capital stock variables is allowed and accounted for in the estimation. To facilitate estimation with a reasonable number of degrees of freedom, I only keep firms that have at least 20 years of consecutive observations; this reduces the baseline sample to 1171 firms from 2037 firms, i.e., $I = 1171$. The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.10: **Bottom-Up Estimation Approach: Capital Misallocation Channel: One-Step Estimation Procedure: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



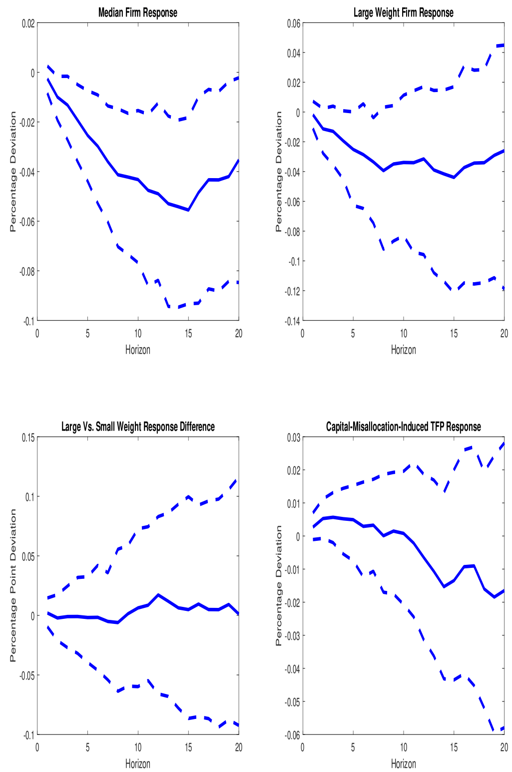
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



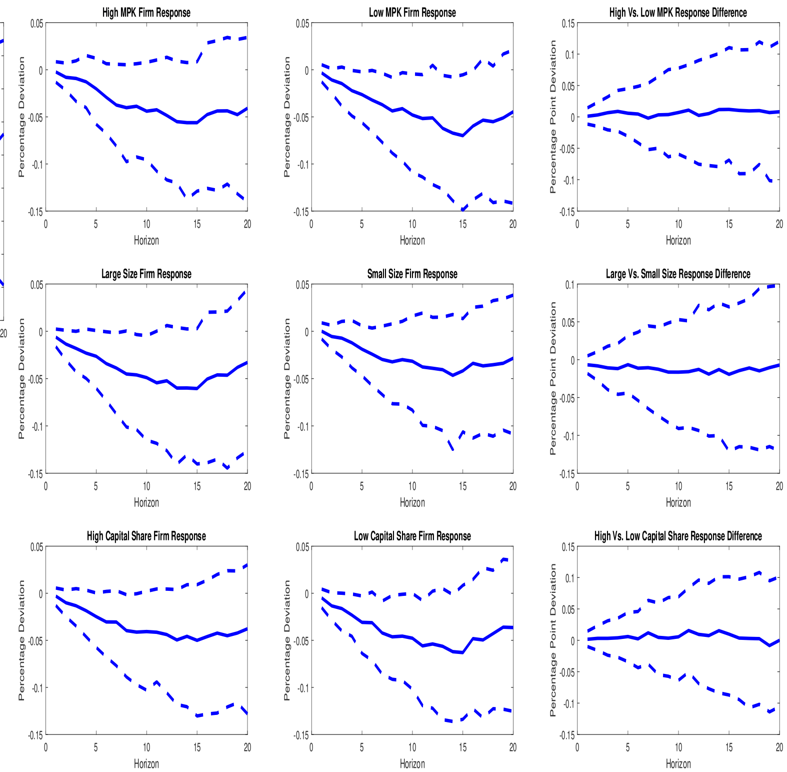
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from a one-step estimation procedure, i.e., a procedure where all the VAR variables are included in lagged form as control variables in the local projection regressions except for EBP which is also included in current form. In this specification the coefficient on the current value of EBP is the coefficient of interest and captures the impulse responses of firm-level real capital stocks to credit supply shocks. As in the near-VAR exercise, I facilitate estimation with a reasonable number of degrees of freedom by only keeping firms that have at least 20 years of consecutive observations; this reduces the baseline sample to 1171 firms from 2037 firms. The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.11: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Adding Firm-Specific Control Variables: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



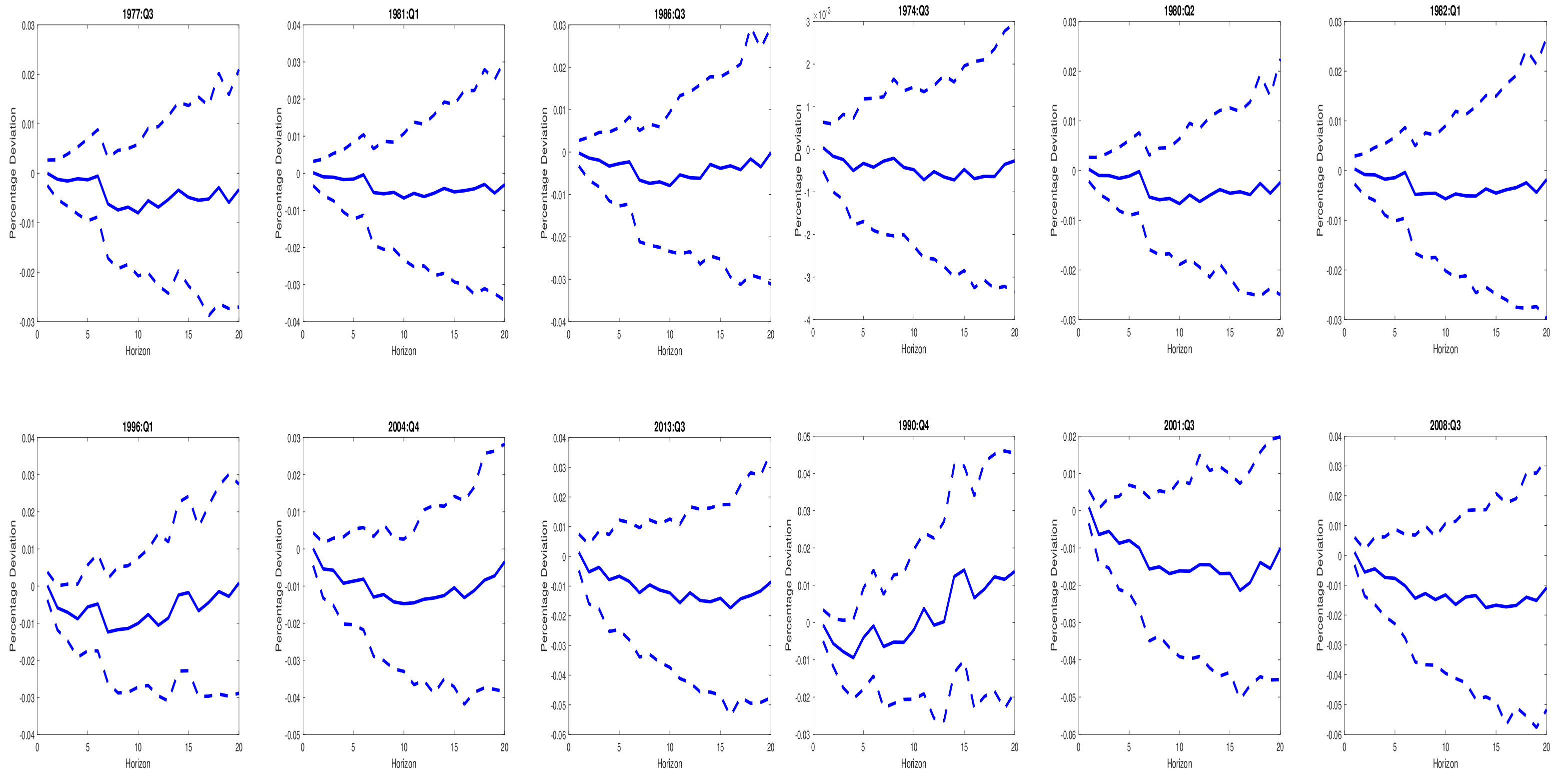
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from adding to the baseline specification 4 lagged values of firm-level leverage (defined as the ratio of total liabilities to total assets) and log-first-differences of sales. The exposition in both figures follows the structure from Figures C.1a and C.1b.

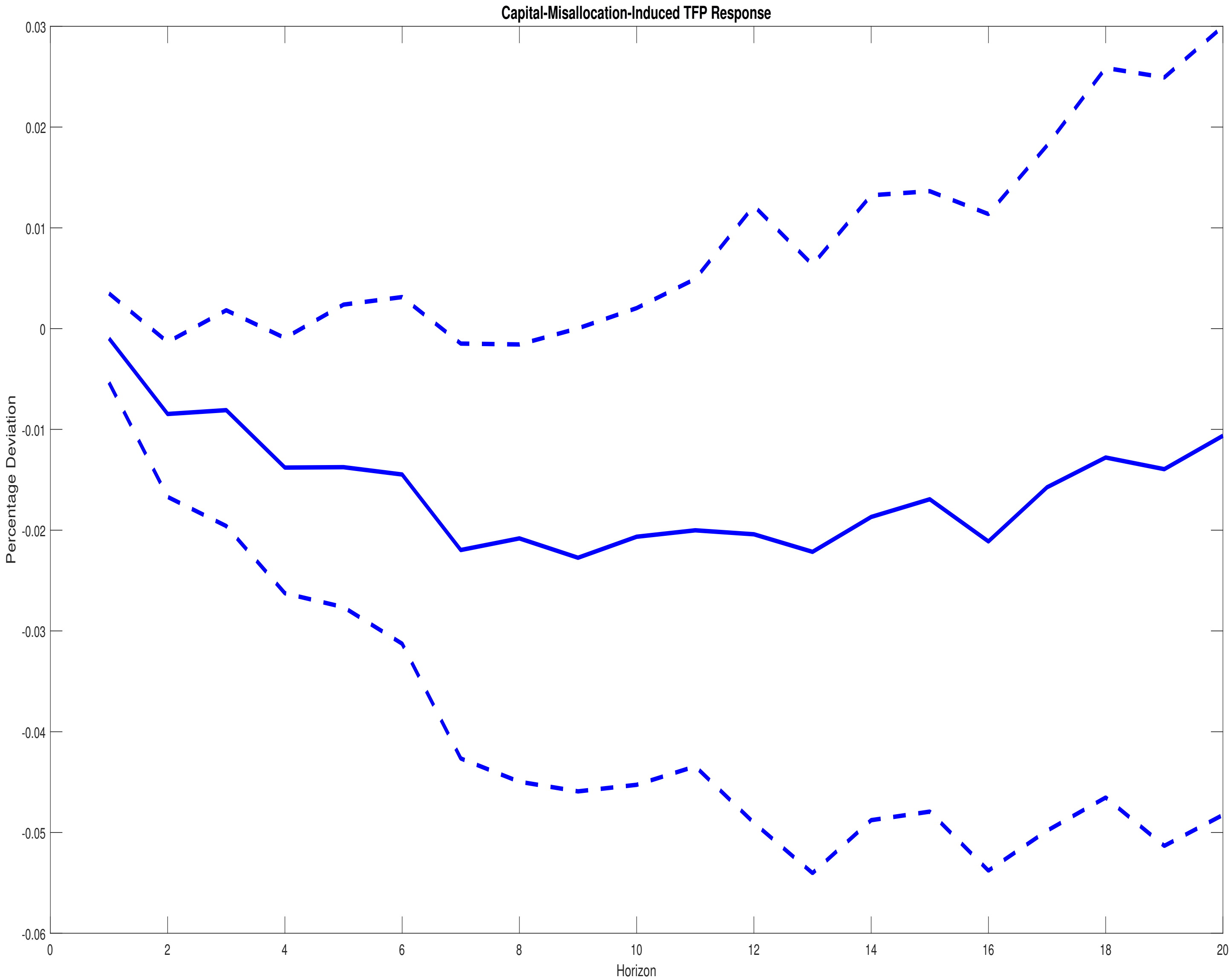
Figure C.12: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Using Lagged Value Rather Than Time-Series Average of MPK_i: (a) Capital-Misallocation-Induced TFP Response for Expansions; (b) Capital-Misallocation-Induced TFP Response for Recessions**.



(a) Capital-Misallocation-Induced TFP Response for Expansions. **(b) Capital-Misallocation-Induced TFP Response for Recessions.**

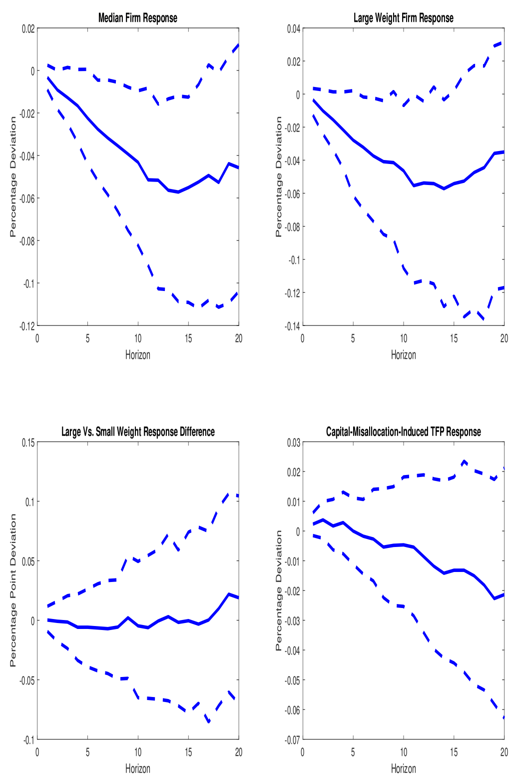
Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from constructing the capital-misallocation-induced TFP response to a one standard deviation credit supply shock on the basis of $MPK_{i,t-4}$, i.e., using the four-lagged value of MPK in the construction of capital misallocation term from Decomposition (4) from the paper instead of MPK's time-series average. Using one-year lagged values instead of time-series averages when constructing the firm-level weights multiplying the log-deviation of capital from Decomposition (4) from the paper results in time-varying weights in the capital misallocation term, thus resulting in the capital-misallocation-induced TFP response being allowed to vary over time. Panel (a) shows the capital-misallocation-induced TFP response for NBER-determined expansions while panel (b) shows the corresponding response for NBER-determined recessions.

Figure C.13: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Using** $MPK_{i,j} - MPK_j$ **Instead of** $MPK_i - MPK$.

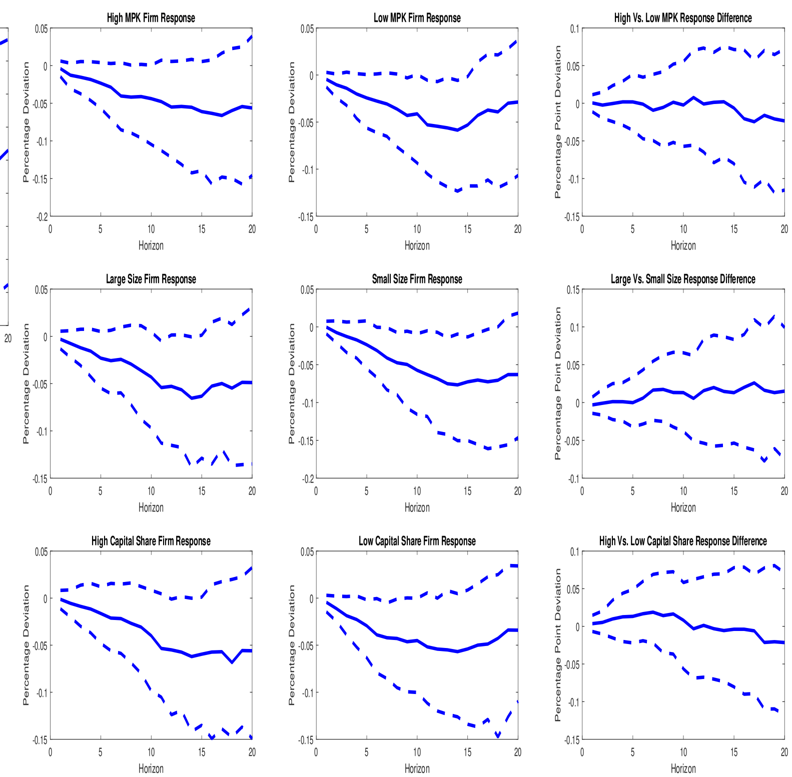


Notes: This figure presents the capital-misallocation-induced TFP response to a one standard deviation credit supply shock from computing $MPK_i - MPK$ Decomposition (4) from the paper in terms of deviations from the industry-average and not the economy-wide average (as is done in the baseline case).

Figure C.14: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Adding Industry Time Fixed Effects: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



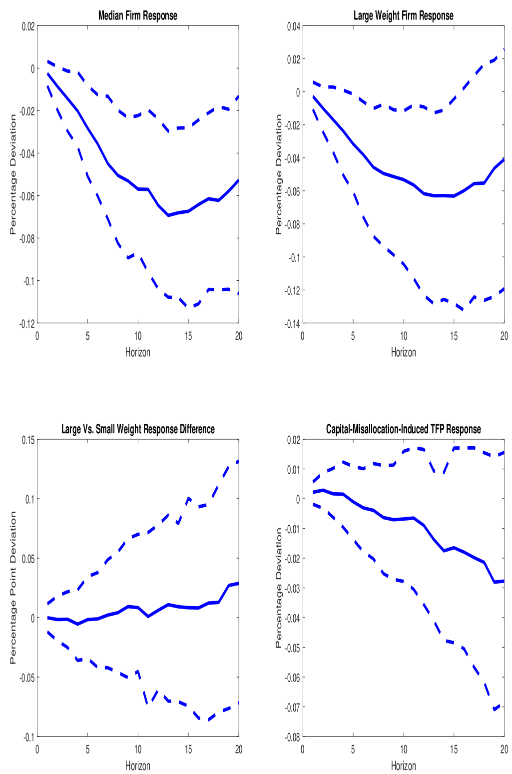
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



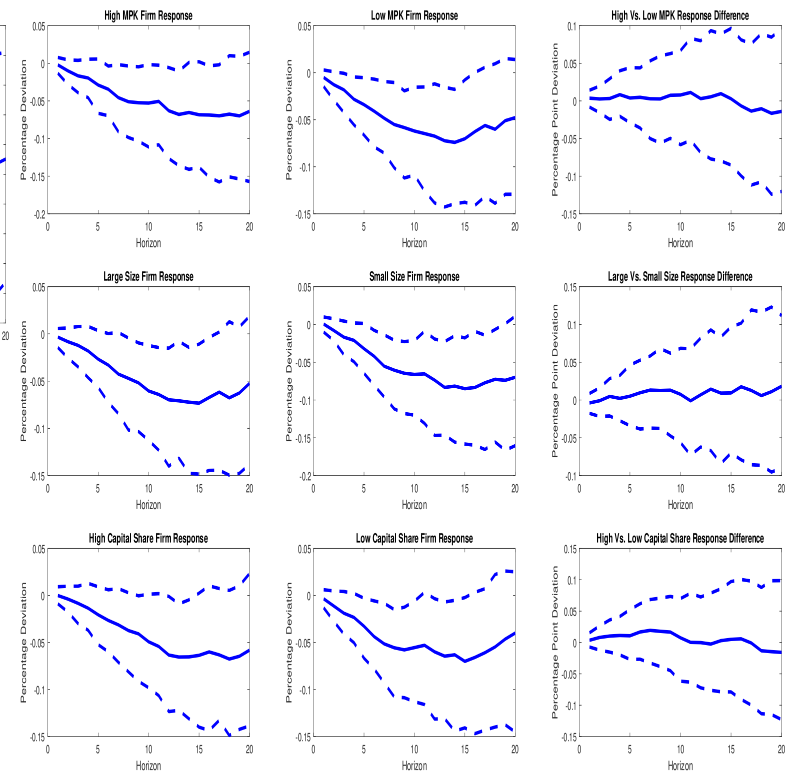
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from including industry time fixed effects (based on SIC 4-digit classification code) in the local projection firm-level regressions. The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.15: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Credit Supply Shock from Gilchrist and Zakrajšek (2012)'s Cholesky Ordering.: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics.**



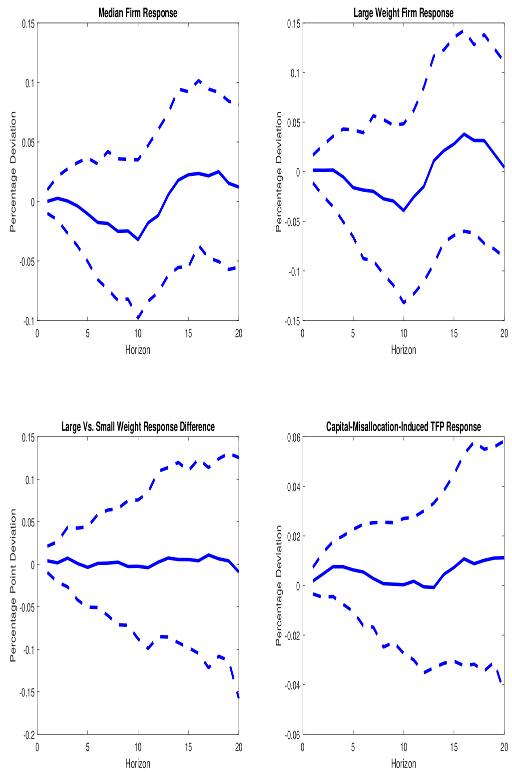
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



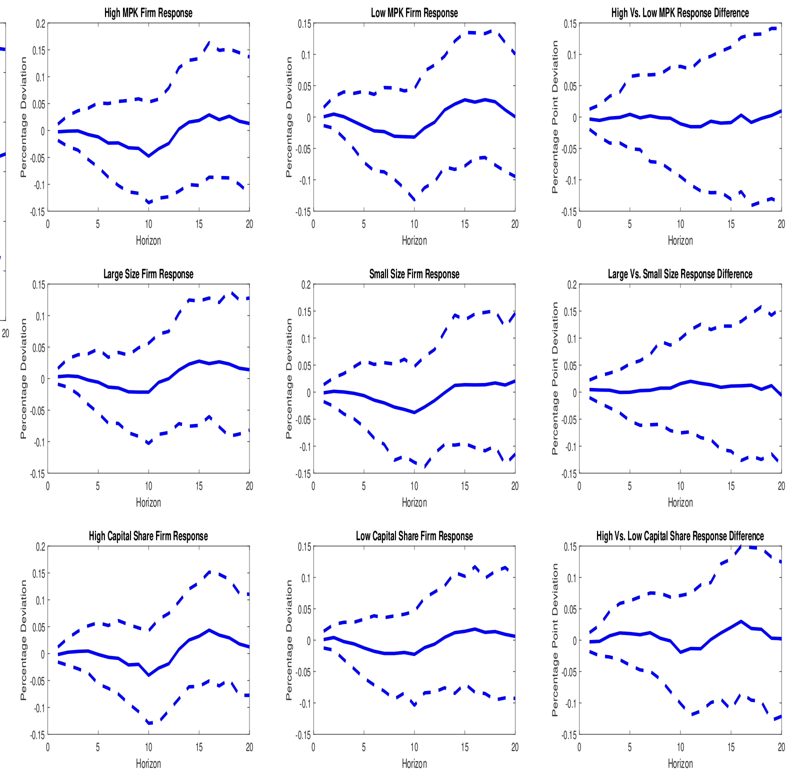
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from a credit supply shock series based on ordering EBP fifth in the VAR (after output, consumption, investment, and inflation) as in Gilchrist and Zakrajšek (2012). The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.16: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Credit Supply Shock from Bassett et al. (2014): (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



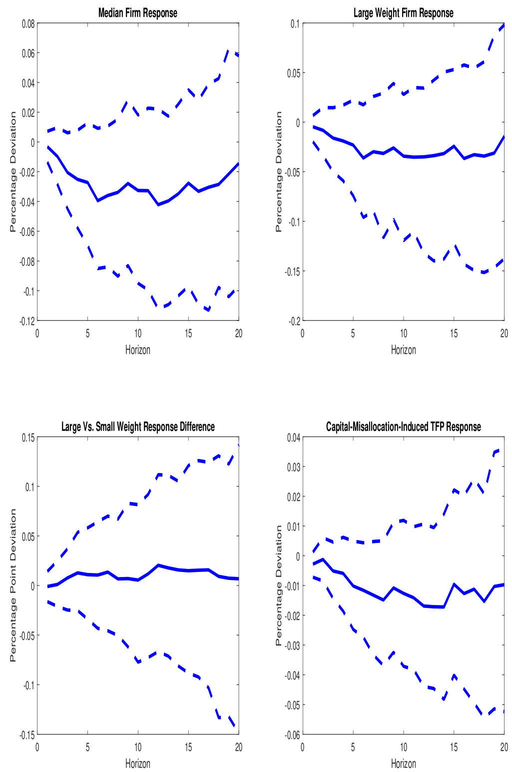
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



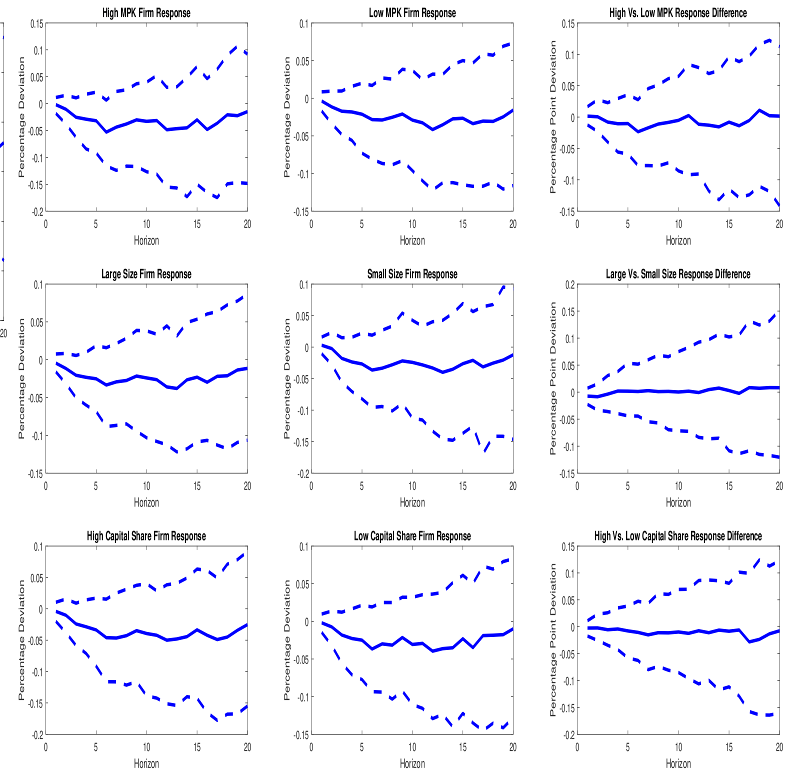
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from a credit supply shock based on the measure of bank lending shocks (BCDZ) calculated by Bassett et al. (2014). The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.17: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Credit Supply Shock from Jermann and Quadrini (2012): (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



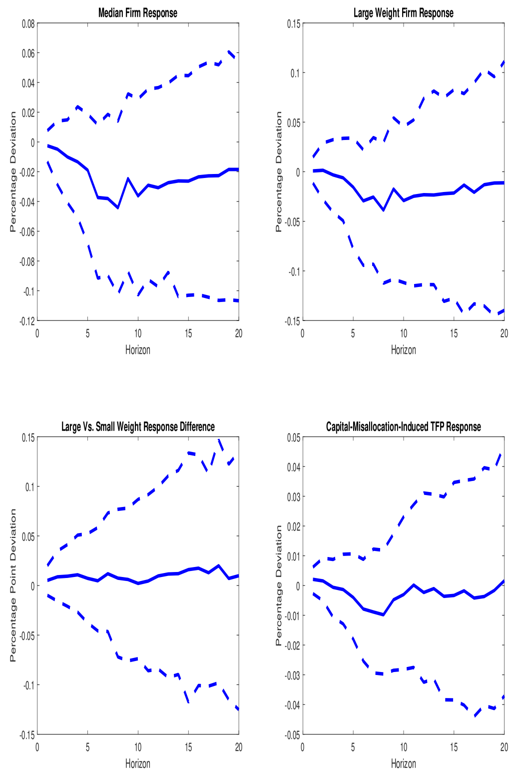
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



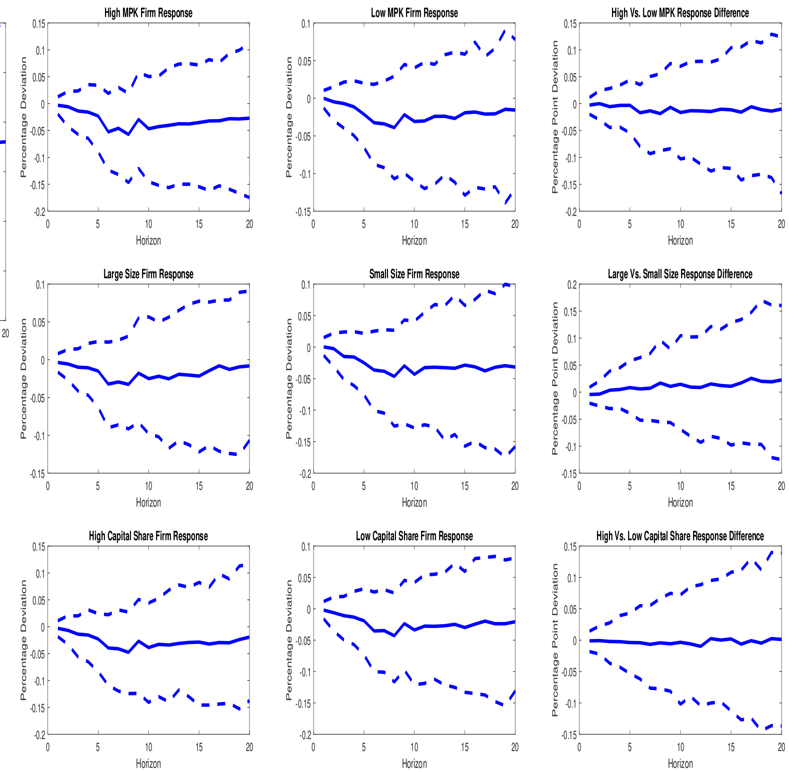
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from a credit supply shock based on the innovations to the financial conditions index (JQ) calculated by Jermann and Quadrini (2012). The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.18: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Credit Supply Shock from Christiano et al. (2014): (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



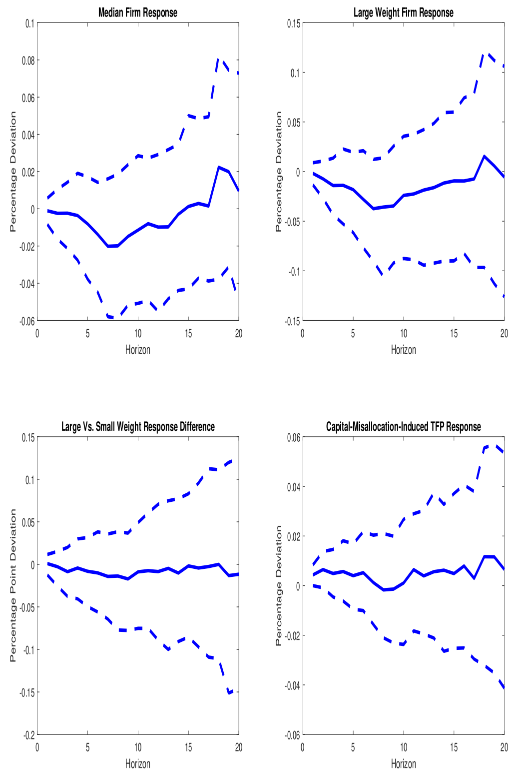
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



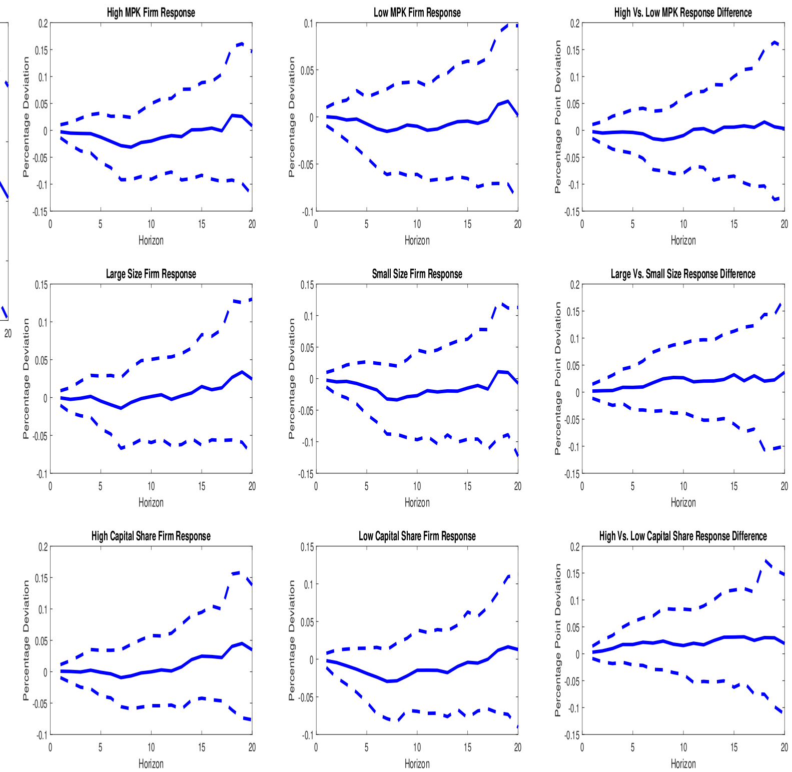
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from a credit supply shock based on the risk shock (CMR) from the DSGE model of Christiano et al. (2014). The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.19: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Credit Supply Shock from Mumtaz et al. (2018): (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



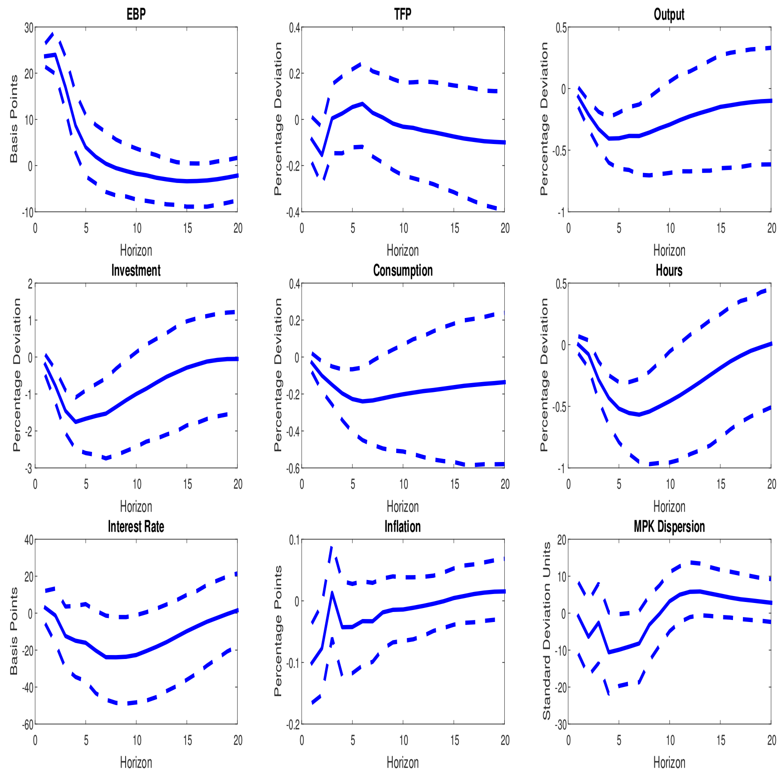
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



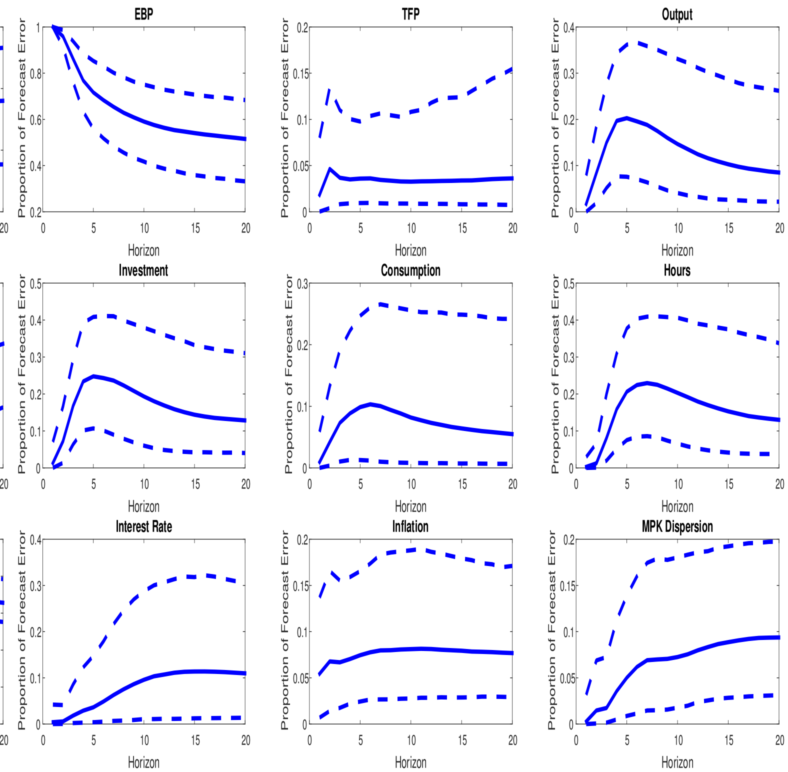
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from a credit supply shock (MPT) developed by Mumtaz et al. (2018) that is based on a search for the words "credit crunch" and "tight credit" using nine U.S. newspapers. The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.20: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Including Cross-Sectional MPK dispersion in the Baseline VAR: (a) Impulse Responses; (b) Contribution to FEV**.



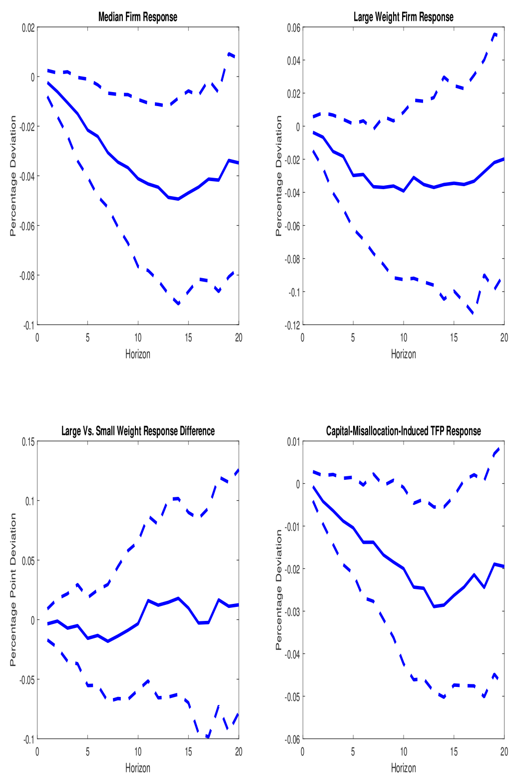
(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock.



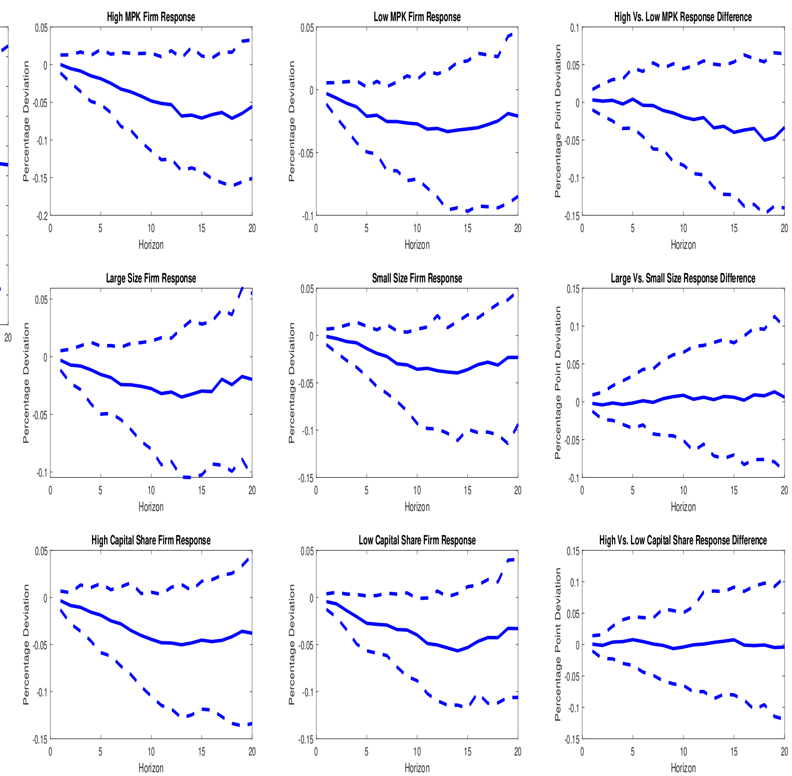
(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shocks to the Forecast Error Variance of the Variables.

Notes: This figure provides an alternative to the baseline bottom-up estimation approach for the capital misallocation channel by measuring capital misallocation via MPK dispersion instead of measuring it with the capital misallocation term from Decomposition (4) from the paper. Practically, the exercise underlying this figure amounts to adding the time series of the cross-sectional standard deviation of $MPK_{i,t}$ from my Compustat sample to the baseline VAR from the top-down analysis and estimating its response to a one standard deviation credit supply shocks. 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 that includes cross-sectional MPK dispersion. Responses are in terms of deviations from pre-shock values (in basis point deviation for EBP and interest rate, percentage point deviation for inflation, standard deviation units for MPK dispersion, and percentage deviation for all other variables). Horizon is in quarters. 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 that includes cross-sectional MPK dispersion. Horizon is in quarters.

Figure C.21: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Sub-Sample Based on Size: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



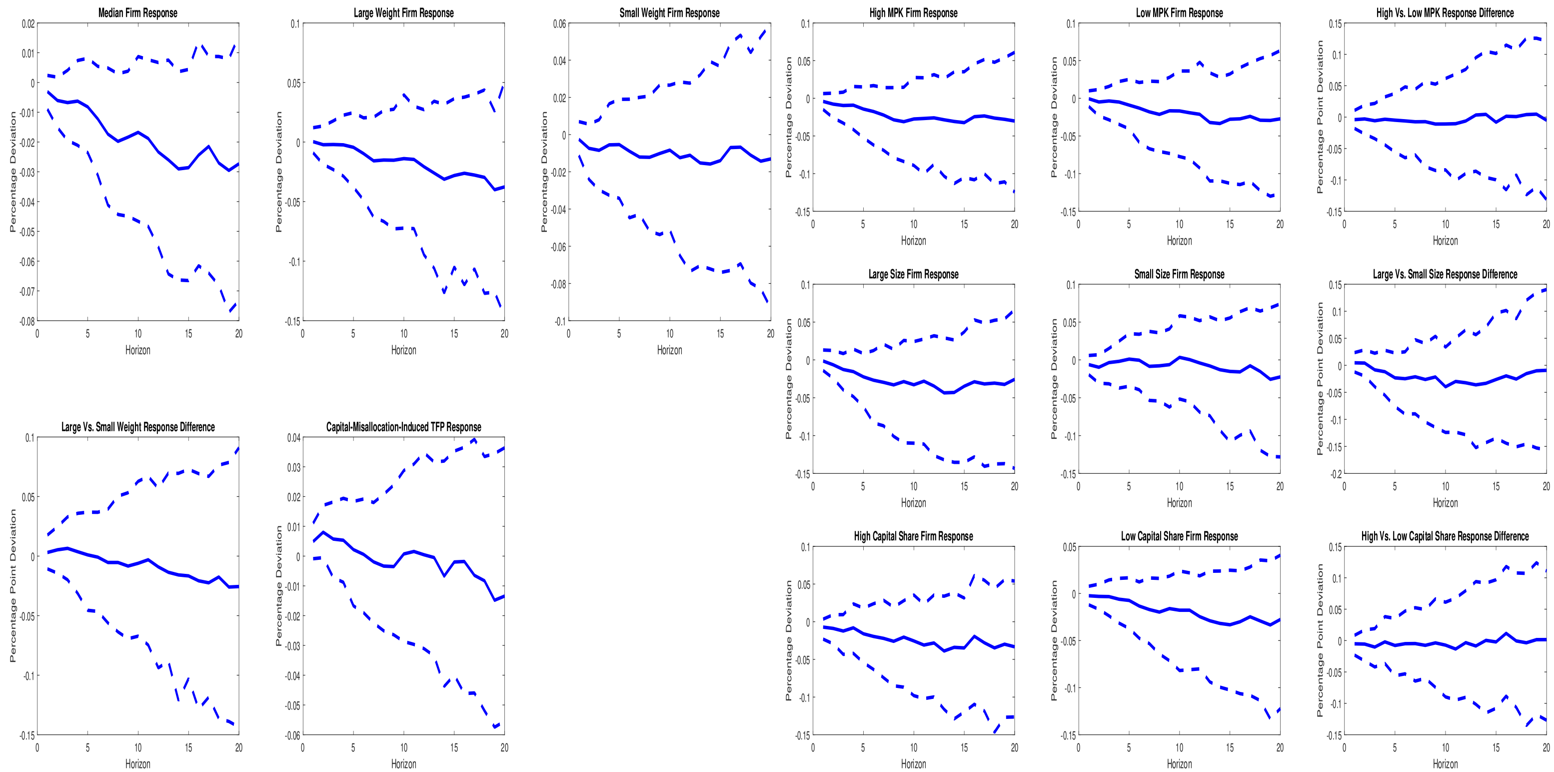
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from constructing a size based sub-sample, i.e., taking the part of my baseline sample that includes firms whose size is less than the median size. The exposition in both figures follows the structure from Figures C.1a and C.1b.

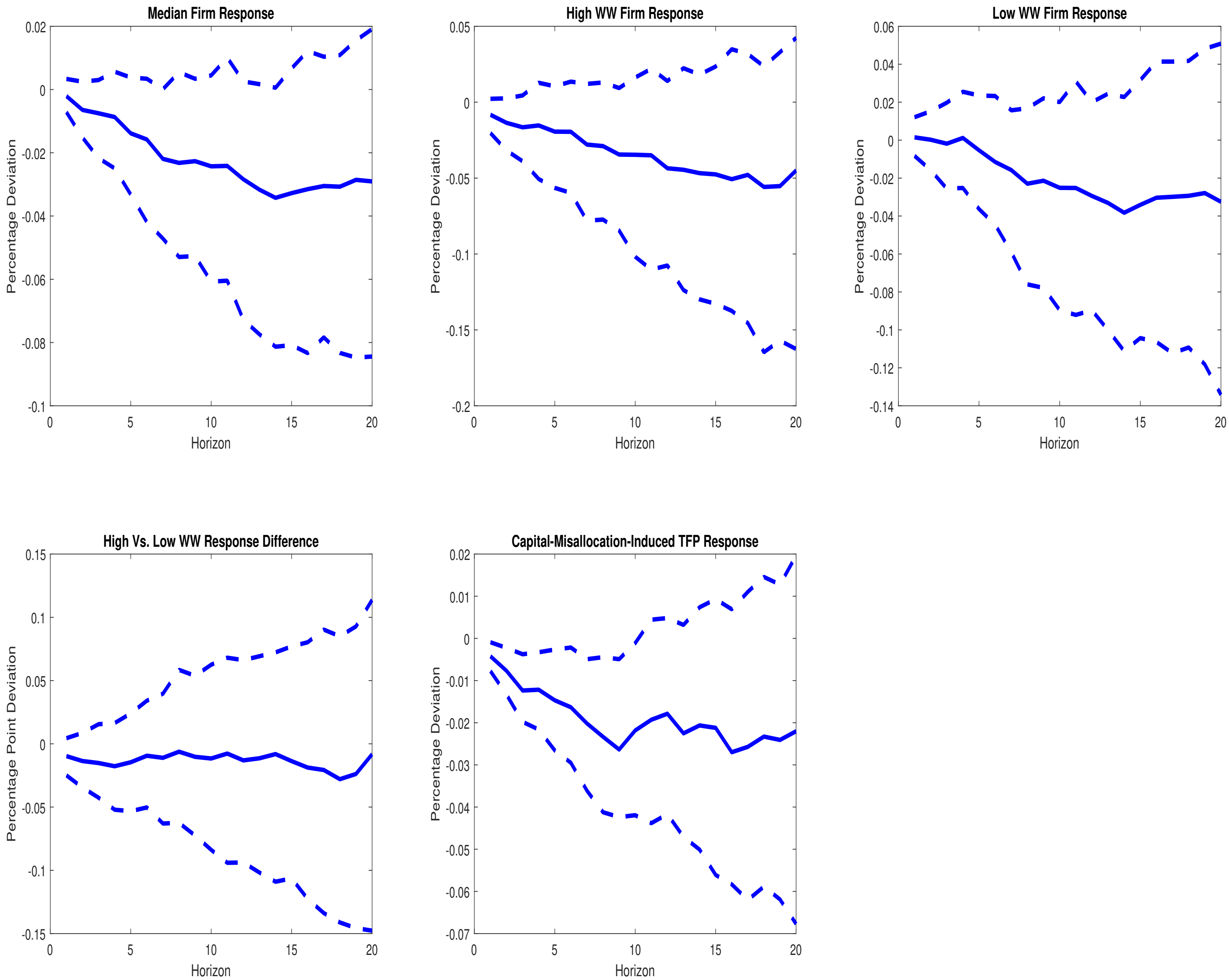
Figure C.22: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Sub-Sample Based on Rollover Risk: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response. **(b) Firm-Level Impulse Responses by Firm Characteristics.**

Notes: This figure presents the results for the bottom-up estimation procedure for the capital misallocation channel analysis from constructing a rollover risk based sub-sample, i.e., I follow Gopalan et al. (2014) and measure rollover risk by the ratio of short-term debt (i.e., having maturities of less than one year) to total debt and then construct my rollover risk based sub-sample as one only including firms whose rollover risk measure is higher than the median rollover risk value. The exposition in both figures follows the structure from Figures C.1a and C.1b.

Figure C.23: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Sorting Firms Along the Whited and Wu (2006) (WW) Financial Constraints Index.**



Notes: This figure is based on my use of the Whited and Wu (2006) financial constraints index (WW) to construct measures of financially unconstrained firms (defined as belonging to the lower quartile of the WW distribution) and financially constrained firms (defined as belonging to the upper quartile of the WW distribution). This figure shows the response of the high WW firm (financially constrained), the low WW firm (financially unconstrained), along with the response differences between each WW pair. The median and 95% posterior bands for each WW category firm response are obtained from computing the 2.5th, 50th, and 97.5th percentiles of the distribution of median response across firms in each WW category. For completeness, the figure also shows the capital-misallocation-induced TFP response and the response of the median firm (constructed as in the baseline case).

Appendix D Robustness Checks: Bottom-Up Approach: Labor Misallocation Channel

This section presents results from four additional exercises which examine the robustness of the baseline results for the bottom-up labor misallocation channel analysis. The first allows and accounts for sign-dependency in the effects of credit supply shocks. The second uses a near-VAR estimation approach instead of local projections based baseline procedure. The third replaces the baseline two-step estimation procedure with a one-step procedure. And the fourth considers alternative credit supply shock series. The results from all of these exercises achieve the goal of bolstering the confidence in the message from the baseline results, with the homogeneity in employment responses of the different firm size categories continuing to hold and the labor-misallocation-induced TFP response remaining negligible.

D.1 Accounting for Sign-Dependency of Impulse Responses

This section's exercise complements those from Sections B.7 and C.6, where I demonstrated that the baseline results from the top-down and bottom-up capital misallocation channel analyses, respectively, are robust to accounting for potential sign-dependency in credit supply shocks' effects. In this section I follow the three-step estimation procedure from Equations (B.1), (B.2), and (B.3), only that Equation (B.3) is now replaced by an equation which uses the cumulative change in logged employment for each of my six considered firm size categories as a function of raw and squared values of credit supply shocks. For convenience and completeness, I present here the precise three-equation system I estimate for the purposes of this section:

$$\begin{aligned}
EBP_t &= C + \Gamma_1^{EBP} EBP_{t-1} + \Psi_1^{EBP} EBP_{t-1}^2 + ... + \Gamma_4^{EBP} FBP_{t-p} + \Psi_4^{EBP} EBP_{t-4}^2 + \quad \text{(D.1)}\\
&+ \Gamma_1^{TFP} \Delta TFP_{t-1} + \Psi_1^{TFP} \Delta TFP_{t-1}^2 + ... + \Gamma_4^{TFP} \Delta TFP_{t-1} + \Psi_4^{TFP} \Delta TFP_{t-1}^2 + \\
&+ \sum_{i=1}^{4} \sum_{j=1}^{4} \Omega_{i,j} EBP_{t-i} \Delta TFP_{t-j} + \epsilon_t, \\
\hat{\epsilon}_t &= \delta + \gamma \hat{\epsilon}_t^2 + \xi_t, \qquad \text{(D.2)}\\
emp_{i,t+h} - emp_{i,t-1} &= \alpha_{i,h} + \Xi_{i,h} \hat{\xi}_t + \Phi_{i,h} \hat{\xi}_t^2 + u_{i,t+h}, \qquad \text{(D.3)}
\end{aligned}$$

where the estimation and associated terminology related to this system corresponds to those from Equations (B.1), (B.2), and (B.3), only that Equation (D.3) differs from Equation (B.3) in that i indexes firm size categories with $i = 1, 2, ..., I$ where $I = 6$; $emp_{i,t+h}$ is the log of firm size category i's employment level; $\alpha_{i,h}$ is the firm size category fixed effect at horizon h; and $\Xi_{i,h}$ and $\Phi_{i,h}$ are the first- and second-order effects of the credit supply shock, where $\Xi_{i,h} + \Phi_{i,h}$ and $\Xi_{i,h} - \Phi_{i,h}$ give the responses of logged employment of firm size category i at period h to a positive and negative one standard deviation credit supply shock at time t, respectively.

The results from this exercise are summarized and presented in Figures D.1a-D.3b, where the exposition structure of each figure pair follows that of baseline Figures 5a and 5b from the paper with Figures D.1a and D.1b corresponding to a positive credit supply shock; Figures D.2a and D.2b corresponding to a negative credit supply shock; and Figures D.3a and D.3b corresponding to the difference between the effects of a positive and negative credit supply shocks. Specifically, the first sub-figure of each figure pair presents the employment responses of the six category size firms to a one standard deviation credit supply shock along with the labor-misallocation-induced TFP response; and the second sub-figure shows the employment response differences across all firm size pairs.

There is strong and significant asymmetry in the employment responses to credit supply shocks, with positive shocks producing a much bigger fall in employment than the corresponding rise in employment induced by negative shocks (simply multiply Figure D.2a by -1 to get the actual change in employment following a negative credit supply shock). Notwithstanding this strong asymmetry, the labor-misallocation-induced TFP response is negligible for both the positive and the negative shock as is the asymmetry in this response. Moreover, the responses across the different firm size categories continue to be quite homogenous regardless of the shock sign. Hence, we can conclude that the main message of the baseline bottom-up labor misallocation channel analysis is robust to allowing and accounting for sign-dependency in impulse responses.

D.2 Near-VAR Instead of Local Projections.

My baseline specification for the bottom-up labor misallocation channel analysis takes the credit supply shock from the baseline VAR and runs local projection regressions of employment for each firm size category on this shock. An alternative specification worth considering as an additional robustness check is a procedure that runs a total of I near-VARs containing the eight variables from the baseline VAR and an additional ninth variable corresponding to $emp_{i,t}$ (logged employment at each firm size category) which is restricted to have no effect on the other variables while being allowed to respond to both their contemporaneous as well as lagged values. Such a nine-variable VAR is not only a *near*-VAR because of its block-recursive structure but also because the sample corresponding to its eight-variable block is larger than that corresponding to the firm size category employment variables block. In my estimations I explicitly account for these unequal samples by assigning the relevant degrees of freedom in the Bayesian estimation procedure of the two blocks.[20]

I assume 4 lags in both blocks, which implies a total of 37 estimated parameters in the firm size category employment block (4 lags of nine variables and a constant). This stresses an advantage of the two-step local projection regression approach used in the baseline analysis already discussed in Section C.7 with respect to the capital misallocation channel analysis. Specifically, the baseline estimation procedure for the labor misallocation analysis conserves on degrees of freedom in the joint estimation of the 6×20 firm size category employment local projection regressions by only including in them one explanatory variable, i.e., the credit supply shock estimated from the baseline VAR (which is the first step of the estimation procedure).

The results from this estimation exercise appear in Figures D.4a and D.4b (which share the same exposition structure as in Figures D.1a and D.1b). The employment response for the different firm size categories is somewhat less persistent than the baseline case, exhibiting more of a hump-shaped nature. But the homogeneity in employment responses across firm size categories remains in place and the labor-misallocation-induced TFP response continues to be negligible at all horizons. While this response is actually positive (as opposed to what theory would usually predict) and statically significant from the impact through the 14th horizon, its magnitude is neg-

[20] I use the Bayesian estimation algorithm for strong block-recursive structure put forward by Zha (1999) in the context of block-recursive VARs, where the likelihood function is broken into the different recursive blocks. In my case, I have only two blocks, where the first consists of the VAR from (B.2) and the second corresponds to the firm size category employment regression. As shown in Zha (1999), this kind of block separation along with the standard assumption of a normal-inverse Wishart conjugate prior structure leads to a normal-inverse Wishart posterior distribution for the block-recursive Equation parameters.

ligible (always below 0.004%) and thus implies that the main message of the paper regarding a weak labor misallocation channel of credit supply shocks is robust to using a near-VAR estimation approach.

D.3 One-Step Procedure Instead of Two-Step Procedure

The baseline specification for the bottom-up approach is effectively a two-step estimation procedure which in the first step estimates the baseline VAR and then in the second step estimates local projection regressions of employment of different firm size categories on the credit supply shock obtained from the first step. An alternative to this estimation approach is to do a one-step estimation procedure where all the VAR variables are included in lagged form as control variables in the local projection regression except for EBP which is also included in current form. In this specification the coefficient on the current value of EBP is the coefficient of interest and captures the dynamic effect of credit supply shocks on firm-level real capital stocks. (It is noteworthy here too, in similar fashion to the discussion in the previous section, that doing the estimation in a one-step procedure is much less efficient in terms of degrees of freedom conservation relative to the baseline two-step case. The one-step estimation procedure adds 33 estimated parameters to the firm size category employment local projection regressions from which the identification of the role of the labor misallocation channel is obtained.)

The results from this estimation exercise appear in Figures D.5a and D.5b (which share the same exposition structure as in Figures C.1a and C.1b). It is clear that the main message of the baseline labor misallocation channel analysis is robust to using a one-step estimation procedure. Employment responses across the considered firm size categories and rather homogenous and the labor-misallocation-induced TFP response is negligible at all horizons.

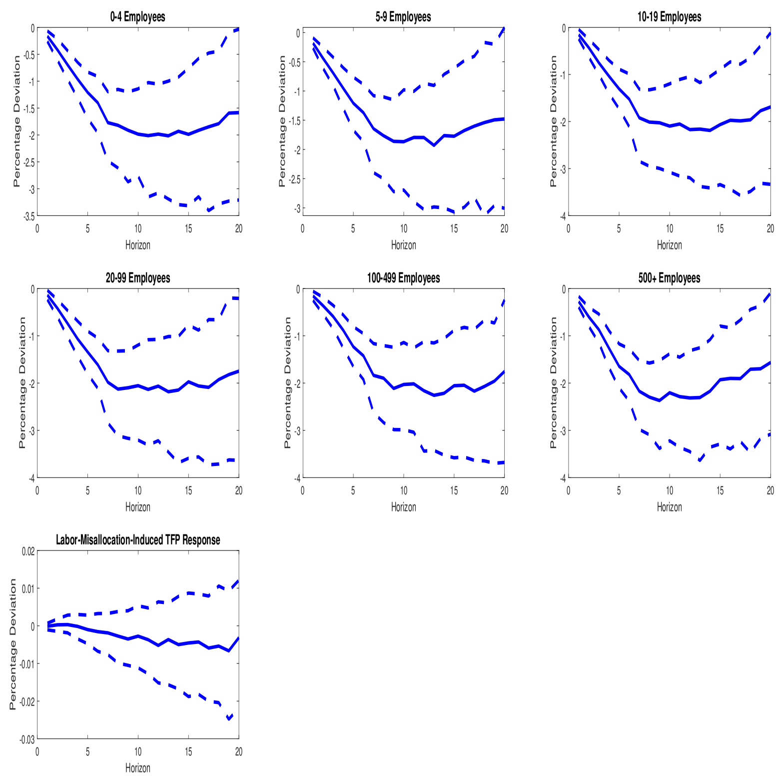
D.4 Alternative Credit Supply Shock Identification

In Sections B.4 and C.13 I considered five alternative credit supply shock series relative to the baseline top-down and bottom-up capital misallocation channel analyses, respectively. I repeat the baseline bottom-up analysis for the labor misallocation analysis for all of these five alternative identification schemes. For convenience, I describe these alternative series again followed by a summary of the results obtained from them.

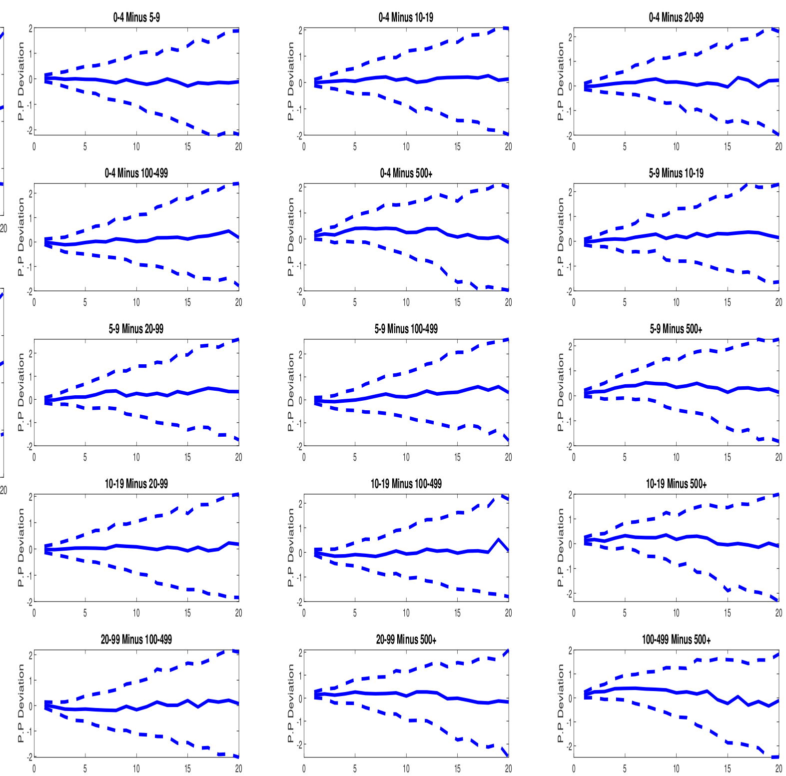
The first alternative series is obtained from a different ordering of the variables in the VAR, ordering EBP fifth in the VAR (after output, consumption, investment, and inflation) as in Gilchrist and Zakrajšek (2012) (the results for this credit supply shock are shown in Figures D.6a and D.6b). The remaining four are all obtained as the reduced form VAR innovations in the following credit supply shock series from Mumtaz et al. (2018) (each replacing EBP in the baseline VAR): the measure of bank lending shocks (BCDZ) calculated by Bassett et al. (2014), covering 1992:Q1-2010:Q4 (the results for this credit supply shock are shown in Figures D.7a and D.7b); the innovations to the financial conditions index (JQ) calculated by Jermann and Quadrini (2012), covering 1984:Q2-2010Q2 (the results for this credit supply shock are shown in Figures D.8a and D.8b); the risk shock (CMR) from the DSGE model of Christiano et al. (2014), covering 1981:Q1-2010:Q2 (the results for this credit supply shock are shown in Figures D.9a and D.9b); and a textual measure of credit supply shocks (MPT) developed by Mumtaz et al. (2018) that is based on a search for the words "credit crunch" and "tight credit" using nine U.S. newspapers, covering 1980:Q1-2012:Q4 (the results for this credit supply shock are shown in Figures D.10a and D.10b).

There are two main takeaways from all of the results for these alternative credit supply shock series. First, the homogeneity in firm size category employment responses observed for the baseline case continues to hold for all of the considered alternative shock series. And, second, the labor-misallocation-induced TFP response continues to be negligible at all horizons for all considered shock series. Hence, we can deduce that the main message from the baseline labor misallocation channel analysis is robust to considering alternative credit supply shock series from the literature.

Figure D.1: **Bottom-Up Estimation Approach: Labor Misallocation Channel: Impulse Responses to a Positive Shock: (a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response; (b) Employment Response Differences Across All Firm Size Pairs**.



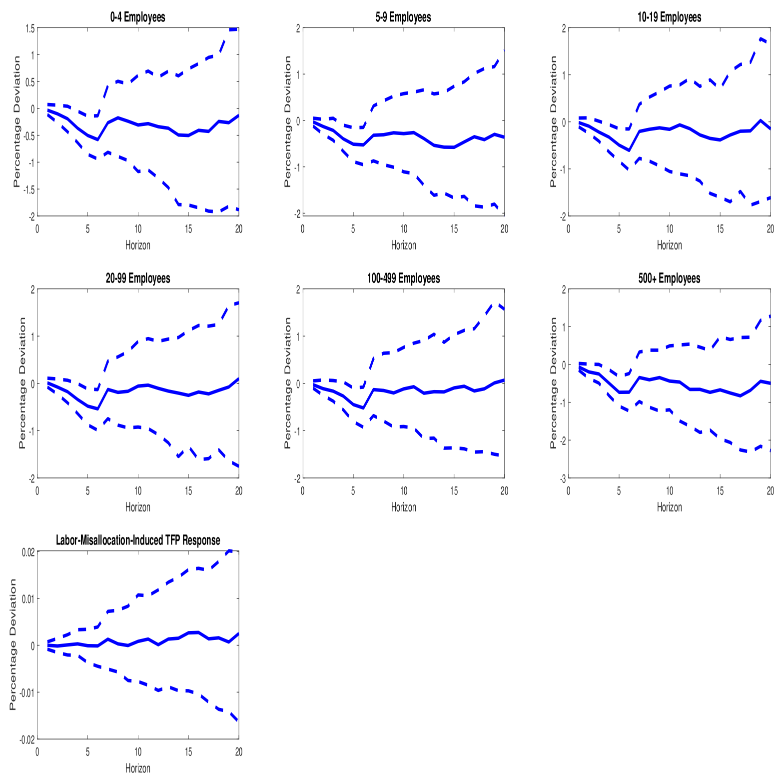
(a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response.



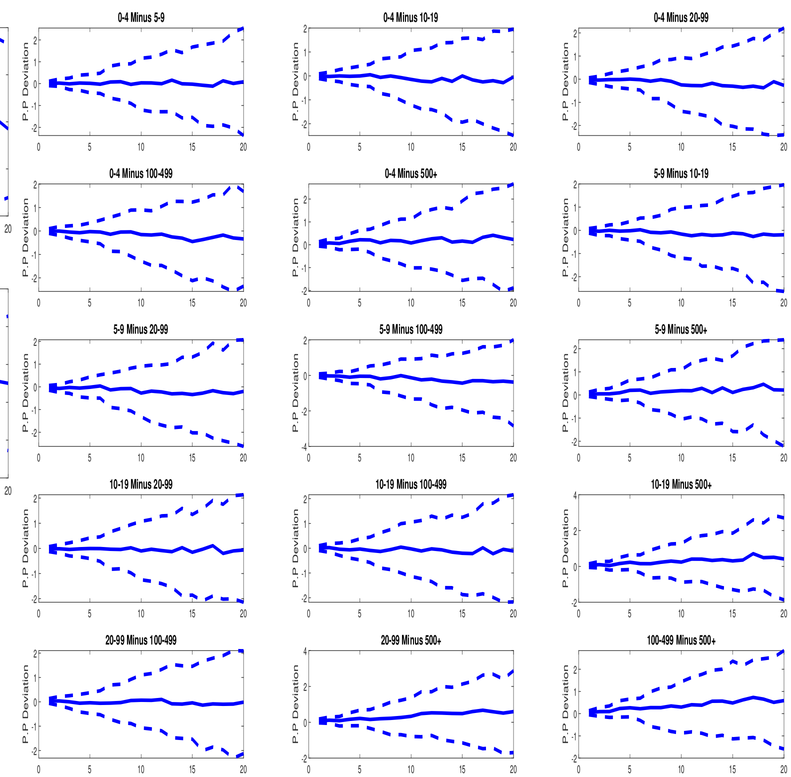
(b) Employment Response Differences Across All Firm Size Pairs.

Notes: This figure presents the results for a positive credit supply shock from the estimation of System (D.1-(D.3). Panel (a): The first six sub-figures in this panel show the median (solid line) and 95% confidence bands (dashed lines) of the employment response of each firm size category to a one standard deviation credit supply shock. The last sub-figure presents the labor-misallocation-induced TFP response computed from the third term from Decomposition (4) from the paper. Responses are in terms of percentage deviations from pre-shock values. Horizon is in quarters. Panel (b): This figure shows the employment response differences for all firm size pairs. Responses are in terms of percentage point deviations from pre-shock values.

Figure D.2: **Bottom-Up Estimation Approach: Labor Misallocation Channel: Impulse Responses to a Negative Shock: (a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response; (b) Employment Response Differences Across All Firm Size Pairs**.



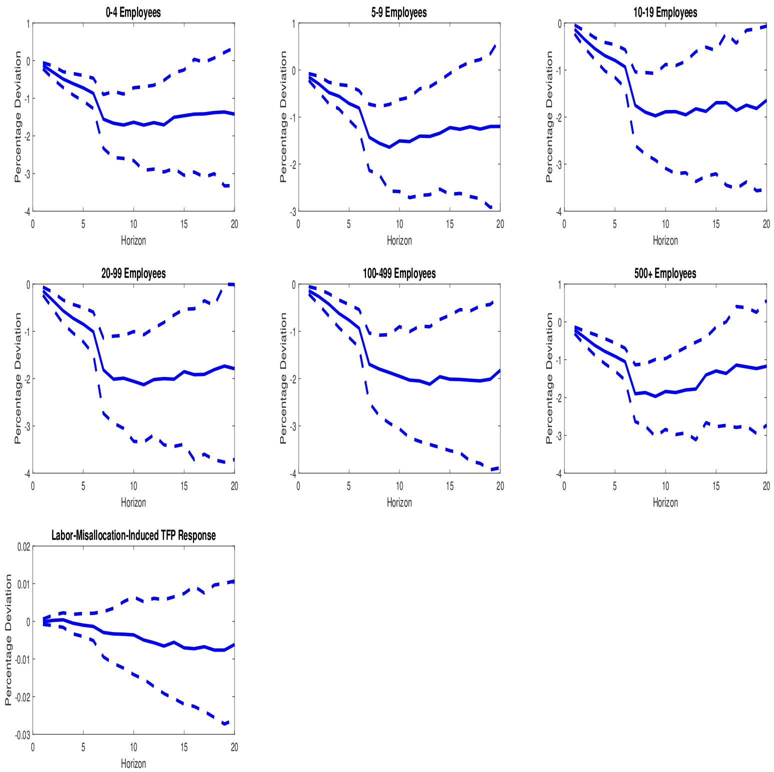
(a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response.



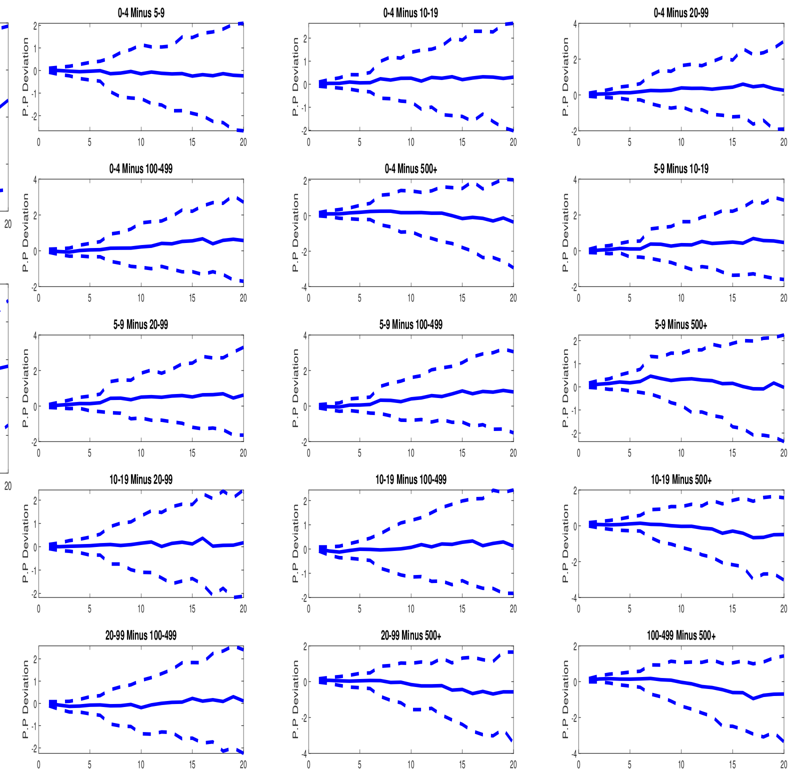
(b) Employment Response Differences Across All Firm Size Pairs.

Notes: This figure presents the results for a negative credit supply shock from the estimation of System (D.1-(D.3). The exposition in both figures follows the structure from Figures D.1a and D.1b.

Figure D.3: **Bottom-Up Estimation Approach: Labor Misallocation Channel: Impulse Response Asymmetry: (a) Employment Response Asymmetry by Firm Size and Labor-Misallocation-Induced TFP Response; (b) Employment Response Asymmetry Differences Across All Firm Size Pairs**.



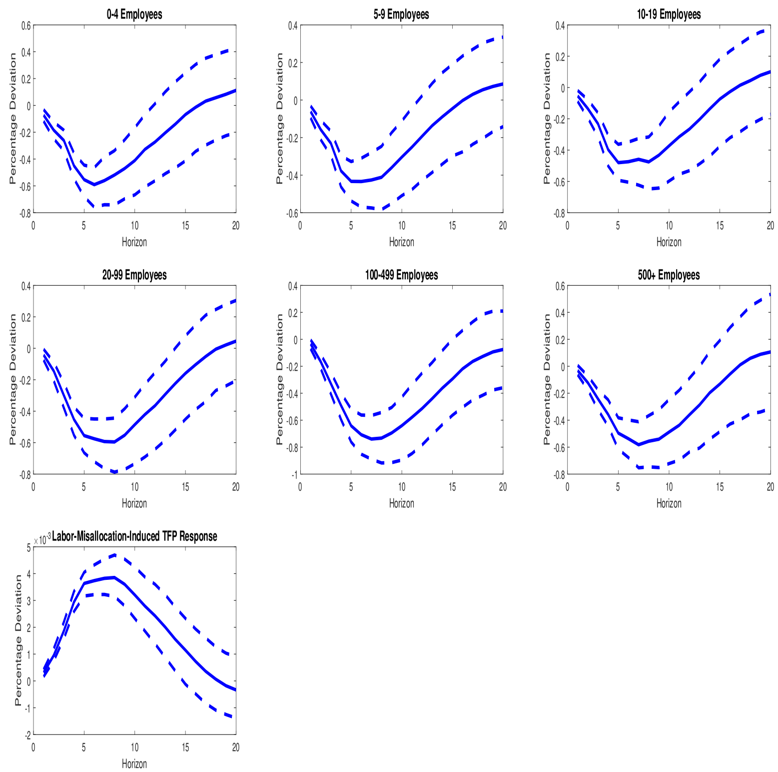
(a) Employment Response Asymmetry by Firm Size and Labor-Misallocation-Induced TFP Response.



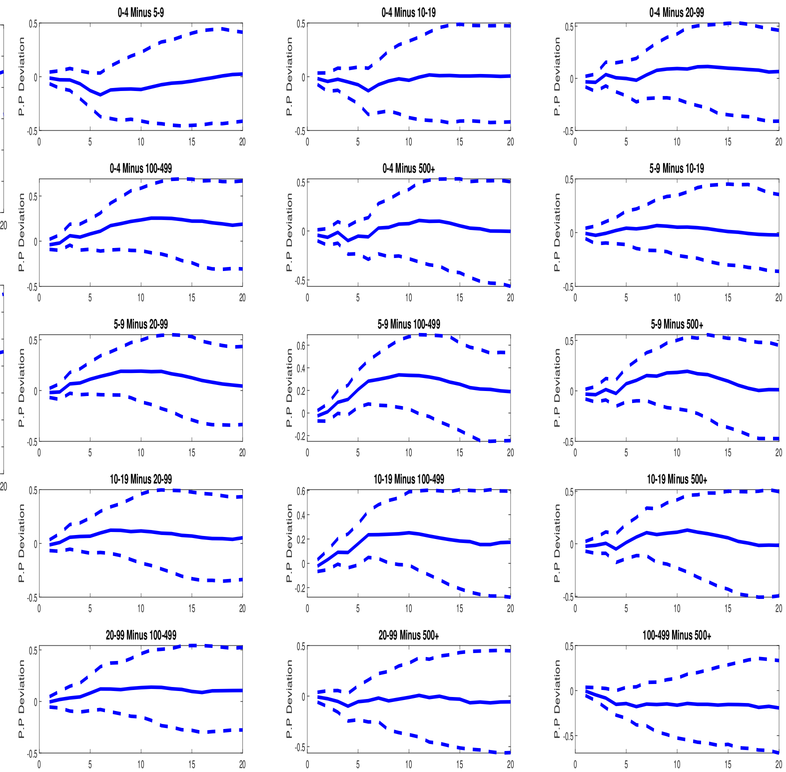
(b) Employment Response Asymmetry Differences Across All Firm Size Pairs.

Notes: This figure presents the results for response asymmetry, calculated as the difference between positive and negative shocks' effects, from the estimation of System (D.1-(D.3). The exposition in both figures follows the structure from Figures D.1a and D.1b.

Figure D.4: **Bottom-Up Estimation Approach: Labor Misallocation Channel: Near-VAR: (a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response; (b) Employment Response Differences Across All Firm Size Pairs**.



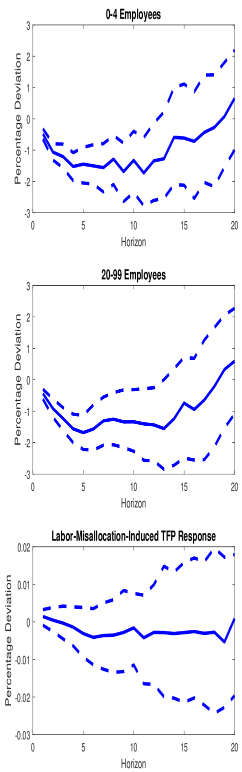
(a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response.



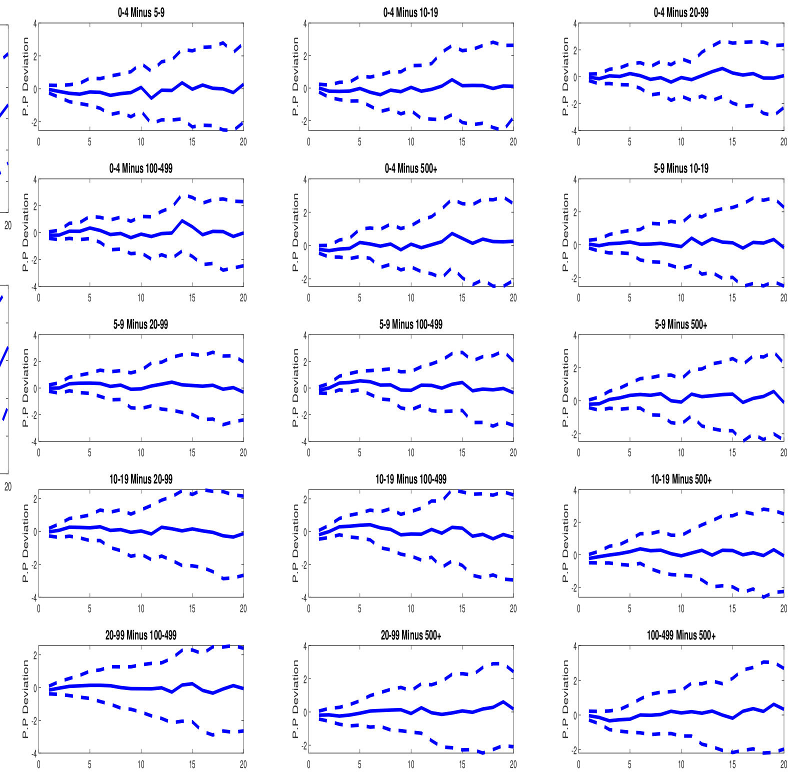
(b) Employment Response Differences Across All Firm Size Pairs.

Notes: This figure presents the results for the bottom-up estimation procedure for the labor misallocation channel analysis from estimation of a near-VAR model, i.e., a procedure that runs a total of I near-VARs (with I being the cross-sectional dimension of the sample, i.e., $I = 6$) containing the eight variables from the baseline VAR and an additional ninth variable corresponding to $emp_{i,t}$ (logged employment for each firm size category) which is restricted to have no effect on the other variables while being allowed to respond to both their contemporaneous as well as lagged values. Moreover, the difference in sample sizes covered by the aggregate variables and the employment level for the different firm size categories is allowed and accounted for in the estimation. The exposition in both figures follows the structure from Figures D.1a and D.1b.

Figure D.5: **Bottom-Up Estimation Approach: Labor Misallocation Channel: One-Step Estimation Procedure: (a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response; (b) Employment Response Differences Across All Firm Size Pairs**.



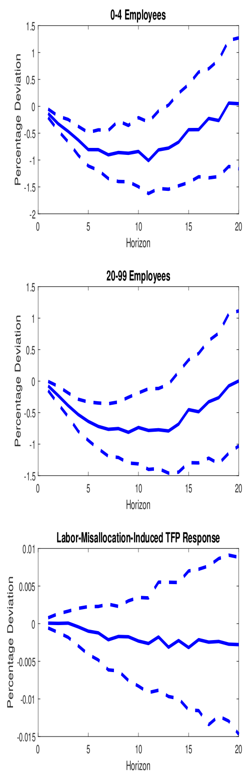
(a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response.



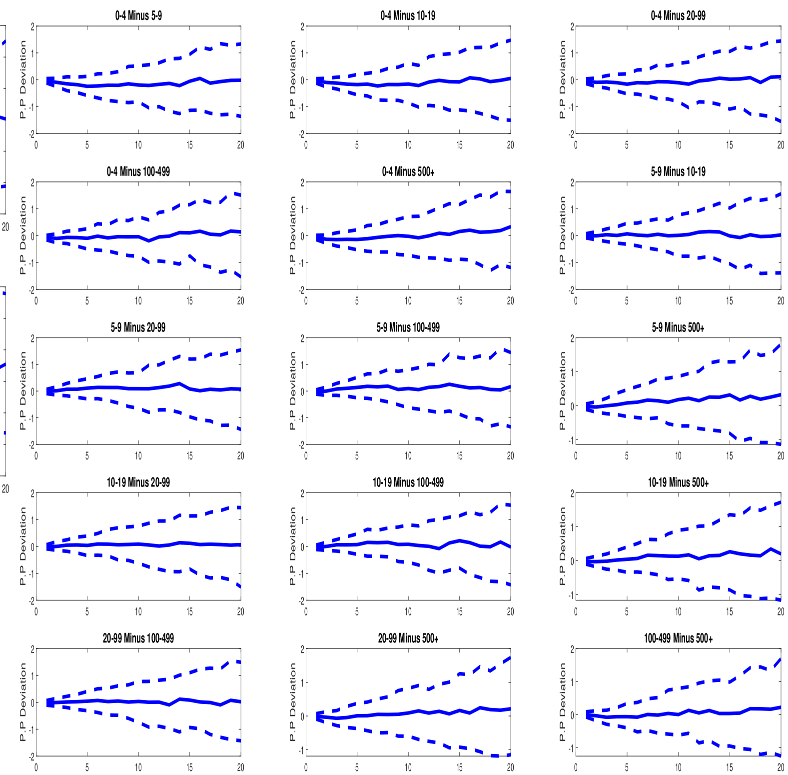
(b) Employment Response Differences Across All Firm Size Pairs.

Notes: This figure presents the results for the bottom-up estimation procedure for the labor misallocation channel analysis from a one-step estimation procedure, i.e., a procedure where all the VAR variables are included in lagged form as control variables in the local projection regression except for EBP which is also included in current form. In this specification the coefficient on the current value of EBP is the coefficient of interest and captures the impulse responses of employment for each firm size category to credit supply shocks. The exposition in both figures follows the structure from Figures D.1a and D.1b.

Figure D.6: **Bottom-Up Estimation Approach: Labor Misallocation Channel: Credit Supply Shock from Gilchrist and Zakrajšek (2012)'s Cholesky Ordering.: (a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response; (b) Employment Response Differences Across All Firm Size Pairs**.



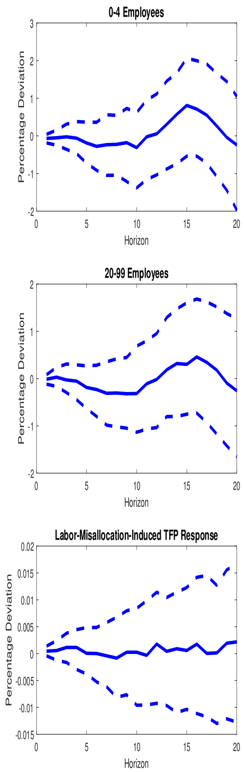
(a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response.



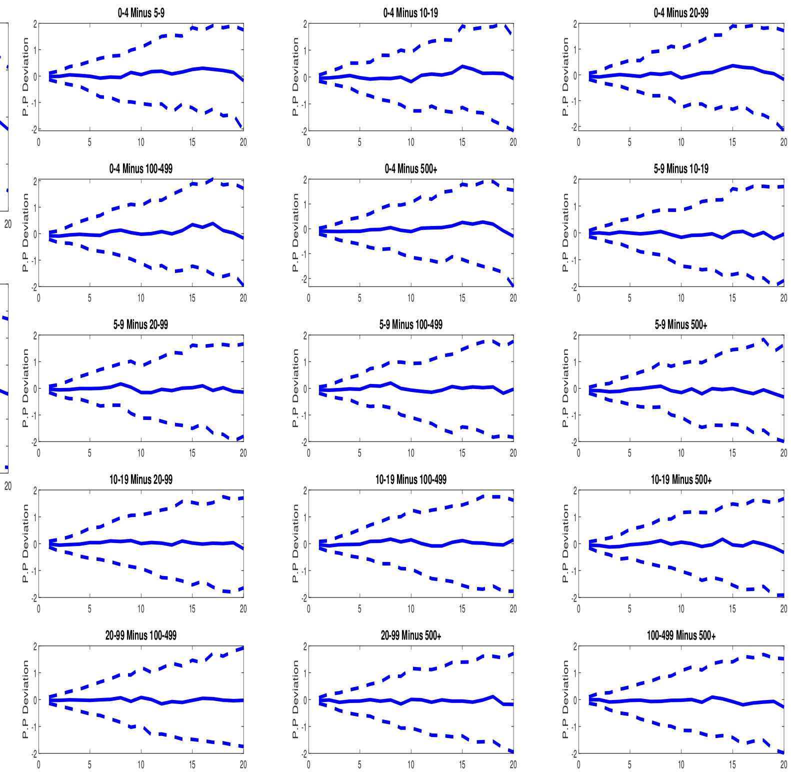
(b) Employment Response Differences Across All Firm Size Pairs.

Notes: This figure presents the results for the bottom-up estimation procedure for the labor misallocation channel analysis from a credit supply shock series based on ordering EBP fifth in the VAR (after output, consumption, investment, and inflation) as in Gilchrist and Zakrajšek (2012). The exposition in both figures follows the structure from Figures D.1a and D.1b.

Figure D.7: **Bottom-Up Estimation Approach: Capital Misallocation Channel: Credit Supply Shock from Bassett et al. (2014): (a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response; (b) Employment Response Differences Across All Firm Size Pairs**.



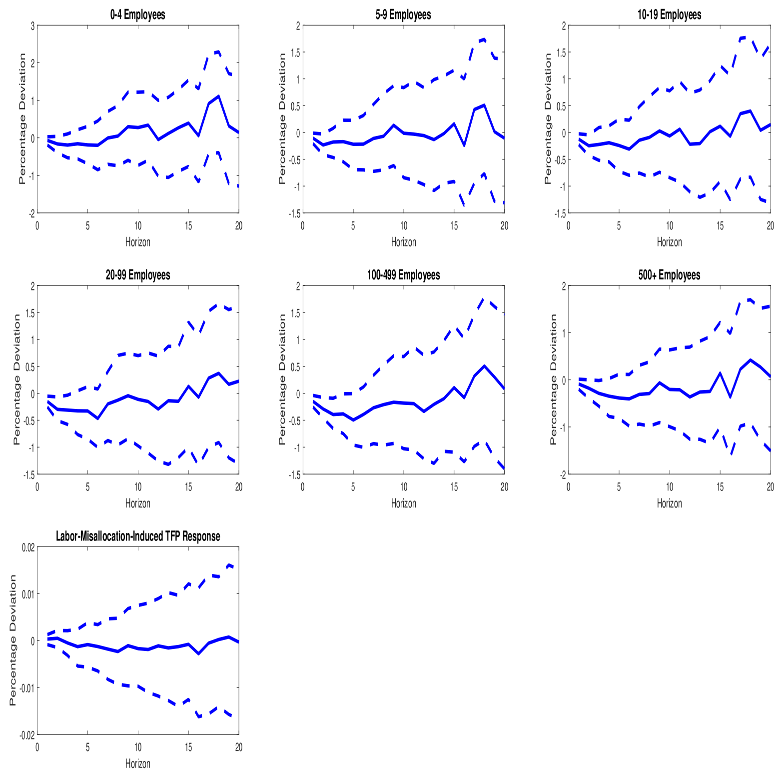
(a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response.



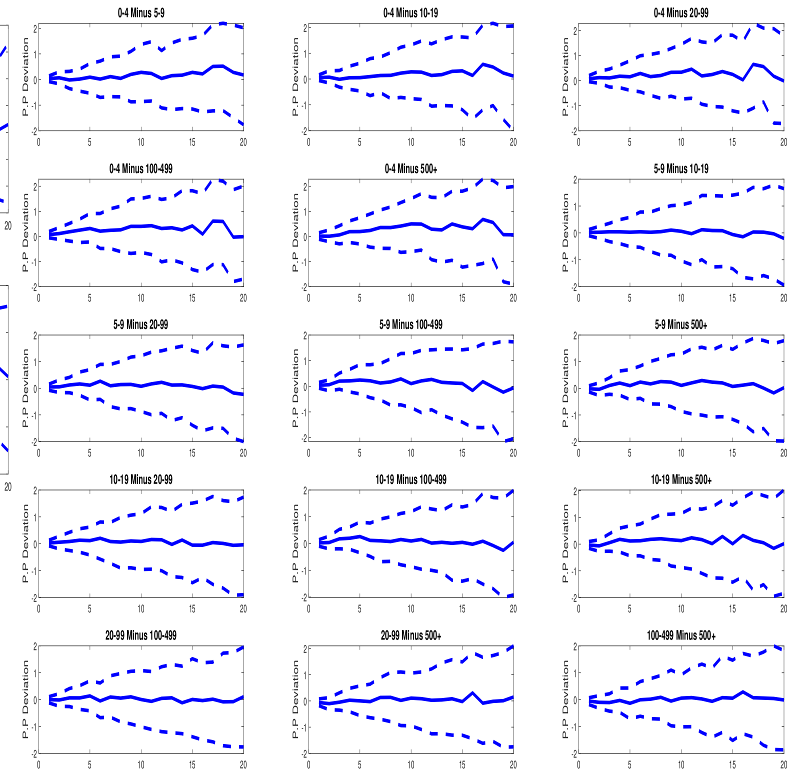
(b) Employment Response Differences Across All Firm Size Pairs.

Notes: This figure presents the results for the bottom-up estimation procedure for the labor misallocation channel analysis from a credit supply shock based on the measure of bank lending shocks (BCDZ) calculated by Bassett et al. (2014). The exposition in both figures follows the structure from Figures D.1a and D.1b.

Figure D.8: **Bottom-Up Estimation Approach: Labor Misallocation Channel: Credit Supply Shock from Jermann and Quadrini (2012): (a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response; (b) Employment Response Differences Across All Firm Size Pairs**.



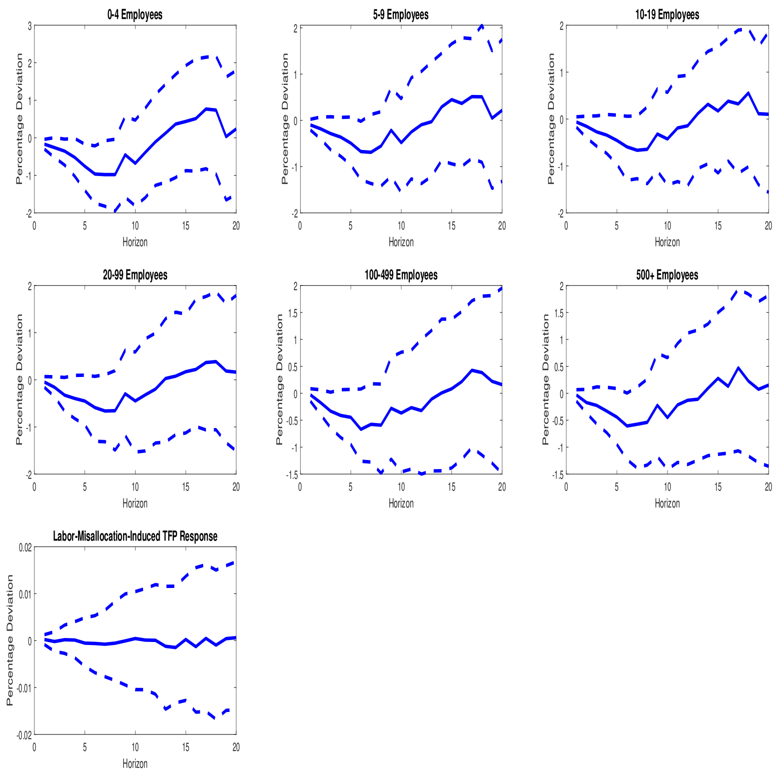
(a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response.



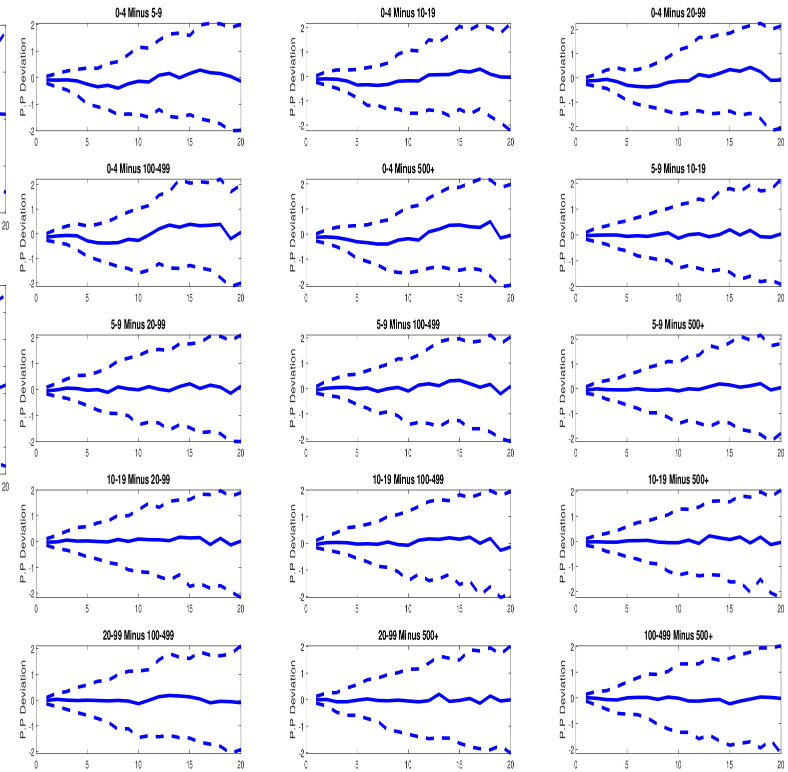
(b) Employment Response Differences Across All Firm Size Pairs.

Notes: This figure presents the results for the bottom-up estimation procedure for the labor misallocation channel analysis from a credit supply shock based on the innovations to the financial conditions index (JQ) calculated by Jermann and Quadrini (2012). The exposition in both figures follows the structure from Figures D.1a and D.1b.

Figure D.9: **Bottom-Up Estimation Approach: Labor Misallocation Channel: Credit Supply Shock from Christiano et al. (2014): (a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response; (b) Employment Response Differences Across All Firm Size Pairs**.



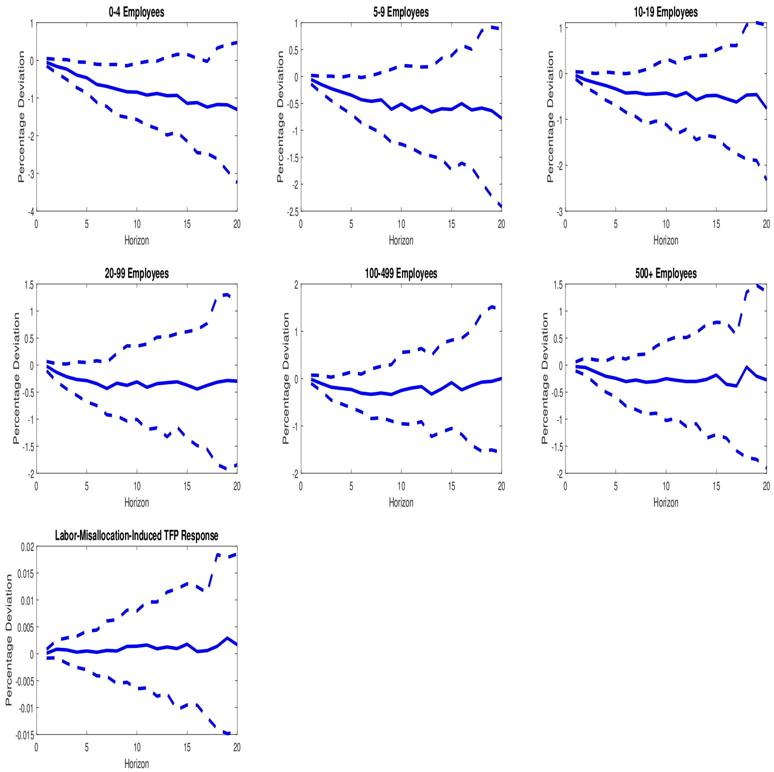
(a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response.



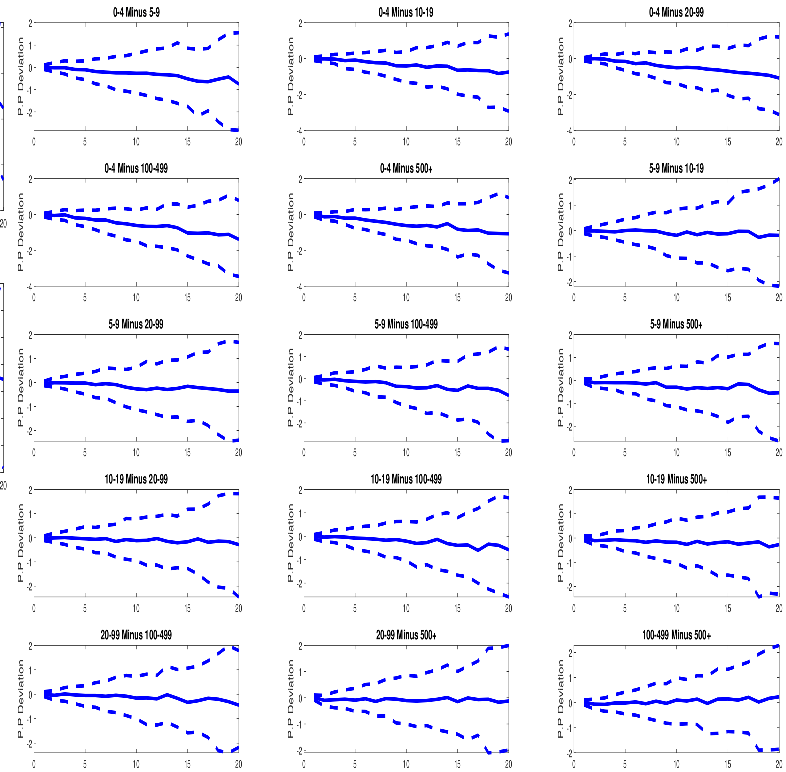
(b) Employment Response Differences Across All Firm Size Pairs.

Notes: This figure presents the results for the bottom-up estimation procedure for the labor misallocation channel analysis from a credit supply shock based on the risk shock (CMR) from the DSGE model of Christiano et al. (2014). The exposition in both figures follows the structure from Figures D.1a and D.1b.

Figure D.10: **Bottom-Up Estimation Approach: Labor Misallocation Channel: Credit Supply Shock from Mumtaz et al. (2018): (a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response; (b) Employment Response Differences Across All Firm Size Pairs.**



(a) Employment Response by Firm Size and Labor-Misallocation-Induced TFP Response.



(b) Employment Response Differences Across All Firm Size Pairs.

Notes: This figure presents the results for the bottom-up estimation procedure for the labor misallocation channel analysis from a credit supply shock (MPT) developed by Mumtaz et al. (2018) that is based on a search for the words "credit crunch" and "tight credit" using nine U.S. newspapers. The exposition in both figures follows the structure from Figures D.1a and D.1b.

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