The TFP Channel of Credit Supply Shocks*

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February 10, 2021

Abstract

Recent work stresses a potentially important relation between credit supply shocks and aggregate TFP based on factor misallocation. I take three steps to examine this relation. First, using state-of-the-art credit supply shock and aggregate TFP measures, I show that an adverse credit supply shock has a weak and very short-lived effect on aggregate TFP. Second, using firm-level data, I show that firm-level capital stock responses to an adverse credit supply shock produce an insignificant and negligible capital-misallocation-induced TFP response. Third, using employment data by fine firm size category classification, I also find a negligible labor-misallocation-induced TFP response. These findings suggest that the TFP channel of credit supply shocks has a limited role in their transmission to the real economy.

JEL classification: D22,D24,E23,E32,E44

Keywords: Total Factor Productivity; Credit Supply Shocks; Capital misallocation; Marginal product of capital; Labor misallocation; Marginal product of labor; Firm-level impulse responses; Bottom-Up Approach; Top-Down Approach

*I am grateful to Olivier Coibion, three anonymous referees, Alex Cukierman, Zvika Eckstein, Tomer Ifergane, Nadav Levy, Rafi Melnick, Omer Moav, Yona Rubinstein, Yaniv Yedid-Levi, and seminar participants at the Interdisciplinary Center Herzliya for helpful comments and suggestions.

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1 Introduction

The recent financial crisis has generated a new wave of interest in research on the role of credit supply shocks in the business cycle. Models with financial frictions mostly stress the link between credit supply shocks and interest-sensitive spending, such as investment, as the basic channel by which these shocks propagate into the real economy (see, e.g., Jermann and Quadrini (2012) and Christiano et al. (2014)). Recently, however, considerable work has emerged studying the potentially important role that capital-misallocation-induced changes in aggregate total factor productivity (TFP) may have in amplifying/moderating credit supply shocks' effects on the real economy (see, e.g., Buera et al. (2011), Pratap and Urrutia (2012), Petrosky-Nadeau (2013), Khan and Thomas (2013), Buera and Moll (2015), Buera et al. (2015), Gopinath et al. (2017), and Buera and Shin (2017)).

Objective and Contribution of this Paper. The main objective of this paper is to determine the quantitative importance of the TFP channel of credit supply shocks. Toward this end, I center my analysis around three natural litmus tests for the importance of this channel. First, a direct estimation of the effect of credit supply shocks on aggregate TFP in the data, while using state-of-the-art measures of these two objects, serves as the first natural litmus test I examine to determine the quantitative importance of the TFP channel of credit supply shocks.

Second, directly estimating the capital-misallocation-induced TFP loss from the aggregation of adverse credit supply shocks' effects on firm-level capital stocks, while using an unrestrictive structural framework to discipline this aggregation, constitutes a second basic litmus test I conduct for ascertaining the magnitude of the capital misallocation channel of credit supply shocks. This channel lies at the heart of how these shocks are predicted to transmit to TFP from a theoretical standpoint and thus must be meaningful for there to be a theory-consistent significant TFP channel of credit supply shocks.

However, financial frictions may also apply to the funding of labor costs and not only capital costs (see, e.g., Gilchrist et al. (2013)), thus opening the door for a possible labor misallocation channel of credit supply shocks. Hence, the third litmus test I conduct is aimed at quantifying this channel by using employment data by fine firm size category classification and aggregating the employment responses of these firm size categories to estimate the labor-misallocation-induced TFP response to credit supply shocks, while using the same unrestrictive structural framework from the second litmus test to discipline this aggregation.

In other words, I directly estimate the TFP channel of credit supply shocks using both a top-down and a bottom-up approach. The defining characteristic of these two approaches is that in both the estimation is based on impulse responses of TFP to credit supply shocks, with the first considering aggregate TFP's response and the second concerning firm-level capital stocks' responses and their aggregation for the capital misallocation channel quantification and employment responses by fine firm size category classification and their aggregation for the labor misallocation channel quantification. Such analysis constitutes a novel contribution to the literature on the TFP channel of credit supply shocks as researchers in this literature have generally opted to study this channel within micro-founded structural models which are inherently more restrictive than the relatively unrestrictive approach I take in this paper and in which credit supply shocks' effects are therefore more tied to the specific structure of the model at hand.

To accomplish my aforementioned objective, this paper unfolds in three parts. The first part lays down a simple structural framework whose purpose is twofold. First, it serves the purpose of fixing ideas and forming a suitable conceptual base for this paper. And second, it serves as the aggregation framework for my bottom-up estimation approach. The second and third parts of this paper conduct the aforementioned top-down and bottom-up analyses.

Underlying Framework. This part lays out a simple structural production framework that serves as the aggregation procedure in the disaggregated third part of my analysis. This framework's unrestrictive nature is appealing in being jointly simple as well as capable of establishing a valuable conceptual base upon which to build the discussion of the empirical results that follow it. In particular, it will prove helpful in facilitating the understanding of what conditions need to materialize in order for there to be a meaningful capital and labor misallocation channels of credit supply shocks. And the straightforward aggregation formula it puts forward will guide the estimation of capital- and labor-misallocation-induced TFP changes following credit supply shocks that I conduct in the third (bottom-up) part of this paper.

Top-Down Approach. Motivated by the notion that a meaningful TFP channel of credit supply shocks is effectively tantamount to a significant response of aggregate TFP to credit supply shocks, this part estimates the response of the utilization-adjusted TFP measure from Fernald (2012) to shocks to the excess bond premium (EBP) measure from Gilchrist and Zakrajšek (2012).[1] This estimation is done within a VAR that includes the aforementioned TFP and EBP measures along with various other macroeconomic variables, where the credit supply shock is identified as the reduced form VAR innovation in EBP. My findings can be summarized as follows. Adverse credit supply shocks are found to have very modest effects on TFP, accounting for roughly only 3% of the forecast error variance of TFP at business cycle frequencies and having insignificant effects on TFP at all horizons except the second horizon. Hence, these results clearly fail to pass the aforementioned first litmus test.

Much of the literature's motivation for studying the TFP channel of credit supply shocks lies in the significantly lower TFP growth rates observed during the financial crisis across much of the developed economies. Two observations are worth mentioning in the context of this observation. First, as discussed in Buera et al. (2015) in the U.S. context, this observation mainly applies to TFP that is not adjusted for input-utilization changes; once TFP is adjusted for such changes as in the case of the Fernald (2012) utilization-adjusted TFP measure, the difference in growth rates between the financial crisis period and other periods is much less stark. Second, utilization-adjusted TFP did experience a moderate decline in the 2 years that *followed* the ending of the Great Recession (2009:Q3-2011:Q3) and, more generally, exhibited much below average growth rates in the post-Great-Recession period. Taken together, these two observations indicate that it is not clear that looking at the data unconditionally implies a conclusive causal relation between credit supply shocks and capital-misallocation-induced changes in TFP. I provide further aggregate evidence consistent with the first aforementioned observation: adverse credit supply shocks significantly

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

reduce unadjusted TFP and account for about 20% of its variation at business cycle frequencies. That these effects effectively vanish for the utilization-adjusted TFP series indicates that credit supply shocks produce sizable unobserved-input-utilization-induced changes in aggregate unadjusted TFP as opposed to generating misallocation-induced changes in true TFP. Moreover, in relation to the second aforementioned observation, my conditional aggregate evidence can also be viewed as an indication that one can not infer casuality running from the adverse credit supply shocks of 2008 and the subsequent, somewhat delayed decline in utilization-adjusted TFP growth rates.

Bottom-Up Approach: Capital Misallocation Channel. The aggregate evidence from the second part of the paper casts serious doubt on there being a meaningful TFP channel of credit supply shocks. But to more formally and forcefully argue against the misallocation based mechanism that is at the core of the theoretical underpinning of this channel, one must turn to firm-level data and attempt to ascertain the capital-misallocation-induced TFP loss resulting from adverse credit supply shocks' effects on firm-level capital stocks. This is precisely what the capital misallocation based analysis of the third part of the paper sets out to do. Specifically, using firm-level data from Compustat on capital stocks, sales, and operative incomes and an aggregation formula that maps firm-level capital stocks' responses to credit supply shocks onto capital-misallocation-induced TFP loss, I demonstrate that such adverse shocks produce an insignificant and negligible capital-misallocation-induced TFP response, with capital stock responses seeming homogeneous across the different firms in my Compustat sample.

Bottom-Up Approach: Labor Misallocation Channel. Since financial frictions can apply to the funding of labor costs just like they do to that of capital costs, I complement the capital misallocation analysis of the third part of the paper with an analysis of the labor misallocation channel. In particular, I use employment data by fine firm size category classification that covers the universe of U.S. firms along with census data on total sales and labor costs by firm size to estimate the labor-misallocation-induced TFP response to credit supply shocks, where the aggregation of employment responses of the firm size categories is disciplined by an aggregation formula that maps these disaggregated employment responses onto labor-misallocation-induced TFP loss. The analysis in this part is much less disaggregated than the capital misallocation estimation analysis and treats each firm size category as a single firm. But under the assumption that firm size captures financial frictions intensity reasonably well so that financial frictions heterogeneity does not play a meaningful role in labor misallocation *within* firm size categories, this analysis is suitable for informing us about the role of a financial-frictions-induced labor misallocation channel. The main takeaway from this exercise is that such a channel is unlikely to be important as the estimated labor-misallocation-induced TFP response is negligible and employment responses across firm size categories are quite homogenous.

Outline. The remainder of the paper is organized as follows. The next section provides a literature review. In the subsequent section the underlying framework for this paper is laid out. Section 4 provides a description of the methodology used in this paper, both in the top-down estimation part of the paper as well as the bottom-up one. Section 5 describes the data and results related to these two estimation parts. The final section concludes.

2 Related Literature

To the best of my knowledge, as already mentioned above, this paper constitutes the first empirical investigation of the TFP channel of credit supply shocks that tries to quantify this channel both from an aggregate standpoint as well as a disaggregated standpoint, being novel in both its model-free top-down approach as well as its mostly structurally unrestrictive bottom-up approach. Nevertheless, considerable work has been undertaken in recent years building structural models that highlight the potential role of capital misallocation in the transmission of credit supply shocks to aggregate TFP changes and in turn to fluctuations in the real economy.[2]

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

[2]This literature can be viewed as a subset of the broader literature that studies the general relation between aggregate TFP and input misallocation (see, e.g., Basu and Fernald (2002), Hsieh and Klenow (2009), Restuccia and Rogerson (2013)), and Gorodnichenko et al. (2018).

of financial frictions, by assuming some type of heterogeneity coupled with some form of financial frictions which together amplify the effects of credit supply shocks through their effect on capital misallocation. While Pratap and Urrutia (2012) impose heterogeneity between intermediate and final goods in the sense that financial frictions only apply to the purchasing of the former, where final-goods producing firms need to finance part of their intermediate-goods purchases,[3] other works have emphasized heterogeneity across borrowing firms/entrepreneurs in terms of the financial frictions and associated borrowing costs facing them (see, e.g., Buera et al. (2011), Gilchrist et al. (2013), Khan and Thomas (2013), Midrigan and Xu (2014), Moll (2014), Buera and Moll (2015), Buera et al. (2015), and Buera and Shin (2017)).[4] Notably, Gilchrist et al. (2013) is an example of a setting where firms fund their labor costs with external credit, not only their capital costs, thus allowing for the possibility of a financial-frictions-induced labor misallocation channel. (Such an extended setting provides a theoretical justification for the consideration of a labor misallocation channel in the analysis of this paper.)

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

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

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

[5]Using a rich set of cross-sectional and time-series observations from establishment-level data and fo-

From an identification standpoint, my paper is also related to the general literature that attempts to identify the macroeconomic effects of credit supply shocks. In general, identification of credit supply shocks has been mostly pursued either by imposing theory-consistent sign restrictions on the responses of certain variables to credit supply shocks (see, e.g., Helbling et al. (2011), Peersman (2011), Meeks (2012), Eickmeier and Ng (2015), and Gambetti and Musso (2017)), or by directly constructing suitable measures of the exogenous component of credit supply and then interpreting the forecast error of these measures as the credit supply shock (see, e.g., Lown and Morgan (2006) ,Gilchrist and Zakrajšek (2012), and Bassett et al. (2014)).[6]

Recent work by Mumtaz et al. (2018) has undertaken a thorough evaluation of these two identification approaches, finding that both do reasonably well when applied to artificial data generated from a suitable DSGE model; however, the latter approach's success was found to hinge on it being used as a proxy SVAR where the credit supply shock is used as an external instrument in the VAR as opposed to an identification based on a recursive SVAR where the shock is not ordered first (as done, e.g., in Gilchrist and Zakrajšek (2012)). Importantly, Noh (2018) and Plagborg-Møller and Wolf (2019) have recently stressed that a recursive SVAR where the proxy variable is ordered first constitutes a valid and more robust identification approach than the proxy SVAR approach;[7] given

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

[6]An additional identification strategy worth highlighting is the one used in Caldara et al. (2016), who jointly identify credit supply shocks and uncertainty shocks within a penalty function approach based method that identifies each shock by requiring it to have maximal effects on its corresponding, appropriate target variable. The impulse responses to the credit supply shocks from Caldara et al. (2016), which use the EBP variable as the target variable for these shocks, are broadly similar to those obtained in Gilchrist and Zakrajšek (2012)'s analysis as well as in mine, with the identification from Caldara et al. (2016) closely corresponding to mine in effective terms as manifested by the very high impact EBP forecast error variance share attributable to their identified credit supply shock (see their Figure 9).

[7]Specifically, these works show that proxy SVAR identification is invalid when the proxy variable shock is non-invertible, whereas ordering the proxy variable first in a recursive SVAR is robust to this non-invertibility issue. (While I show in Appendix B.1 of the online appendix to this paper that non-invertibility does not seem to be a meaningful concern in my analysis, this result from Noh (2018) and Plagborg-Møller and Wolf (2019) still speaks to an important dimension along which an identification strategy of the kind I am pursuing in this paper is superior to the proxy SVAR approach.) Moreover, notably, these works also show that the presence of measurement error in the proxy variable only affects the estimated impulse

that this type of recursive SVAR model is precisely the one I use in this paper to identify credit supply shocks, my identification approach can be viewed as a reliable strategy for identifying credit supply shocks.

3 Underlying Framework

In what follows I lay out a simple structural framework which is meant to accomplish two objectives. The first, more general one, is to fix ideas and form a suitable conceptual base for this paper's entire empirical analysis. The second, specific to the third part of the paper that pursues a bottom-up estimation approach on the basis of firm-level data for the capital misallocation channel analysis and fine firm size category classification data for the labor misallocation channel analysis, is to provide a clear mapping between capital and labor misallocation and aggregate TFP which in turn operationalizes the third part of the paper. This mapping, while produced here in a rather simple setting, is advantageous in that it is based on an unrestrictive set of assumptions.

Production. There are I firms indexed by i with $i = 1, 2, ..., I$, with each firm producing good $Y_{i,t}$ using the following technology:

$$Y_{i,t} = A_{i,t} K_{i,t}^{\alpha_{i,K}} L_{i,t}^{\alpha_{i,L}}, \tag{1}$$

where $A_{i,j,t}$ is a random idiosyncratic productivity shock with $\mathbb{E}(A_{i,t}) = 1$; $K_{i,t}$ is physical capital of the i-th firm with $0 < \alpha_{i,K} \leq 1$ representing firm i's capital's share in its production process; and $L_{i,t}$ is labor input of the i-th firm with $0 < \alpha_{i,L} \leq 1$ representing firm i's labor's share in its production process.

Aggregation and Capital and Labor Misallocation. I now define aggregate TFP and decompose it into a pure technological term and capital and labor misallocation terms. Toward this end, let aggregate output Y_t be defined as

$$Y_t = \sum_{i=1}^{I} Y_{i,t}, \tag{2}$$

responses through a scaling factor, leaving the estimation of the shape of the impulse response function unbiased.

and let aggregate TFP A_t be defined as

$$A_t = \frac{Y_t}{K_t^{\alpha_K} L_t^{\alpha_L}}, \tag{3}$$

where $K_t = \sum_{i=1}^{I} K_{i,t}$ and $L_t = \sum_{i=1}^{I} L_{i,t}$ are the aggregate capital and labor inputs in the economy, respectively, and $\alpha_K = \sum_{i=1}^{I} \frac{Y_i}{Y}\alpha_{i,K}$ and $\alpha_L = \sum_{i=1}^{I} \frac{Y_i}{Y}\alpha_{i,L}$ with Y_i and Y representing the steady state values of $Y_{i,t}$ and Y_t, respectively. Log-linearizing aggregate TFP about its steady state as well as the steady state values of $A_{i,t}$, $K_{i,t}$, and $L_{i,t}$ for all i obtains (after some tedious algebra)

$$\hat{A}_t = \sum_{i=1}^{I} \frac{Y_i}{Y}\hat{A}_{i,t} + \sum_{i=1}^{I} \alpha_{i,K}\frac{Y_i}{Y}\frac{MPK_i - MPK}{MPK_i}\hat{K}_{i,t} + \sum_{i=1}^{I} \alpha_{i,L}\frac{Y_i}{Y}\frac{MPL_i - MPL}{MPL_i}\hat{L}_{i,t}, \tag{4}$$

where variables without a time index represent steady state values and hatted variables represent log-deviations of variables from their steady states; $MPK_i = \alpha_{i,K}K_i^{\alpha_{i,K}-1}L_i^{\alpha_{i,L}} = \alpha_{i,K}\frac{Y_i}{K_i}$ represents the steady state value of the marginal product of capital of firm i and $MPK = \sum_{i=1}^{I} \frac{MPK_i K_i}{K}$ represents the steady state value of the average, or aggregate, marginal product of capital in the economy; $MPL_i = \alpha_{i,L}K_i^{\alpha_{i,K}}L_i^{\alpha_{i,L}-1} = \alpha_{i,L}\frac{Y_i}{L_i}$ represents the steady state value of the marginal product of labor of firm i and $MPL = \sum_{i=1}^{I} \frac{MPL_i L_i}{L}$ represents the steady state value of the average, or aggregate, marginal product of capital in the economy; and the three terms in Decomposition (4) represent aggregate pure technology change, capital-misallocation-induced TFP change, and labor-misallocation-induced TFP change, respectively.

That is, deviation of aggregate TFP from pure aggregate technology change (i.e., $\sum_{i=1}^{I} \frac{Y_i}{Y}\hat{A}_{i,t}$) can arise only if there exists dispersion in steady state marginal products of capital and/or marginal products of labor across firms, in which case variation in firm-level capital stocks and/or employment can lead to TFP gains or losses. E.g., in the presence of an adverse aggregate credit supply shock which lowers the capital and labor of firms that are less (more) credit constrained by less (more), and assuming that more credit constrained firms are more productive (i.e., having higher MPK and MPL), we would observe a capital- and labor-misallocation-induced drop in aggregate TFP and output due to the effective reallocation of capital and labor from more productive firms to less productive ones. The theoretical literature has mainly focused on capital-misallocation-based mechanisms that are capable of generating TFP-reducing misallocation of capital (rather than labor). The reason for this is that theoretical models with financial frictions usually model capital costs, rather than labor costs, as being externally funded and thus the assumed financial frictions directly apply to capital choice and associated MPK heterogeneity. E.g., such a capital-misallocation-based mechanism can arise in frameworks that allow for heterogenous initial wealth levels of entrepreneurs in need of external funding for capital and a financial friction that limits their borrowing capacity as a function of their wealth; in such frameworks one can obtain a meaningful way by which credit supply shocks produce capital misallocation (see, e.g., Khan and Thomas (2013), Buera et al. (2015), and Buera and Moll (2015)).

In line with this theory-consistent focus on the capital misallocation channel, my bottom-up approach is first applied to studying this channel using Compustat firm-level data. However, in Section 6.2 I also turn to apply my bottom-up approach to studying the labor misallocation channel by using employment data by six firm size categories that covers the universe of U.S. firms along with census data on total sales and labor costs by firm size. The theoretical motivation for doing this lies in the simple observation that allowing for financial frictions' heterogeneity in a setting where labor costs are also externally funded has the potential of also producing a meaningful labor misallocation channel on top of a capital misallocation channel (see, e.g., Gilchrist et al. (2013)). In such a setting MPL dispersion that happens in tandem with variation in firm-level labor inputs can lead to TFP gains or losses.

It is noteworthy that one could still argue for a meaningful utilization misallocation channel at work that is not accounted for in Decomposition (4). Such a channel can arise if, following an adverse credit supply shock, credit constrained firms with high MPK and MPL lower their input utilization rates more than less credit constrained firm with lower MPK and MPL. My inability with the data at my disposal to construct a direct measure of firm-level utilization rate prevents me from directly estimating this channel. However, I believe that my capital and labor misallocation channel analyses go an important way toward alleviating the concern that such a channel is meaningful in the data. Since unobserved utilization rates are intrinsically connected to factor inputs, the negligible roles I find for the capital and labor misallocation channels in my empirical analysis is informative for an unlikely important role for a utilization misallocation channel. This assertion is based on the notion that if the input to which the utilization applies does not produce meaningful misallocation, it seems unlikely that its utilization rate will. More broadly, putting all of this paper's results together, i.e., unimportant TFP response to credit supply shocks and negligible labor and capital misallocation channels, makes it unlikely that there is a meaningful utilization misallocation channel.

Implications for Top-Down Estimation Approach. From an empirical standpoint, under the fairly weak assumption that aggregate technology does not move in response to credit supply shocks and that the main misallocation based mechanism by which these shocks can move TFP is rooted in capital and labor markets' frictions heterogeneity,[8] a direct implication of Decomposition (4) is that aggregate TFP movements driven by credit supply shocks must be due to capital- and labor-misallocation-induced changes.[9] I.e., for the misallocation-induced TFP channel of credit supply shocks to be meaningful, a suitable measure of aggregate TFP must significantly move following such shocks. In other words, Decomposition (4) provides a sound rationale for using my top-down estimation approach as the first litmus test for the relevance of an input-misallocation-based TFP channel of credit supply shocks.

Implications for Bottom-Up Estimation Approach. I will use the mapping between aggregate TFP and capital and labor misallocation implied by Decomposition (4) to discipline the aggregation of the firm-level capital and firm-size-category-level employment impulse responses to credit supply shocks I estimate in my bottom-up approach part of the paper. This disciplining will allow me to directly estimate the capital- and labor-misallocation-induced TFP change which takes place after a credit supply shock. As such, this part of the paper serves as a vital, complementary analysis to the top-down estimation part.

[8]While I abstract from markups here, Decomposition (4) can be viewed as a special case of the rather general decomposition of aggregate TFP growth as the sum of technological growth and various misallocation terms developed in the seminal work of Basu and Fernald (2002), including terms related to markups in addition to capital and labor misallocation. Taken together, the results from the top-down and bottom-up estimation approaches suggest that it is unlikely that any meaningful misallocation based mechanism is at work in the presence of credit supply shocks.

[9]The assumption that technology is unaffected by credit supply shocks is what the literature on the TFP channel of credit supply shocks normally assumes. While recent evidence from Italian matched firm-bank data by Manaresi and Pierri (2017) shows a negative relation between credit supply contraction and firm-level technology, the structural interpretation of my results still follows the baseline lens through which researchers study the TFP channel of credit supply shocks in focusing on its underlying input misallocation mechanism.

4 Methodology

This section elucidates the methodology used in the empirical analysis undertaken in this paper. I first describe the estimation used in the top-down empirical approach after which I turn to presenting the general lines of the estimation underlying the bottom-up empirical approach. Further technical details of this estimation approach are shown in Appendix A of the online appendix to this paper.

4.1 Top-Down Econometric Approach

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

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

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + ... + B_p y_{t-p} + B_c + u_t, \tag{5}$$

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

$$u_t = A v_t, \tag{6}$$

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

I place the EBP variable in the first position in the VAR and identify the credit supply shock as the unrestricted VAR innovation in EBP. The idea behind this simple identification strategy is based on the reasonable notion that the credit supply shock is the only shock which has a contemporaneous effect on EBP.[10] I follow the conventional Bayesian approach to estimation and inference by assuming a diffuse normal-inverse Wishart prior distribution for the reduced-form VAR parameters. I generate 2000 posterior draws of impulse responses and forecast error variance (FEV) contributions and construct my estimated median and 95% posterior bands of impulse responses and FEV contributions from their corresponding posterior distributions.

4.2 Bottom-Up Econometric Approach

This approach uses the credit supply shock series obtained from the VAR in (5) as regressors in local projection regressions which facilitate the quantification of the capital and labor misallocation channels. For the former channel, I estimate firm-level local projection regressions where the outcome variable is firm-level real capital stock; for the latter channel, I estimate local projection regressions for my six considered firm size categories, where the outcome variable is employment for each firm size category. The system comprising of (5) and the latter local projection regressions is estimated via a Bayesian estimation and inference procedure that assumes a diffuse normal-inverse Wishart prior distribution for the local projection regressions' coefficients and residual variance. To account for correlations of the error term across firms and time, I apply a correction to the standard errors within my Bayesian estimation procedure, based on Driscoll and Kraay (1998) and following Auerbach and Gorodnichenko (2012)'s use of this correction in a classical setting, which accounts for arbitrary spatial and temporal correlations of the error term. In doing

[10] Gilchrist and Zakrajšek (2012) identified a credit supply shock by restricting the EBP shock to have a zero contemporaneous effect on output, consumption, investment, and inflation. I refrain from imposing such restrictions as they are mostly at odds with economic theory's implications for credit supply shocks and thus, as demonstrated by the Monte Carlo evidence from Mumtaz et al. (2018), imposing such potentially erroneous restrictions can bias the identification of the credit supply shock. Nevertheless, my baseline results are robust to adding such restrictions, as shown in Appendix B.4 of the online appendix to this paper.

so I accord with the reasoning from Miranda-Agrippino and Ricco (2020), who estimate a hybrid VAR-local-projections model and follow the suggestion from Müller (2013) to increase estimation precision in the presence of a misspecified likelihood function (as in mine and their setting) by replacing the original posterior's covariance matrix with an appropriately modified one. I discuss my Bayesian estimation and inference approach in more detail below and Appendix A of the online appendix to this paper provides full technical details of my estimation procedure. I now turn to a general description of the estimation procedure.

Econometric Specification and Estimation. The estimation proceeds in two steps. The first step estimates the credit supply shock series from the VAR in (5) as already explained in Section 4.1. The second step runs local projection regressions of the relevant outcome variable on raw values of the credit supply shock series from the first step. For the capital misallocation channel analysis, the outcome variable is firm-level real capital stock levels; for the labor misallocation channel analysis, the outcome variable is employment for each of the six firm size categories I consider in that analysis. (That is, in the labor misallocation channel analysis I effectively treat the employment of each firm size category as 'firm-level' employment, with the effective unit of observation being each of the six considered firm size categories.)

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

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + ... + B_p y_{t-p} + B_c + u_t, \tag{7}$$

$$x_{i,t+h} - x_{i,t-1} = \gamma_{i,h} + \Xi_{i,h}\hat{u}_{1,t} + \epsilon_{i,t+h}, \tag{8}$$

where System (7) is simply the VAR from (5); i indexes firms for the capital misallocation analysis and firm size categories for the labor misallocation channel analysis with $i = 1, 2, ..., I$;[11] t indexes time; $u_{1,t}$ is the first element of u_t and represents the true residual from the EBP equation belonging to the VAR in (7), with its standard deviation being denoted by $\sigma_{1,u}$; $\hat{u}_{1,t}$ is the estimated residual from the EBP equation (the first equation from (7), normalized to have unit variance); $x_{i,t+h}$ is the

[11]For the capital misallocation analysis, the unit of observation is each firm in the Compustat data and therefore $I = 2037$, a much larger number than the corresponding cross-sectional dimension in the labor misallocation channel analysis where $I = 6$, i.e., the number of firm size categories.

log of firm i's real capital stock for the capital misallocation channel analysis and the log of firm size category i's employment for the labor misallocation channel analysis;[12] γ_i is the firm fixed effect; $\Xi_{i,h}$ is the effect of a one standard deviation credit supply shock on the relevant outcome variable at horizon h; and $\epsilon_{i,t+h}$ is the residual of Equation (8) with standard deviation $\sigma_{\epsilon,h}$. For future reference, let the stacked $(kp+1)$xk $B = [B_1, ..., B_p, B_c]'$ matrix represent the reduced form VAR coefficient matrix. Hence, the reduced form VAR parameters can be summarized by the coefficient matrix B and variance covariance matrix Σ, such that the joint estimation of (7) and (8) requires estimating B, Σ, $\gamma_{i,h}$, $\Xi_{i,h}$, and $\sigma_{\epsilon,h}$ for $i = 1, 2, ..., I$.

I estimate Equations (7) and (8) 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 the VAR from (7) and the second corresponds to Equation (8). 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 (8) is 2 (shock variable and the constant) and recalling that the cross-sectional dimension is I, let the stacked $2I$x1 coefficient matrix $Q_h = [\Xi_{1,h}, ..., \Xi_{I,h}, \gamma_{1,h}, ..., \gamma_{I,h}]'$ represent the coefficients from Equation (8). Hence, recalling that $\sigma_{\epsilon,h}$ represents the standard deviation of the (pooled) residual from Equation (8) at each horizon h, the parameters to be estimated from Equation (8) can be summarized by the coefficient matrix Q_h and residual variance $\sigma_{\epsilon,h}$. I assume a diffuse normal-inverse Wishart prior distribution for both $[B, \Sigma]$ and $[Q_h, \sigma_{\epsilon,h}]$; 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 spatial and temporal correlation in $\epsilon_{i,t+h}$), I apply a correction to $\sigma_{\epsilon,h}$ based on Driscoll and Kraay (1998) which accounts for arbitrary spatial and temporal correlations of the

[12] Logged real capital stocks and employment are 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 in this part of the paper.

error term.

Operationally, for each posterior draw of the coefficients from the VAR in (5), I collect the estimated residual from the first equation of this VAR ($\hat{u}_{1,t}$) and use its raw value divided by the drawn value of $\sigma_{1,u}$ (i.e., $\sqrt{\Sigma_{1,1}}$) to form a posterior distribution for $\Xi_{i,h}$, allowing me to produce the posterior distribution of impulse responses of firm-level real capital stock levels (for the capital misallocation channel analysis) and employment by firm size category (for the labor misallocation channel) to a one standard deviation credit supply shock. To estimate the capital-and labor-misallocation-induced TFP changes following a credit supply shock, I use the second and third terms from Decomposition (4) for each draw from the posterior distribution of firm-level real capital stock responses and firm size category employment responses, respectively; this in turn produces a posterior draw of the capital- and labor-misallocation-induced TFP changes that takes place after a credit supply shock. (I defer details on the data used to calibrate this decomposition for the capital and labor misallocation channels to Sections 6.1.1 and 6.2.1, respectively.) I generate 500 such posterior draws from which I am then able to estimate the median impulse responses of firms' real capital (for the capital misallocation channel analysis) or employment by firm size category (for the labor misallocation channel analysis) to credit supply shocks along with their posterior confidence bands as well as the median and posterior bands of the estimated capital- or labor-misallocation-induced TFP change. Appendix A of the online appendix to this paper contains the specific details of the posterior simulator I use to obtain these estimates.

5 Empirical Evidence: Top-Down Approach

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

5.1 Data

The baseline VAR includes eight variables: EBP, TFP, output, hours, consumption, investment, inflation, and interest rates. For the TFP series, I employ the quarterly series on TFP for the U.S. business sector, adjusted for variations in factor utilization (labor effort and capital's workweek), constructed by Fernald (2012).[13] The adjustment Fernald (2012) makes for factor utilization changes is an important element underlying the construction of his TFP measure, greatly contributing to it being the state-of-the-art TFP measure used in the literature.

As discussed above, the variable I use to measure credit supply shocks is the excess bond premium (EBP) series from Gilchrist and Zakrajšek (2012), who use micro-level data to construct a credit spread index which they decompose into a component that captures firm-specific information on expected defaults and a residual component that they term as the excess bond premium (EBP). An updated series of the EBP variable is available from Favara et al. (2016).[14] It is in quarterly frequency and covers the sample period 1973:Q1 to 2017:Q3. Quarterly values are averages of corresponding raw monthly values.

The nominal series for output, consumption, and investment are taken from the Bureau of Economic Analysis (BEA). Output is measured as GDP, consumption as the sum of non-durables and services consumption, and investment is the sum of personal consumption expenditures on durables and gross private domestic investment. The nominal series are converted to per capita terms by dividing them by the civilian non-institutionalized population aged sixteen and over. I use the corresponding chain-weighted deflators to obtain the real series. The hours series is log of per capita total hours worked in the non-farm business sector. Inflation is measured as the percentage change in the CPI for all urban consumers and the nominal interest rate is the three month Treasury Bill rate.[15] The data series span the period 1973:Q1-2017:Q3.

5.2 Results

I first present the impulse responses and variance decomposition results with respect to the credit supply shock for the baseline VAR, which includes utilization-adjusted TFP; I then present results from a VAR that includes instead a TFP measure that does not adjust for utilization changes.

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

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

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

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

Figures 1a and 1b depict the median and 97.5th and 2.5th percentiles of the posterior distributions of impulse responses and contribution to forecast error variance (FEV) at all horizons up to the 5 year one, respectively. Similar to the results from Gilchrist and Zakrajšek (2012), an adverse credit supply shock (of one standard deviation) produces a significant recession accompanied by a drop in inflation and interest rates, with output, investment, consumption, and hours dropping by 0.40%, 1.67%, 0.23%, and 0.53%, respectively, after one year. The respective median FEV shares are also economically large for these variables, with the one-year FEV shares standing at 20%, 25%, 10%, and 21%.

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

VAR With Unadjusted TFP Measure. The main merit of the Fernald (2012) utilization-adjusted TFP measure is the fact that it accounts for unobserved factor utilization changes. As such, it provides for a clean, purified measure of aggregate TFP that serves well for the purposes of this paper. To study the TFP channel of credit supply shocks, which is based on a capital misallocation based mechanism, one must employ a TFP measure that is not contaminated by cyclical utilization changes. This is made clear by looking at the behavior of utilization-adjusted TFP alongside unadjusted TFP, both from Fernald (2012), during recession periods and in particular the Great

Recession period.

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

I now show conditional evidence that accords well with the unconditional evidence from Figure 2 on the importance of controlling for factor utilization changes for the purposes of this paper. Figures 3a and 3b correspond to Figures 1a and 1b, only that unadjusted TFP replaces utilization-adjusted TFP in the VAR. While results for the other variables are robust to this replacement, it is clear that the unadjusted TFP measure behaves very differently from the utilization-adjusted one, significantly falling for six quarters following the shock. The decline in unadjusted TFP is both statistically and economically significant, bottoming at -0.28% after 3 quarters. The corresponding FEV shares tell a similar tale: credit supply shocks account for about 20% of the business cycle variation in unadjusted TFP. These results stress that unobserved factor utilization is strongly affected by credit supply shocks and not accounting for this may lead to erroneously inferring that a misallocation based mechanism is at work in response to adverse credit supply shocks while in fact it is mainly the mere decline in unobserved factor utilization that drives the negative response of unadjusted TFP.[16]

In Appendix B of the online appendix to this paper I examine the robustness of the baseline results from the top-down approach along eight dimensions. The first speaks to the possibility that

[16]Note that, in similar fashion to the inability of aggregate inputs' responsiveness to shocks to inform us about a meaningful misallocation channel arising from the disaggregated variation in these inputs, this observed responsiveness of aggregate factor utilization to credit supply shocks does not imply a meaningful utilization misallocation channel of credit supply shocks.

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.

6 Empirical Evidence: Bottom-Up Approach

In this section the main results of the bottom-up empirical approach are presented. Section 6.1 provides a brief description of the data and presents the main empirical results from the capital misallocation channel analysis. Section 6.2 provides details and results from an exercise that applies the bottom-up approach to the estimation of the role of the labor misallocation channel.

6.1 Bottom-Up Approach: Capital Misallocation Channel

6.1.1 Data

I use quarterly Compustat data to construct firm-level real capital stock levels and to discipline the calibration of the capital misallocation term from Decomposition (4). Only firms that have at least 10 years of consecutive observations and posses non-negative average capital shares and marginal products of capital (MPKs) (whose measurement is explained below) are kept in the sample. To ensure a reasonable level of balancing in the panel as well as a reasonable number of years for which data after the financial crisis is available, I remove firms whose data ends prior to 2013.

The sample resulting from the above-described cleaning procedure is an unbalanced panel that covers 1973:Q1-2017:Q3 and a total of 2037 firms, with a total number of 196,769 observations. All raw data series extracted from Compustat were seasonally adjusted using ARIMA X12. I now discuss the different variables I construct and use in my analysis.

Real Capital Stocks. Firms' real capital stock levels are constructed using the perpetual inventory method, i.e., they are obtained as the sum of current and historical net real investment levels. Owing to lack of *quarterly* firm- or industry-specific investment deflators in my data, I resort to using U.S. nonresidential fixed investment deflator when deflating firms' nominal capital stock levels into real ones with the nominal stocks being measured by the firms' *net property, plant, and equipment* (Compustat item PPENT) values.

Specifically, I define the real capital stock in the initial period for each firm as its nominal capital stock. Then, I construct real net investment levels in each subsequent period as the first-difference of the corresponding period's nominal capital stock divided by the corresponding U.S. nonresidential fixed investment deflator. Real capital stock levels are then computed as the sum of current and historical net real investment levels.

In Decomposition (4) there are three additional firm-specific variables, on top of real capital stock, needed to compute the capital misallocaion term: MPK, capital share, and firm size in terms of sales. I now turn to describing the details underlying the construction of these variables.

Marginal Product of Capital, Capital Share, and Sales. Under Cobb-Douglas production functions, such as the one used in Section 3, MPK of firm i in period t can be written as $\alpha_{i,K}\frac{Y_{i,t}}{K_{i,t}}$. I measure firms' capital shares ($\alpha_{i,K}$'s) as their operating income (Compustat item OIBDP), i.e., income before interest and depreciation expenses, as share of their sales (Compustat item SALE). The basis for this measurement is that, under the assumption of zero pure profits, operating income measures the share of production attributable to capital. In Appendix C.1 of the online appendix to this paper I relax this assumption and test the robustness of my results to allowing for positive pure profits when measuring firms' capital shares.

Under the assumption of equality between capital prices and output goods prices, $\frac{Y_{i,t}}{K_{i,t}}$ can be measured as the ratio of firms' nominal sales to one-quarter lagged nominal capital stock; then, multiplying this ratio by the capital share provides the firm-level MPK measure I use in this paper. This MPK measure effectively amounts to measuring MPK with the ratio of operating income to capital (see, e.g., Gilchrist and Himmelberg (1995)). Notably, for my purposes, it is actually sufficient to make the somewhat weaker assumption that there is homogeneity in the output-capital price ratio across the different firms, as opposed to within-firm output-capital price equality, in order to validate my nominal output-capital ratio based measurement of MPK. While this assumption is not innocuous, I am making it here due to data constraints for the baseline analysis while relaxing it in Appendix C.4 of the online appendix to this paper by considering a much smaller sample limited to manufacturing firms. This assumption is also implicitly made by various papers in the literature that have measured logged MPK with the log of the revenue to capital ratio (see, e.g., David et al. (2018), Li et al. (2018), and David and Venkateswaran (2019)[17]).

The last missing piece needed to operationalize the measurement of the capital misallocation term from Decomposition (4) is firm size, i.e., $\frac{Y_{i,t}}{Y_t}$. I measure this ratio by dividing each firm's nominal sales in each period by total sales of all firms during that period.

The variables needed for the calibration of the capital misallocation term from Decomposition (4) are in steady state terms (aside, of course, from log-deviations of capital stock from steady state). Hence, I take averages along the time dimension of each required firm-level variable. Specifically, capital share α_i for each firm is computed as the average over time of the ratio of operating income to sales. Steady state MPK for firm i (i.e., MPK_i from Decomposition (4)) is computed as the average over time of the product of its capital share and sales-to-capital ratio. Steady state MPK for the overall economy (i.e., MPK from Decomposition (4)) is computed in two steps. First, for each period, I compute the ratio of the cross-sectional sum of the product between K_i and MPK_i to total capital stock in the economy. Second, I take the time-series average of this ratio and define it as MPK. Lastly, I compute each firm's steady state size (i.e., $\frac{Y_i}{Y}$) also in two steps, first computing the ratio of a firm's sales to total sales in a given period and then taking the time-series average of this series to be $\frac{Y_i}{Y}$.

Summary Statistics. Table 1 provides summary statistics (number of firms and observations along with averages and medians of firm MPKs, capital shares, and sizes) for the Compustat firm-

[17] David and Venkateswaran (2019) actually use the logged ratio of value added to capital to measure logged MPK, assuming a share of intermediates of 0.5 owing to data limitations. I do not account for the presence of firms' intermediate goods purchases in my baseline analysis also due to data limitations but assuming a 0.5 share of intermediates as in David and Venkateswaran (2019) has no bearing on my results. And, importantly, also when I use Compustat's cost of goods sold item as an imperfect measure of intermediate consumption and alter my aggregation framework accordingly, I find results that are broadly similar to the baseline ones (see Appendix C.2 of the online appendix to this paper).

level data used in my analysis across the entire distribution of firms. Table 2 shows median values of firms' MPKs, capital shares, and sizes across the MPK-sorted distribution of firms. Specifically, I order firms into four groups according to their MPKs where the first group corresponds to firms having MPKs that are below the first quartile, the second group corresponds to the 25%-50% range of MPKs, and the third and fourth correspond to the 50%-75% and 75%-100% ranges, respectively. For each group of firms, Table 2 presents the median of MPK, capital share, and firm size (all defined as described above).

Table 1 stresses that there is a strong right skewness in the distribution of all three considered variables in the table, especially for firm MPKs and sizes, as evidenced by the large positive gaps between these variables' average and median values. Turning to Table 2, while firm size seems to be somewhat correlated with firm MPK (albeit in a non-monotonic way), there does not seem to be a systematic relationship between capital share and MPK. With respect to the relation between MPK and size, it is clear that relatively small firms in the Compustat sample tend to have relatively high MPKs. This fact is borne out by the fact that the median firm sizes of the first two groups are roughly twice as high as those of the other two groups. This is consistent with the fact that for 91% of the firms in the sample $MPK_i > MPK$, i.e., 91% of the firms have higher MPKs than the aggregate (weighted average) MPK, which results from there being many small firms with relatively high MPKs. A sectoral inspection of this fact reveals that it is effectively driven by service industries, an issue I revisit and address in Appendix C.3 of the online appendix to this paper. I now turn to the impulse responses from the baseline model.

6.1.2 Results

Exposition Structure. The results from the bottom-up estimation approach are summarized and presented in Figures 4a and 4b. The first sub-figure of these two figures depicts real capital stock's response for the 'median firm' with respect to a positive one standard deviation credit supply shock. This median firm estimate is computed as follows. For each posterior draw of firm-level responses, I take the median of these responses (with there being a total of 2037 such responses in each horizon) and then construct the posterior distribution of responses of the 'median firm' based on 500 posterior draws. What appears in the first sub-figure of Figures 4a is the median of this distribution along with its 97.5th and 2.5th percentile bands.

The next two sub-figures present real capital stock's response for the 'large weight firm' and the 'small weight firm', with the weights corresponding to the term $\alpha_{i,K}\frac{Y_i}{Y}\frac{MPK_i-MPK}{MPK_i}$ from Decomposition (4). Specifically, these responses are constructed as follows. For each posterior draw of firm-level responses, I take the median of the upper (lower) quartile range of these responses and then construct the posterior distribution of responses of the 'large weight firm' ('small weight firm') based on 500 posterior draws. What then appears in the second and third sub-figures of Figure 4a is the median of these two distributions along with their 97.5th and 2.5th percentile bands, respectively. The fourth sub-figure of Figure 4a shows the median and 97.5th and 2.5th percentile bands of the difference between the large and small weight firm responses. The fifth and last sub-figure shows the median and 97.5th and 2.5th percentile bands of the estimated capital-misallocation-induced response of TFP, which is computed from $\sum_{i=1}^{I}\alpha_{i,K}\frac{Y_i}{Y}\frac{MPK_i-MPK}{MPK_i}\hat{K}_{i,t+h-1}$ (with $h=1,...,20$ corresponding to the horizons following the shock taking place in period t and $\hat{K}_{i,t+h-1}$ representing the firm-level real capital stock response at horizon h) for each posterior draw of firm-level responses and then computing the median and 95% confidence bands of the resulting distribution.

The exposition and construction procedure of the objects in Figure 4b follow the structure from sub-figures 2-4 of Figure 4a 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 ($\frac{MPK_i-MPK}{MPK_i}$). The motivation for showing the responses of firms with high versus low such weight components is to try to learn about any meaningful heterogeneity in firm-level capital stock responses which can in turn lead to capital misallocation.

Main Takeaway. The last sub-figure of Figure 4a carries with it the most important message of the bottom-up capital misallocation channel analysis in showing that there does not seem to be a meaningful capital misallocation channel of credit supply shocks, which is in line with what the top-down estimation approach delivered as well. The implied response of TFP is insignificant and negligible for all horizons, hovering around a nil response at business cycle frequencies. This trifling capital-misallocation-induced TFP dynamics is in stark contrast to what theoretical models focusing on the TFP channel of credit supply shocks usually predict to take place after such shocks.

While real capital stock does significantly decline for the 'median firm' (see the first sub-figure of Figure 4a), falling in a statistically significant way from the 2nd horizon onwards, there is no apparent difference between real capital stock response for firms with large weights compared to small weights. And this statement also holds when looking at the response differences from Figure 4b for the different weight components. In other words, the heterogeneity that needs to be in place for there to be a meaningful TFP channel of credit supply shocks is simply not present.

In Appendix C of the online appendix to this paper I consider the robustness of the baseline results from the bottom-up capital misallocation channel analysis along sixteen dimensions, including various alterations of the baseline model specification and baseline sample; in all of these specifications I find the baseline result of a negligible capital-misallocation-induced TFP response and homogeneous firm-level responses to remain intact.

6.2 The Role of Labor Misallocation and External Validity for the Whole Economy

This section discusses and addresses two concerns arising from the bottom-up capital misallocation analysis from the previous section. While these two concerns are not connected a priori, the exercise conducted in this section is arguably suitable for jointly addressing both of them; hence, I choose to treat them jointly in this section.

The first concern is that the evidence from the previous section on a weak capital misallocation channel, even when put together with the top-down analysis results, is not sufficient for conclusively concluding that the TFP channel of credit supply is weak. The reason for this is that, given the partial coverage of U.S. firms by Compustat (this is the basis for my second concern, which I discuss in detail below), there could still be a meaningful labor misallocation channel of credit supply shocks co-existing with the evidence from the previous section. While the previous section's goal of quantifying the TFP channel of credit supply shocks through the capital-misallocation-induced TFP response to credit supply shocks follows the literature's theory-consistent choice to mostly look at this channel through the lens of capital misallocation, one can also find justification for also looking at the labor misallocation channel from a theoretical standpoint as models containing financial frictions and some suitable heterogeneity where borrowing finances labor cost (in addition to capital costs) may have the potential of producing a meaningful labor misallocation channel of credit supply shocks (see, e.g., Gilchrist et al. (2013)). Hence, in order to make the claim of a weak TFP channel of credit supply shocks more reliable, it is also worthwhile to confirm that labor misallocation does not play a meaningful role in the presence of a credit supply shocks.

The second concern is that, while an important advantage of the Compustat data I use in my firm-level capital misallocation channel analysis relative to other firm-level data sources is that it is available in quarterly frequency and covers all sectors in the economy, one may argue that the external validity of my results for the economy as a whole is limited given Compustat's partial coverage of the universe of U.S. firms. In particular, small firms are effectively excluded from Compustat data which in turn enhances the concern about the limited external validity of my results from the capital misallocation channel analysis. Compustat still covers a considerable part of the economy, with the total capital stock from my baseline Compustat sample accounting for an average share of 42% in total U.S. firms' capital stock (as measured by BEA annual data on the value of total stock of structures and equipment in the U.S. economy). However, this 42% share is clearly far from perfect and emphasizes a well known limitation and concern related to Compustat data that is important to address.

Section 6.2.1 presents the details and results from an estimation exercise that estimates a negligible role of the labor misallocation channel of credit supply shocks, thus addressing the aforementioned first concern, while doing this by considering data that covers employment and total sales and labor costs data by firm size for the universe of U.S. firms, thus addressing the second aforementioned concern regarding external validity (at least as it pertains to the role of labor misallocation). Granted, one may still be concerned that the capital misallocation channel estimated in this paper does not cover the entire universe of U.S. firms. However, putting all of this paper's results together, i.e., unimportant TFP response to credit supply shocks, negligible labor misallocation channel for the universe of U.S. firms, and negligible capital misallocation channel for a sample of firms covering 42% of total capital of U.S. firms, makes it rather unlikely that there is a meaningful capital misallocation channel in place for the omitted firms from the bottom-up capital misallocation channel analysis.

The motivation for looking at firms' behavior broken down by their sizes is derived from the literature's emphasis on firm size as a proxy for financial frictions' intensity, where small firms are considered to be much more credit constrained than large ones. This emphasis was initiated, at least from a macroeconomic standpoint, by the seminal work of Gertler and Gilchrist (1994) who provided evidence from the US Census Bureau's Quarterly Financial Report (QFR) that firm size serves as a proxy for financial constraints, as small firms are more likely to be bank-dependent and less likely to have access to broader capital markets. As discussed in Crouzet and Mehrotra (2020), measuring financial constraints in empirical work in corporate finance effectively always involves the use of firm size, either by itself or as part of a constructed financial constraints index (see Farre-Mensa and Ljungqvist (2016) and references therein).

6.2.1 Bottom-Up Approach: Labor Misallocation Channel

Decomposition (4) stresses that the deviation of aggregate TFP from pure aggregate technology change (i.e., $\sum_{i=1}^{I} \frac{Y_i}{Y} \hat{A}_{i,t}$) can arise not only from dispersion in steady state marginal products of capital across firms but also from dispersion in steady state marginal products of labor. Such latter dispersion, happening in tandem with variation in firm-level labor inputs, can lead to TFP gains or losses. I.e., in the presence of an adverse aggregate credit supply shock which lowers labor input of firms that are less (more) credit constrained by less (more), and assuming that more credit constrained firms have a higher MPL, we would observe a labor-misallocation-induced drop in aggregate TFP and output due to the effective reallocation of labor from higher MPL firms to lower MPL firms. Such a labor-misallocation-based mechanism could potentially arise in the same theoretical settings normally used in the literature for accommodating a meaningful capital misallocation channel if those settings allowed for financial frictions to apply to externally funded labor costs. E.g., a labor misallocation channel can arise in frameworks that allow for heterogenous initial wealth levels of entrepreneurs and a financial friction that limits their borrowing capacity as a function of their wealth, where this borrowing is used to finance labor costs.

In what follows, I present the data underlying the estimation of the labor-misallocation-induced TFP response to a one standard deviation credit supply shock, i.e., $\sum_{i=1}^{I} \alpha_{i,L} \frac{Y_i}{Y} \frac{MPL_i - MPL}{MPL_i} \hat{L}_{i,t+h-1}$

(with $h = 1, ..., 20$ corresponding to the horizons following a shock taking place in period t and $\hat{L}_{i,t+h-1}$ representing the employment response by firm size category at horizon h), as well as the results from this estimation. The estimation of impulse responses is based on the estimation of Equations (7) and (8) in a manner akin to the procedure used for the capital misallocation channel analysis, only that now the unit of observation is each of the six firm size categories considered in the labor misallocation channel analysis and the outcome variable is employment for each size category.

Data. I use quarterly employment data for six firm sizes available from the Bureau of Labor Statistics (BLS) National Business Employment Dynamics (BDM) database, covering the sample 1993:Q1-2017:Q3, as well as annual census data from the Statistics of U.S. Businesses (SUSB) database, which contains data on the distribution of employment, payrolls, and sales for 1988-2017 and thus allows me to construct $\alpha_{i,L}$, $\frac{Y_i}{Y}$, and MPL_i by firm size (with a total of six size categories). These measures are combined with the estimated impulse responses of labor input by six firm size categories to a one standard deviation credit supply shock (i.e., $\hat{L}_{i,t+h-1}$) in order to construct an estimate of the labor-misallocation-induced TFP response. As such, this exercise allows to estimate the labor misallocation channel of credit supply shocks *across* these six size categories while effectively accounting for the entire universe of U.S. firms.[18] (Note that this exercise does not account for possible labor misallocation *within* each size category arising from credit supply shocks. However, to the extent that financial frictions' magnitude is well proxied for by firm size and does not vary significantly within each size category, this exercise can be meaningfully informative for the quantitative importance of financial frictions' heterogeneity for the labor misallocation channel of credit supply shocks.)

The SUSB division of firm size categories is less fine than that of BDM (6 versus 8 categories) and therefore dictates the firm size categorization in this exercise: Category 1: 1-4 employees;

[18] An additional potential way to estimate the labor-misallocaion-induced TFP response is via Compustat data on labor input and labor compensation. While such data exits in annual frequency, I have found these data series to have a lot of missing observations that render them inapplicable for the purposes of this section's estimation exercise. Specifically, making the baseline requirement that only firms that have at least 10 years of consecutive observations are kept in the sample resulted in a sample containing only two firms.

Category 2: 5-9 employees; Category 3: 10-19 employees; Category 4: 20-99 employees; Category 5: 100-499 employees; and Category 6: 500+ employees. $L_{i,t}$ is measured by BDM's total quarterly employment for the corresponding size category; $\alpha_{i,L}$ is measured from SUSB by the time-series average of the ratio of each firm size category's payroll to its sales, where payroll is total employee compensation and sales (termed receipts in SUSB) is operating revenue for goods and services provided; $\frac{Y_i}{Y}$ is measured from SUSB by the time-series average of each firm size category's sales to total sales in the corresponding period; MPL_i is the time-series average of $\alpha_{i,L}\frac{Y_i}{L_i}$, where Y_i is sales deflated by annual CPI;[19] and MPL is computed as the time-series average of the ratio of the cross-sectional sum of the product between L_i and MPL_i to total labor input in the economy. All time-series averages from the SUSB database are taken over 1997, 2002, 2007, and 2012, as these are the only available years for sales data.

The measurement of all the objects described above puts me in a position to estimate the labor-misallocation-induced response of TFP at horizon h to a one standard deviation credit supply shock, i.e., $\sum_{i=1}^{I}\alpha_{i,L}\frac{Y_i}{Y}\frac{MPL_i-MPL}{MPL_i}\hat{L}_{i,t+h-1}$. In other words, I utilize the third term from Decomposition (4) to discipline the aggregation of employment responses by firm size category so as to obtain an estimate of labor-misallocation-TFP response.

Results. The results from this exercise are presented in Figures 5a and 5b. Figure 5a presents the employment responses of the six firm size categories to a one standard deviation credit supply shock along with the labor-misallocation-induced TFP response. Figure 5b shows the employment response differences across all firm size pairs. Employment significantly falls for all firm size categories, with the trough for all of them occurring at around the two-year mark in the range of 0.7%-0.9%. The similarity in responses across firm size categories is apparent, with response differences being insignificant for all considered size pairs.[20] And, accordingly, the labor-

[19] This implies that MPL for each firm size category is measured by the real wage in that category. MPL is highest in the 500+ size category, with the following ordering and relative MPL size with respect to the 500+ size category's MPL: 100-499 size category ranks second with a 14.4% lower MPL; the 0-4 size category is third with a 16.5% lower MPL; the 20-99 size category is fourth with a 21.8% lower MPL; and the 10-19 and 5-9 size categories are second to last and last with 27.4% and 31.4% lower MPLs, respectively.

[20] This conditionally similar behavior of employment along the firm size dimension is broadly consistent with the results from Crouzet and Mehrotra (2020). Using firm-level data from new confidential Census data and dividing firms by book asset size, they show that sales and fixed investment do not respond to

misallocation-induced TFP response is both statistically and economically insignificant, further supporting the main message of this paper regarding a weak TFP channel of credit supply shocks.

In Appendix D of the online appendix to this paper I consider the robustness of the baseline results from the bottom-up labor misallocation channel analysis along four dimensions. The first is allowing and accounting for sign-dependency in the estimation of the impulse responses to the credit supply shock. The second is considering a near-VAR estimation approach. The third is applying a one-step estimation approach instead of the baseline two-step approach. And the fourth is considering alternative credit supply shock series relative to the baseline identification. In all of these specifications I find the baseline result of a negligible labor-misallocation-induced TFP response and homogeneous employment responses across firm size categories to remain intact.

7 Conclusion

This paper has contributed to our understanding of the quantitative importance of the TFP channel of credit supply shocks by providing three sets of conclusive evidence. The first documents a weak, short-lived response of aggregate TFP to credit supply shocks and can thus be viewed as representing evidence from a top-down approach indicative of a weak TFP channel of credit supply shocks. The second constitutes direct evidence on a weak capital misallocation channel by estimating firm-level capital stock responses to credit supply shocks and aggregating them with a theory-consistent aggregation formula which implies a insignificant and negligible capital-misallocation-induced TFP response. The third uses this aggregation formula to aggregate employment responses for six firm size categories and finds a negligible labor-misallocation-induced

monetary shocks in a statistically significant differential manner along the firm size dimension (in contrast to inventory investment, which does fall significantly more for smaller firms). (From an unconditional standpoint, Crouzet and Mehrotra (2020) do find that the top 0.5% of firms by book asset size are less cyclically sensitive than the bottom 99.5% of firms.) They additionally find that debt does not respond differently along the firm size dimension, which supports their argument that financial constraints do not amplify the sales and investment fluctuations of small firms. However, it is noteworthy that Crouzet and Mehrotra (2020) do not interpret their findings as being a basis for rejecting that firm size may be an important determinant of financial constraints (their data still shows that smaller firms rely more heavily on bank debt and on short-term debt), but rather as informing us that these constraints are not a meaningful amplification mechanism for the cyclical behavior of smaller firms. In this respect, the evidence provided in this section on the likely weak magnitude of a financial-frictions-induced TFP channel of credit supply shocks seems to be consistent with the message from Crouzet and Mehrotra (2020).

TFP response.

Importantly, the results of this paper for the top-down analysis were obtained using a model-free approach while those for the bottom-up analysis relied on a largely unrestrictive structural framework. As such, as a whole, the analysis of this paper does not place considerable restrictions on the data, but instead lets the data indicate rather freely whether there is a meaningful TFP channel of credit supply shocks. Hence, such identification approach is arguably sufficiently reliable for guiding model builders in developing theories that accord with its results.

This paper's results also deliver noteworthy policy implications. While it is rather clear that policies directed at reducing capital and labor misallocation in general can produce significant long-term welfare gains, the evidence put forward in this paper suggests that specific policies enacted to counteract potential capital and labor misallocation in the presence of credit supply shocks may be unwarranted.

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Table 1: **Summary Statistics for Compustat Sample**.

Variable	No. of Firms	No. of Obs.	Avg./Med. MPK	Avg./Med. Capital Share	Avg./Med Size
	2037	196,769	44.6%/20.8%	20.7%/17.1%	0.06%/0.008%

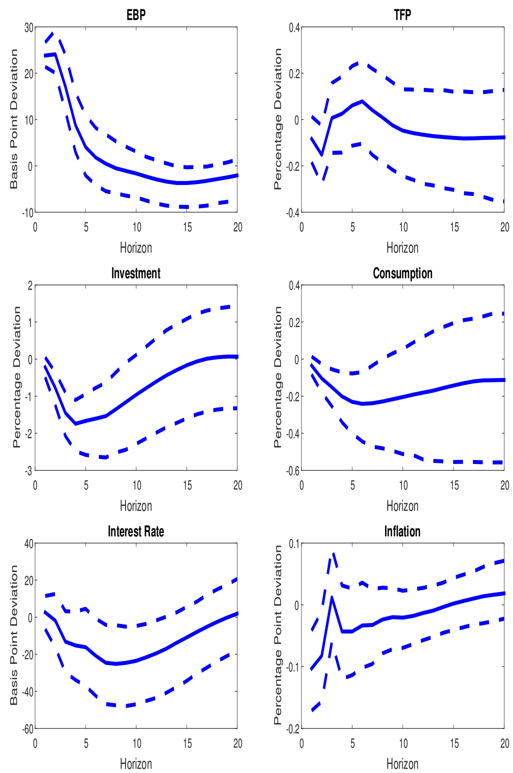
Notes: This table presents the number of firms and observations along with averages and medians (separated by /) of MPK, capital share, and firm size (in terms of sales share of aggregate sales) for the entire distribution of Compustat firms used in the capital misallocation channel analysis.

Table 2: **Firm Characteristics Across MPK Quartiles**.

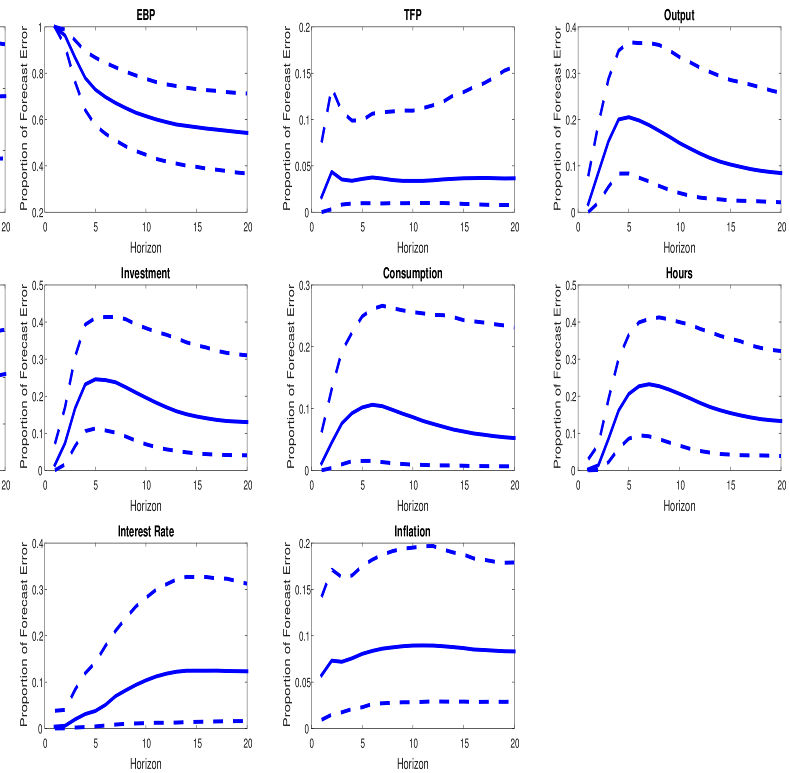
Variable	1st MPK Quartile	2nd MPK Quartile	3rd MPK Quartile	4th MPK Quartile
MPK	5%	14.3%	29.4%	71.3%
Capital Share	19.3%	12.9%	18%	22.7%
Size	0.012%	0.012%	0.005%	0.006%

Notes: This table presents the medians of MPK, capital share, and firm size (in terms of sales share of aggregate sales) for MPK-sorted groups of firms from the Compustat sample used for the capital misallocation channel analysis. I consider four such groups defined according to the quartiles of the MPK distribution across firms.

Figure 1: **Baseline VAR: (a) Impulse Responses; (b) Contribution to FEV**.



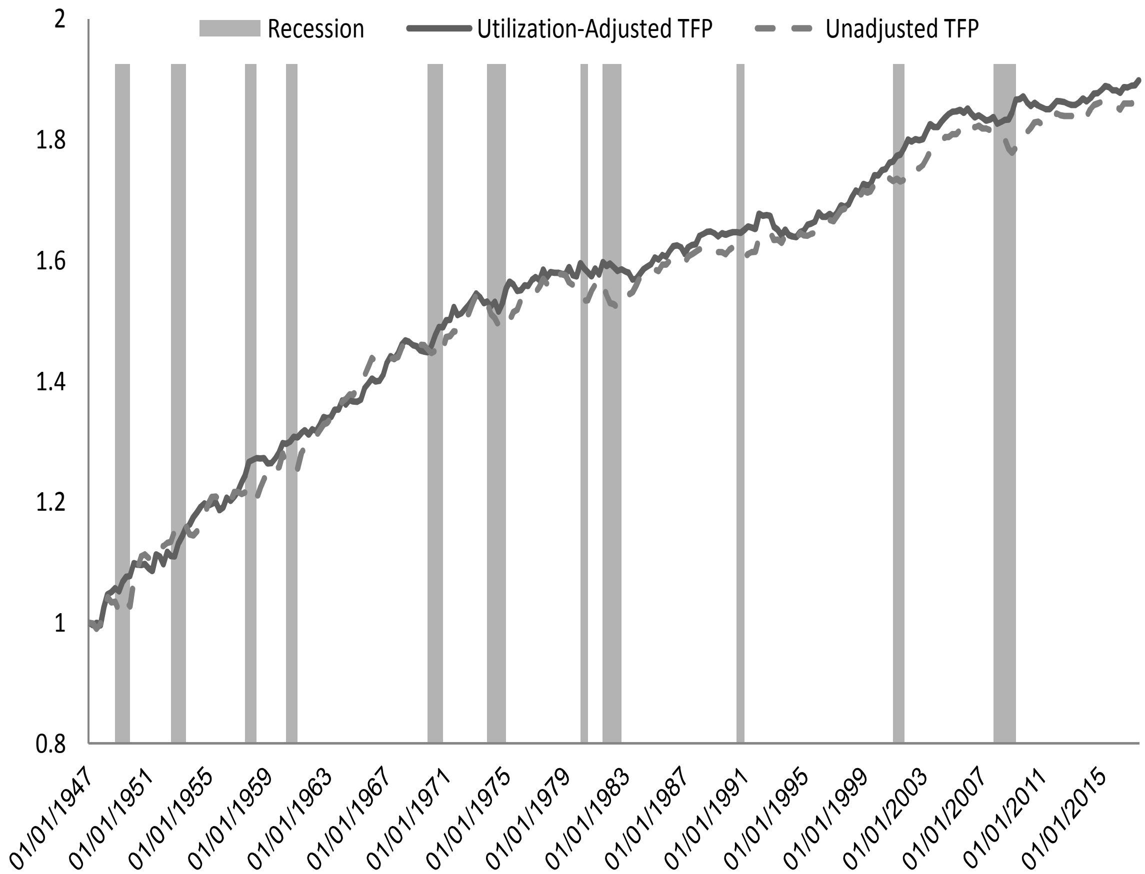
(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock.



(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.

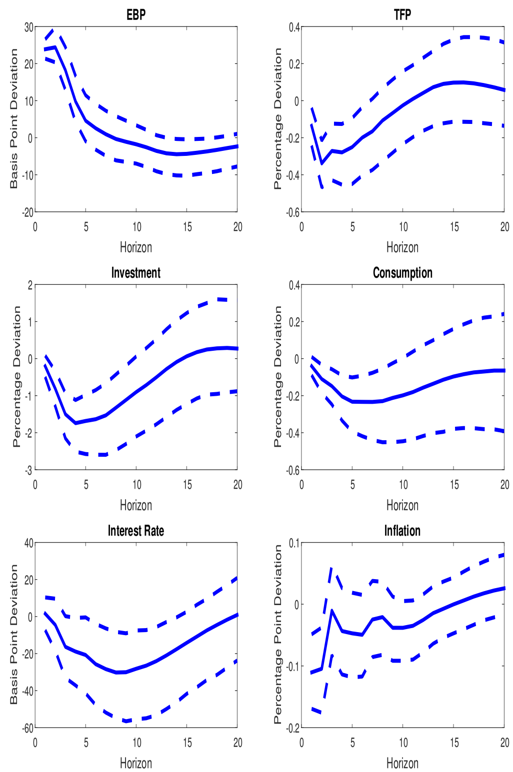
Notes: Panel (a): The solid line is the median impulse response and the dashed lines are the 97.5th 2.5th percentiles of the posterior distributions of impulse responses. Responses are in terms of deviations from pre-shock values (in basis point deviation for EBP and interest rate, percentage point deviation 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 2.5th percentiles of the posterior distribution of FEV contributions. Horizon is in quarters.

Figure 2: **Time Series of Utilization-Adjusted TFP and Unadjusted TFP.**

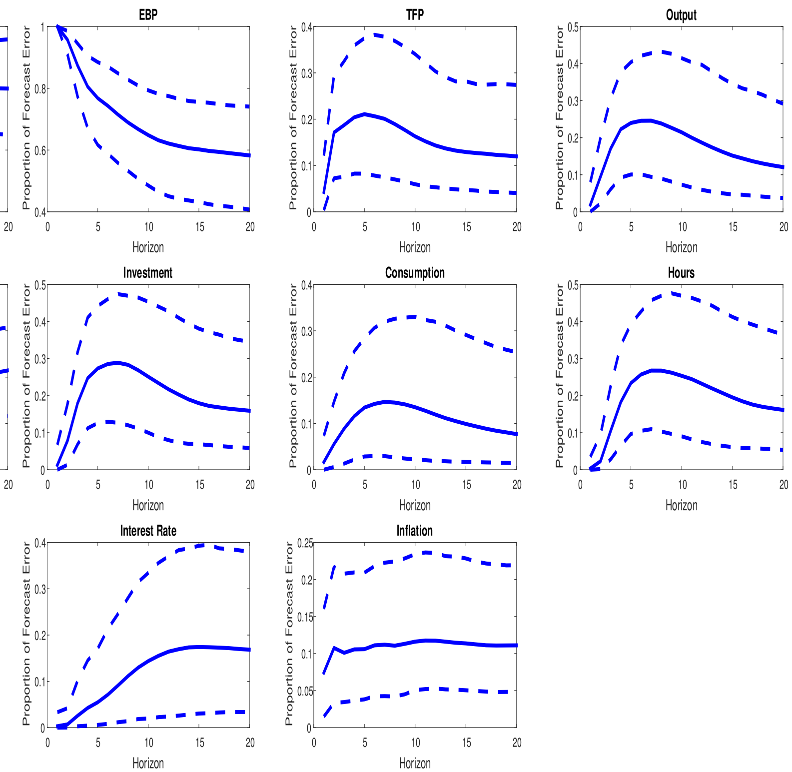


Notes: This figure presents the time series of logs of utilization-adjusted TFP (solid line) and unadjusted TFP (dashed line), where the latter is a TFP measure that does not account for factor utilization changes. Both measures are taken from Fernald (2012) and cover the period 1947:Q1-2017:Q3. U.S. recessions are represented by the shaded areas.

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



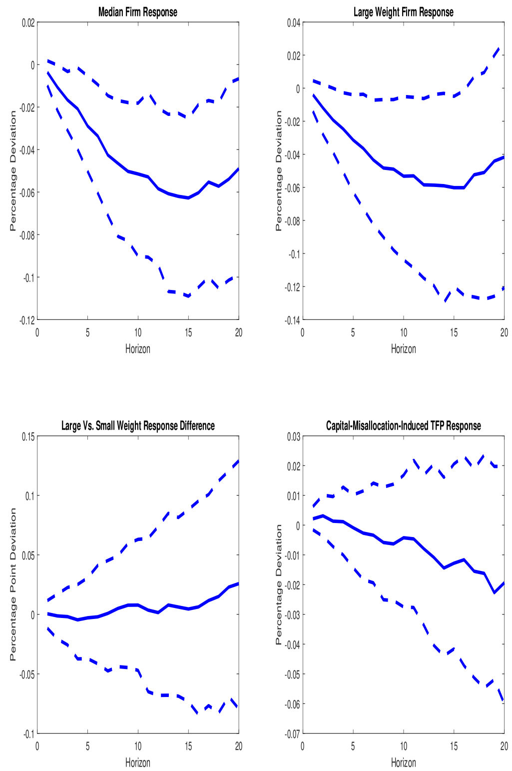
(a) The Median and 97.5th and 2.5th percentiles of the Impulse Responses to a One Standard Deviation Credit Supply Shock.



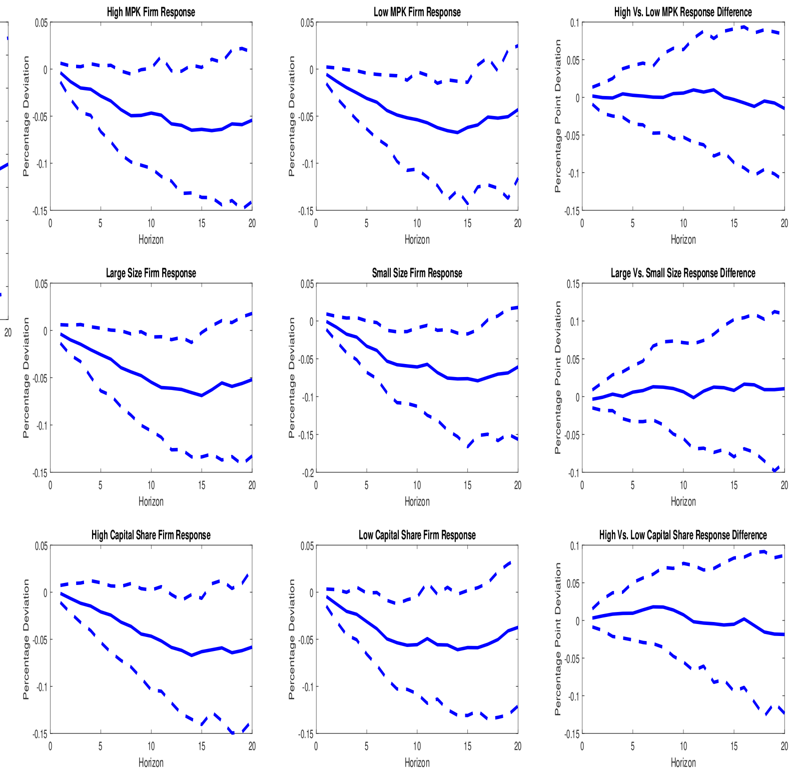
(b) The Median and 97.5th and 2.5th Percentiles of the Contribution of Credit Supply Shocks to the Forecast Error Variance of the Variables.

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 with the Fernald (2012) unadjusted TFP measure, i.e., one that does not adjust for factor utilization changes. 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 with the Fernald (2012) unadjusted TFP measure, i.e., one that does not adjust for factor utilization changes. Horizon is in quarters

Figure 4: **Bottom-Up Estimation Approach: Capital Misallocation Channel: (a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response; (b) Firm-Level Impulse Responses by Firm Characteristics**.



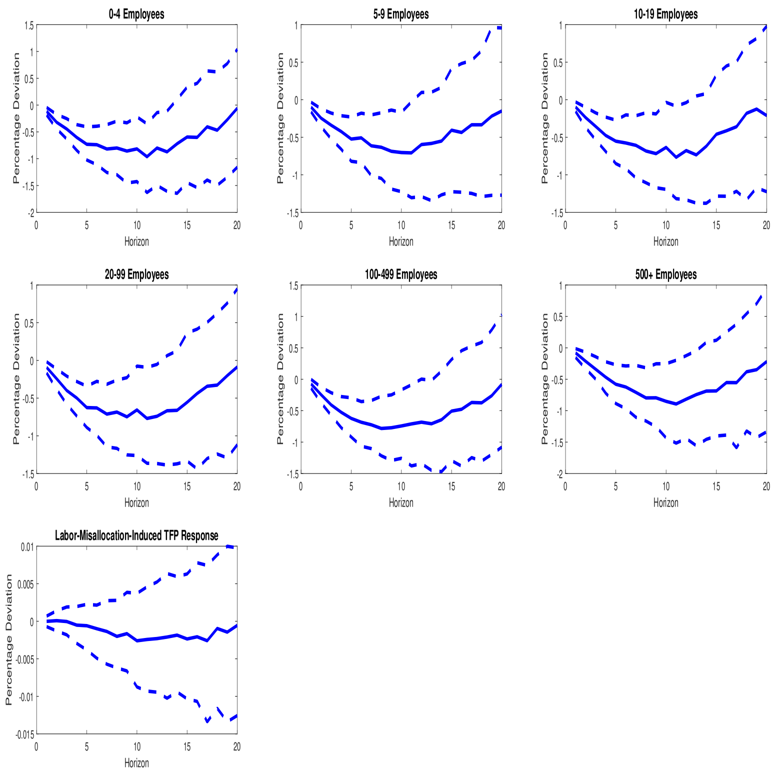
(a) 'Median Firm' Capital Response and Capital-Misallocation-Induced TFP Response.



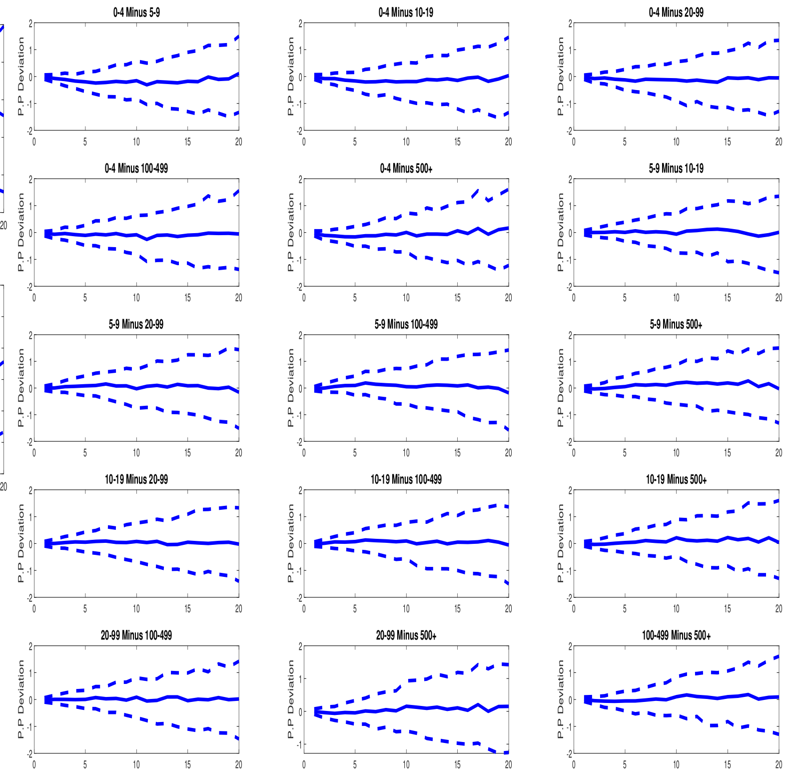
(b) Firm-Level Impulse Responses by Firm Characteristics.

Notes: This figure presents the results from the bottom-up estimation procedure for the capital misallocation channel. 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) (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 4a 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 5: **Bottom-Up Estimation Approach: Labor Misallocation Channel: (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 from the bottom-up estimation procedure for the labor misallocation channel. 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). 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. Horizon is in quarters.