ASSESSING THE MACROECONOMIC IMPACT OF BANK INTERMEDIATION SHOCKS: A STRUCTURAL APPROACH

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Abstract. We take a structural approach to assessing the empirical importance of shocks to the supply of bank-intermediated credit in affecting macroeconomic fluctuations. First, we develop a theoretical model to show how credit supply shocks can be transmitted into disruptions in the production economy. Second, we utilize the unique micro banking data to identify and support the model's key mechanism. Third, we find that the output effect of credit supply shocks is not only economically and statistically significant but also consistent with the VAR evidence. Our mode estimation indicates that a negative one-standard-deviation shock to credit supply generates a loss of output by one percent.

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I. Introduction

Since the classic works of Townsend (1979) and Williamson (1987), there has grown a large body of theoretical literature that argues for the importance of the supply channel of bank-intermediated credit in the business cycle.[1] Despite the impact of this rich literature on academic research and policy discussions alike, the theory has *not* been tested against the data. The lack of progress reflects the difficulty of separating the supply and demand of bank-intermediated credit. This challenging identification problem needs to be reckoned with as it holds the key to assessing the empirical relevance of the literature.

This paper takes a first step to bridge the gap between the theory on the one hand and the empirical evidence derived from the micro survey data on the other. To this end, we build a theoretical model on the aforementioned literature and confront the model with the U.S. data. At the heart of our model is a bank intermediation process that involves costly monitoring in the spirit of Townsend (1979), Williamson (1987), and Greenwood, Sanchez, and Wang (2010). In our model, an exogenous negative shock to bank intermediation leads to an increase of banks' intensity in monitoring and reassessing business activities. Since monitoring or verification is costly, the overall intermediation cost increases as well, which in turn reduces bank-intermediated credit supply. As a result, both business lending and aggregate output fall. The process is propagated by the fall of firms' net worth via the standard financial accelerator channel.

While our model builds on the common theme that bank intermediation costs influence the amount of bank loan supply and hence aggregate output—a supply-side story of bank intermediation, it is tailored to fit to the data. In particular, the model's bank intermediation channel is identified by the micro survey data constructed by Bassett, Chosak, Driscoll, and Zakrajšek (2014) (BCDZ hereafter). Follow BCDZ, we construct the indictor series of bank-intermediated credit supply by utilizing both the quarterly Consolidated Report of Condition and Income (Call Report) and the Federal Reserve Board's Senior Loan Officer Opinion Survey (SLOOS) on Bank Lending Practices. We call this indicator "the series of credit supply changes." As articulated by BCDZ, the series of credit supply changes is purged of demand-related factors as well as the factor affecting banks' capital position and provides "a more accurate measure of movements in the supply of bank loans available to potential borrowers." The series disciplines the model's intermediation process by mapping the data series directly to the bank intermediation costs in the model.

We estimate the model using the credit supply series and several standard macro series. We find that the model implied impulse responses of bank loans and aggregate output to shocks to bank intermediated credit supply are remarkably consistent with our own vector

[1]It is impossible to give an exhaustive list of papers in this voluminous literature. For an example of recent papers, see Greenwood, Sanchez, and Wang (2010) and the references therein.

autoregression (VAR) evidence as well as the VAR evidence provided by BCDZ. This finding is important as it provides a strong support for the model's mechanism that transmits a credit supply shock into macroeconomic fluctuations.

Our paper is closely related to the literature on the role of financial factors in the business cycle. The bulk of the recent literature largely abstracts from the intermediation process and instead focuses on the role of borrowers' net worth or corporate bond spreads in propagating shocks originating in other sectors of the economy (e.g, Bernanke, Gertler, and Gilchrist (1999), Christiano, Motto, and Rostagno (2014), Gilchrist and Zakrajšek (2012a)). A notable exception is Jermann and Quadrini (2012), who shift attention back to the role of disruptions that originate directly in the financial sector (the so-called "financial shocks") as a source of business cycle fluctuations. In Jermann and Quadrini (2012), however, financial shocks stem from disruptions in the liquidity of firms' assets and thus they mainly capture variations in *demands for bank credit*. Several other papers have studied the source of bank's distress from two approaches. The first approach focuses on banks' incentive problems and the effect of changes in banks' net worth or their ability to absorb disruptions hitting their liabilities (e.g., Gertler and Kiyotaki (2010), Gertler and Karadi (2011), Christiano and Ikeda (2013), and Quadrini (2015)). The second approach focuses on how banks' liquidity mismatch opens up the possibility of bank runs (e.g., Diamond and Dybvig (1983) and Gertler and Kiyotaki (Forthcoming)).

Consistent with BCDZ's new data on changes in bank intermediated credit supply, our paper places a new emphasis on disturbances to the intermediation process as a source of credit supply disruption, which is independent of banks' current or expected capital position (or net worth). The intermediation technology or process in our model follows Greenwood, Sanchez, and Wang (2010), who extend the framework of Williamson (1987) to allow for a stochastic monitoring technology and an endogenous monitoring intensity. While Greenwood, Sanchez, and Wang (2010) focus on financial development, the goal of our paper is to assess the quantitative impact of disruptions in bank intermediation on business cycles.

According to our survey data, when senior loan officers tighten lending standards, part of their effort is devoted to intense monitoring activities such as the tightening of loan covenants and changes in the lending standards. These activities are closely related to increasing costs associated with frequent assessments of the riskiness of business credit lines. It is this part of the credit supply channel that our theoretical model emphasizes and BCDZ's econometric methodology is designed to capture. By removing other factors influencing lending standards such as spreads, tolerance for risks, banks' balance-sheet problems, and other bank-specific problems, we build the tight connection between monitoring intensity and supply-side variations in lending standards, which makes it feasible to identify our model's monitoring intensity directly by the series of credit supply changes. The micro survey data

used for constructing such a series provides an ideal measure to disentangle different sources contributing to changes in each bank's lending standards, ranging from demand factors to macroeconomic uncertainty or outlook. Through the lenses of our structural model, the newly constructed series of credit supply changes helps identify not only the source of credit supply disruptions but also the mechanism that transmits these disturbances into fluctuations in bank loans and aggregate output.

Another paper that seeks to disentangle credit supply from credit demand shocks by imposing a structural framework on financial data is Gilchrist and Zakrajšek (2012b) (GZ hereafter). To our knowledge, GZ is a first paper to assess the empirical importance of a credit supply shock within the general equilibrium framework. There are two important differences between our paper and theirs. First, GZ use the estimated financial bond premium, a component representing cyclical changes in the relationship between default risks and the credit spread, as a proxy for an exogenous disturbance to the efficiency of private financial intermediation. Such a measure of distress in the financial sector, as GZ argue, more or less captures a change in the capital position of broker-dealers, which may be more general than the banking system itself. By contrast, our model is consistent with the measure of credit supply changes *independent of* factors affecting banks' current or future capital positions. Second, the model GZ use to identify a credit supply shock is the standard dynamic stochastic general equilibrium (DSGE) model augmented with Bernanke, Gertler, and Gilchrist (1999)'s financial accelerator. That framework assumes a deterministic monitoring outcome under the constant monitoring intensity, implying no endogenous variations in the cost of bank intermediation. Such endogenous variations hold the key to our model's mechanism.

As previously discussed, there are two credit supply factors. One is a change in the bank's income and balance sheet (liquidity and net worth), and the other is driven purely by intermediation costs such as monitoring, supervision, and verification activities. The microdata separate these two supply factors and as discussed in Section II.1, problems in banks' balance sheets are *not* an important factor contributing to output contraction during the recessions. The microdata further show that demand factors and macroeconomic conditions such as their outlook and uncertainty are very important in shaping the business cycle. Thus what mechanism would transmit credit supply changes, independent of banks' balance sheets, credit demand factors, and other macroeconomic factors, into macroeconomic fluctuations is the focus of this paper, a focus that is necessary for assessing the empirical significance of the theoretical literature on the role of bank intermediation.

The rest of the paper is organized as follows. Section II discusses how the data are constructed for estimating our structural model. Section III presents the structural model with bank intermediation. Section IV discusses the empirical results from the estimation in light of the BCDZ evidence and our own VAR evidence and analyzes the key transmission

mechanism and its relation to identification via the newly constructed series of credit supply changes. Section V offers concluding remarks.

II. Construction of the data

Most of the data must be reconstructed ourselves to be as consistent as possible with the theoretical model developed in Section III. Construction of bank-level survey data and bank loans is a particularly involved process. This section provides the detailed description pertinent to estimation of our structural model.

II.1. **Micro-level banking data.** We follow the BCDZ methodology and take two steps to construct the quarterly series of credit supply changes. We first construct a diffusion index for senior officers' lending standards by combining the SLOOS and Call Report microdata sets. The reason for using these micro bank-level datasets is that the diffusion index is a weighted index with the weight being the outstanding loan of *each bank*. After we obtain the diffusion index, we construct the credit supply indicator by purging the diffusion index of demand-related factors as well as other supply-related factors such as banks' capital position (net worth). The final series accounts only for changes in banks' intermediation intensity in the assessment of risks of business lending.

Our sample from 1990Q2 to 2014Q4 covers a longer period than BCDZ's. A longer sample is not the main reason for us to construct our own series. The goal of this paper is to assess whether the theoretical literature on bank intermediation has empirical significance. Thus, the main reason for us to construct our own dataset is to carefully select categories of the survey so as to be as consistent as possible with the scope of our structural model. This construction requirement applies to the other time series discussed in Section II.2.

II.1.1. *Changes in lending standards.* SLOOS asks banks about changes in their lending standards from April 1990 until now.[2] Participating banks are asked about whether and how they have changed their lending standards in the following loan categories or types (type k in our notation): commercial and industrial loans (C&I loans); commercial real estate; residential mortgage for purchasing home; home equity lines of credit; credit cards; auto loans; and consumer loans other than credit cards or auto loans. The questionnaire is of the following form: "*Over the past three months, how have your bank's credit standards for approving loans of type k changed?*". Banks are requested to respond to this questionnaire with the scale ranging from 1 to 5, where 1 means "eased considerably", 2 "eased somewhat",

[2]April 1990 corresponds to 1990Q1 in our sample since banks' answers correspond to lending standard changes in the previous quarter. We use the 1990Q1 observation as a lagged variable to construct the series of credit supply changes discussed later in Section II.1.4. Thus our effective sample starts in 1990Q2.

3 "about the same or unchanged", 4 "tightened somewhat", and 5 "tightened considerably". Based on banks' answers, we create the categorical variable $I_{ik,t}$ as

$$I_{ik,t} = \begin{cases} -1 & \text{if bank } i \text{ reports easing standards on loan category } k \text{ in quarter } t \\ 0 & \text{if bank } i \text{ reports no changes in standards on loan category } k \text{ in quarter } t \\ 1 & \text{if bank } i \text{ reports tightening standards on loan category } k \text{ in quarter } t \end{cases}.$$

To calculate aggregate changes in banks' lending standards, we use each bank's outstanding loan amount of type k from the Call Report to construct a composite index for each bank. The composite index is calculated as

$$\Delta S_{i,t} = \sum_k \omega_{ik,t-1} \times I_{ik,t}, \tag{1}$$

where $\omega_{ik,t-1}$ is the share of bank i's loan amount in category k at the end of quarter $t-1$. We sum over k for C&I loans, auto loans, and consumer loans other than credit cards or auto loans. We thus exclude any financings related to home equity or consumers' credit cards because our theoretical model does not build in these features.

With the composite index for *each bank*, we calculate the aggregate diffusion index of changes in lending standards as a weighted average of composite indexes by each bank's loan share:

$$\Delta S_t = \sum_i w_{i,t-1} \times \Delta S_{i,t}, \tag{2}$$

where $w_{i,t-1}$ is the loan share of the respondent bank i at the end of quarter $t-1$. This diffusion index is between -1 and 1. The SLOOS questionnaire also asks senior loan officers about lending standards applied to large/medium firms and small firms separately. The constructed diffusion index does not differ much across these two types of firms.

Figure 1 plots the constructed aggregate diffusion index. The series indicate that bank lending standards began to tighten in 2007 and reached its peak in the middle of the recent recession. Understanding the sources driving the tightening of lending standards and the transmission mechanism for such tightening to affect the real economy is therefore central to understanding the role of bank intermediation in the Great Recession.

II.1.2. *Supply and demand.* The tightening of bank lending standards can be driven by both demand and supply factors. Senior loan officers in the SLOOS are asked of the possible reasons why the bank tightens or loosens the standards. The choices include a) the bank's current or expected capital position, b) economic outlook and uncertainty, c) industry-specific problems, d) tolerance for risk, and e) competition from other banks or nonbank lenders. The exact wording of the questions has changed somewhat over time. For example, prior to the 1995Q2 survey, banks were not asked about "tolerance for risk"; "uncertainty" about

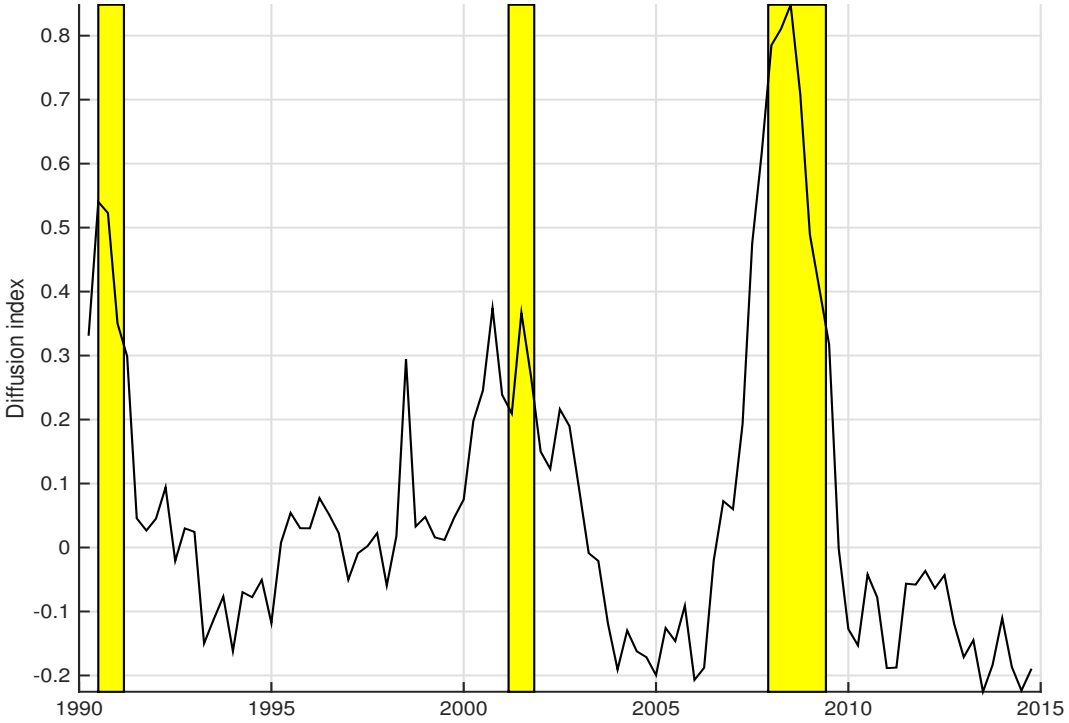

FIGURE 1. The constructed aggregate diffusion index of changes in lending standards. The shaded bars represent NBER-dated recessions.

the economic outlook was *not* a part of the questionnaire prior to the 1998Q4 survey. The overall design of the questionnaire, however, has been consistent over time.

To each of the questions, the survey requests that the officers respond with one of the three answers: (1) "Not important", (2) "Somewhat important", and (3) "Very important". Figures 2 and 3 display the response results for two conceptually important factors: banks' capital position and economic outlook (and uncertainty).[3] Respondents who say they tighten the standards are represented by bars above zero on the y-axis (e.g., if 50% of the respondents say they tighten the standards, the positive portion of the bar adds up to 50). Those who say they ease the standards are represented by bars below zero on the y-axis. As revealed in Figure 2, banks' capital position is not an important supply factor, even during the Great Recession period. Bassett and Covas (2013) further show that this result is not biased, partly because respondents' answers are confidential. By contrast, as shown in Figure 3, economic outlook and uncertainty emerges as a very important demand factor (in fact, the most important factor among all the reasons considered). This evidence supports the position

[3]Prior to 1995Q2, the wording of survey questions was slightly different about the reasons for tightening or easing standards. Instead of responding to whether the reasons were "very", "somewhat", or "not" important, the respondents were asked to state whether or not economic outlook or capital position is the main reason for tightening or easing the standards. The survey results are similar. That is, banks' capital position is not the main reason but economic outlook is more likely to be the main reason for a change.

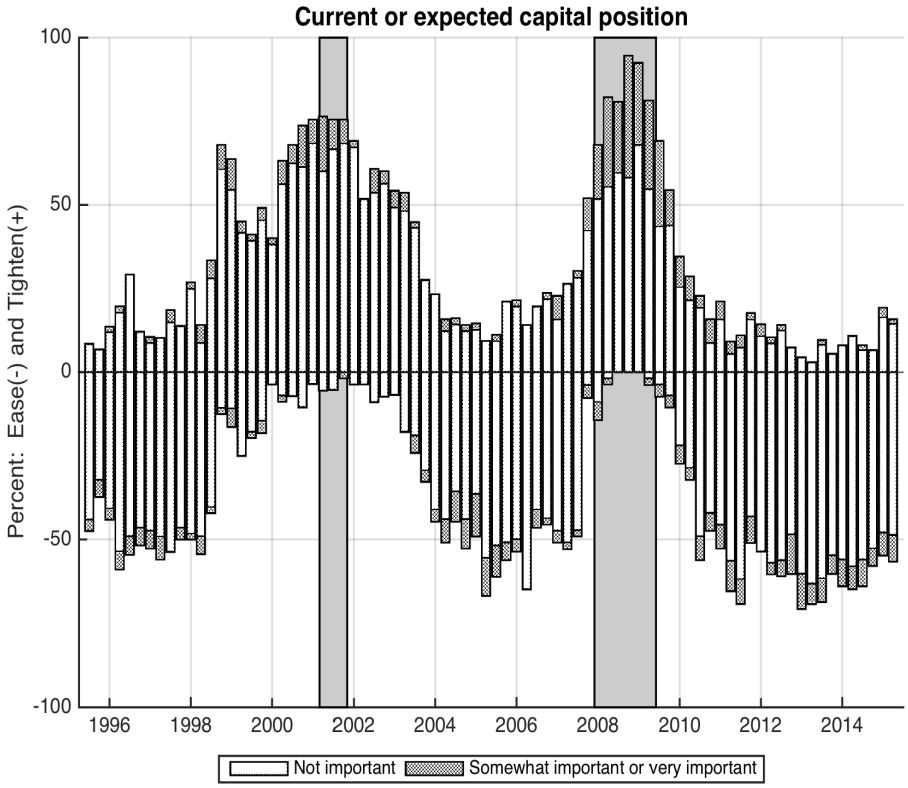

FIGURE 2. Reasons for changes in lending standards. The shaded longest bars represent NBER-dated recessions.

taken by Christiano, Motto, and Rostagno (2014) that banks' balance sheets may not be an important reason for output contraction during the Great Recession.

II.1.3. *Demand for C&I loans.* The strong demand factor argued above is further supported by the survey data on demands for C&I loans. Since the 1992Q1 SLOOS survey, senior loan officers have been asked how demand for C&I loans has changed over the past three months (apart from seasonal variation).[4] The respondents are requested to select one of the following answers: is loan demand (1) "substantially stronger", (2) "moderately stronger", (3) "about the same", (4) "moderately weaker", or (5) "substantially weaker"? Up until the 1997Q3 survey, the questions about demand for large, medium, and small firms had been asked separately. Since the 1997Q3 survey, the questions for large and medium firms have been combined. In Figure 4, we combine the 1992Q1-1997Q2 responses for large and

[4]The wording of the question has changed slightly over time. At one point between the 1994Q1 and 1997Q1 surveys, the question began to include the parenthetical note to consider only "actual extensions of credit as opposed to undrawn lines." Then, in the 1997Q3 survey, the wording of the question's parenthetical note changed to consider only "actual disbursements of funds as opposed to requests for new or increased lines of credit."

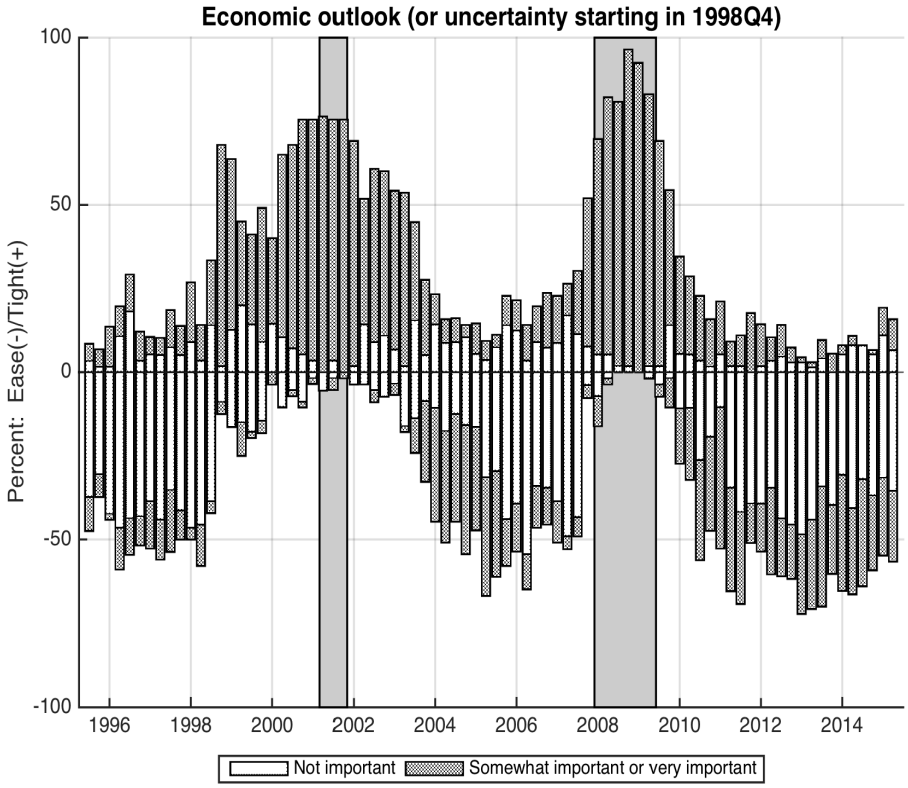

FIGURE 3. Reasons for changes in lending standards. The longest shaded bars represent NBER-dated recessions.

medium firms into one response.[5] Since the 1997Q3 survey, respondents have also been asked a follow-up question (with various parts) about how important various reasons are for weaker or stronger demand. Financing needs for inventories, investment in plant or equipment, and accounts receivable are generally a somewhat or very important reason for stronger or weaker loan demand. Thus, demand for C&I loans are mostly related to investment fluctuations.

As one can see from Figure 4, there are some differences in responses regarding large/medium firms and small firms, but the differences pale in comparison to the similarity of responses. For both large and small firms, weaker demand for C&I loans is cited most by senior loan officers during the recession period. The near symmetry between large and small firms about their weak demand during recessions mirrors the symmetry of banks' lending standards applied to large and small firms. In our benchmark model, we treat all firms the same as an approximation. We also consider a scenario in which large firms may not rely on banks' loans to finance their investment, while small firms continue to rely on such loans.

[5]If the response for medium firms is left blank, we assume that the response would have been the same as for large firms. If the response for large firms is left blank, we assume that the response would have been the same as for medium firms. If both responses are present, we use both responses with a half weight attached to each.

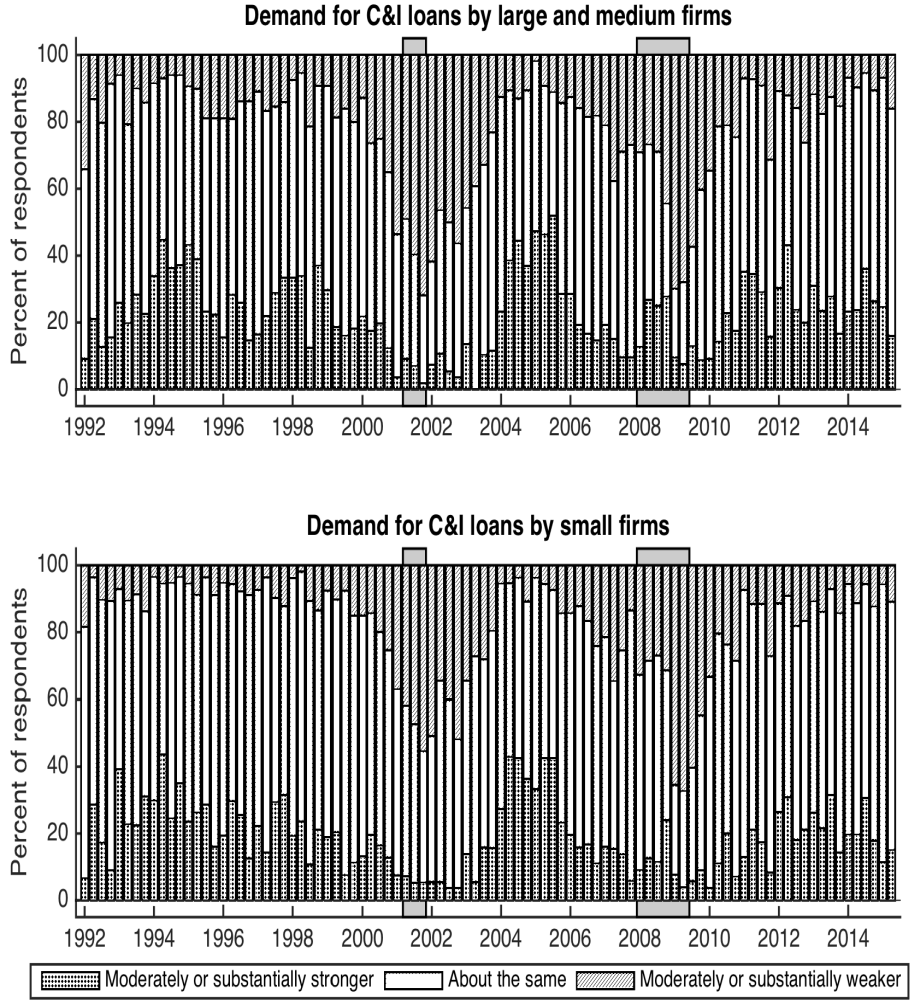

FIGURE 4. Demand factors for C&I loans. The shaded bars outside the scale between zero and one represent NBER-dated recessions.

II.1.4. *A pure measure of movements in credit supply.* As documented in the previous two sections, problems in banks' balance sheets are not an important reason for banks to change lending standards, while macroeconomic conditions and demand factors play a very important role in banks' lending behavior. The other credit supply channel, what we call "the bank intermediation" channel, should not be contaminated by all other factors. To achieve this goal, one must eliminate the endogeneity created by demand factors and macroeconomic conditions (including outlook, uncertainty, and interest spreads) as well as the effects of banks' income and balance sheets. BCDZ propose a careful econometric methodology for removing such endogeneity and provides "a pure measure of movements in the effective supply of bank-intermediated credit." We follow their methodology and construct the quarterly series of credit supply changes with a narrower definition to be consistent with our theoretical model (i.e., a measurement excluding residential mortgage to purchase home, home equity

lines of credit, and credit cards). This series is reported in the top left panel of Figure 5 and as one can see, it remained at the very high level for 6 quarters before it peaked in 2008Q3. Compared to the aggregate diffusion index in Figure 1, the series of supply changes in bank-intermediated credit is more volatile, which may reflect inclusion of measurement errors. These measurement errors are effectively purged off by the VAR analysis presented in Section II.3.

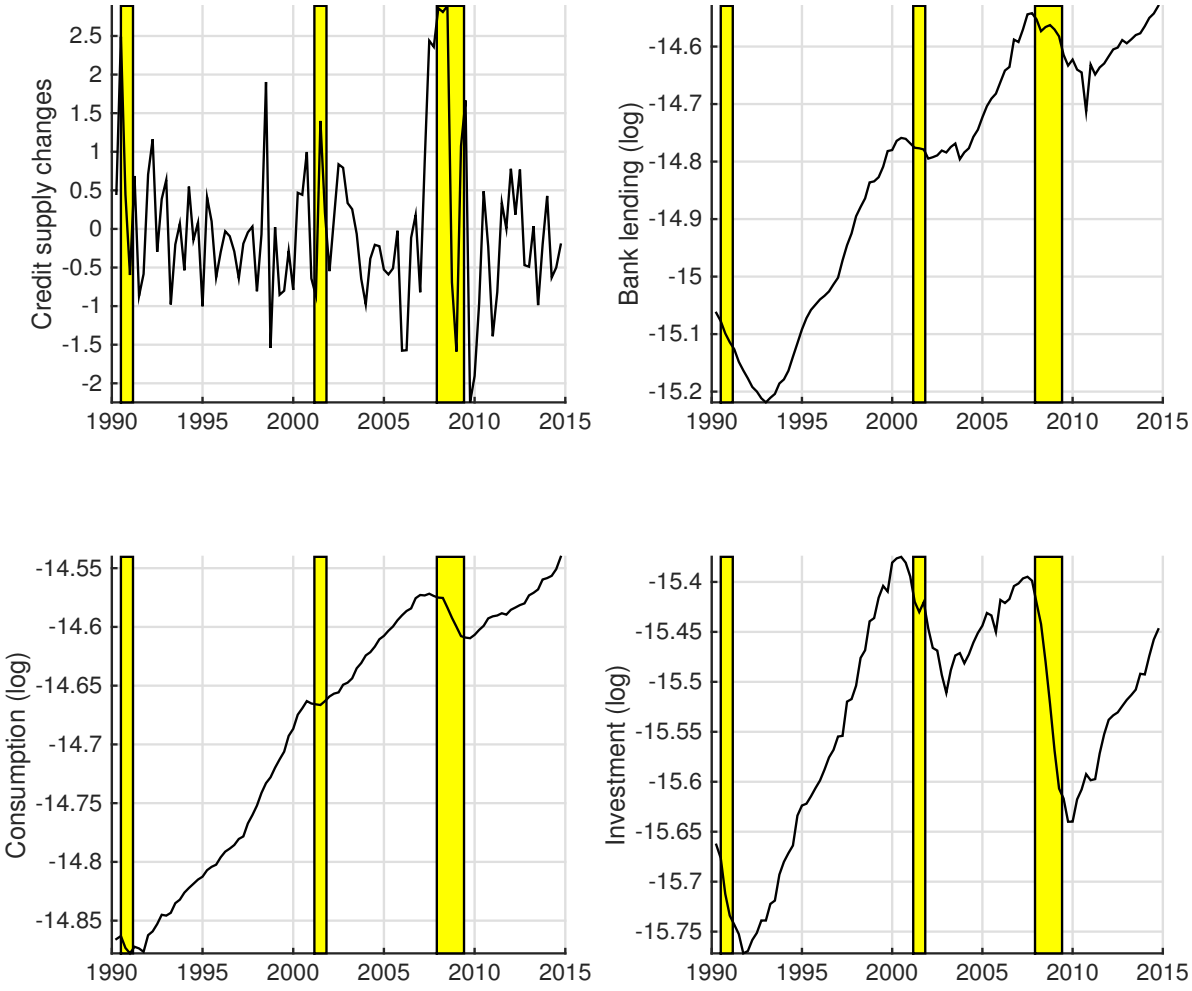

FIGURE 5. The constructed U.S. time series used for estimation of the structural model. The shaded bars represent NBER-dated recessions.

II.2. **Business lending and other macro variables.** To get an accurate measure of loan activities, BCDZ argue that the series of business lending should comprise business loans and unused commitments to the lines of credit. From the Call Report microdata set we construct the nonfinancial business portion of this series to be consistent with our theoretical model developed in Section III. This task proves to be challenging, but the constructed series is useful for estimation of many structural models. To accomplish this task, we follow the instruction book of the Federal Financial Institutions Examination Council (FFIEC)

(see http://www.ffiec.gov/pdf/FFIEC_forms/FFIEC031_FFIEC041_201503_i.pdf). The book (page 156) includes detailed instructions to banks about how to exclude loans to financial institutions from loans secured by real estate. We first obtain C&I loans and other loans to nonfinancial institutions excluding those secured by residential real estate. We then obtain automobile loans and other consumer loans excluding loans outstanding on credit cards. We sum all these components to obtain the series of "nonfinancial business loans."

For unused commitments to the lines of credit, the Call Report has three components: (1) commercial real estate, construction, and land development with commitments to fund loans secured by real estate; (2) commercial real estate, construction, and land development with commitments to fund loans not secured by real estate; (3) other unused commitments. The third component is used by BCDZ. Since the series of "other unused commitments" includes loans to financial institutions and non-business loans, we use the portion of C&I loans only. Prior to 2010, "other unused commitments" does not have a breakdown for commitments to C&I loans, so we construct a proxy series by computing the ratio of "used commitments to C&I loans" to "other unused commitments" in 2010Q1 and multiplying "other unused commitments" prior to 2010Q1 by this ratio. We thus construct the series of "nonfinancial business commitments."

The total "nonfinancial business lending" made by banks is defined as the sum of nonfinancial business loans and nonfinancial business commitments so constructed. In our theoretical model, we can interpret unused commitments as the loans committed at the beginning of the period prior to its use at the end of the period. For estimation of our structural model, we use either nonfinancial business lending (including nonfinancial business commitments) or nonfinancial business loans (excluding nonfinancial business commitments), the results do not change. For this reason, we focus on the series of nonfinancial business lending, which is consistent what BCDZ recommend. What is different from BCDZ is that we exclude loans to financial institutions, consumer credit cards, and unused commitments to home equity lines of credit. We include automobile loans and consumer loans for other consumer durables because we follow the convention in the real business cycle literature and treat consumer durables as a part of investment goods in our theoretical model.

To be also consistent with our model, we construct the nominal consumption series as the sum of nominal nondurable goods and nominal consumption services excluding housing services, the nominal investment series as the sum of nominal equipment, intellectual property products investment, and PCE consumer durables, and the labor hours series as aggregate hours in the business sector excluding those for finance and insurance industries, where PCE stands for "personal consumption expenditures." More involved effort is devoted to construction of the aggregate price index for consumption, which is computed as the Tornqvist

price index for PCE nondurables and and services excluding housing services, and the annual capital stock consistent with the definition of the investment series. All the nominal variables are divided by the aggregate price index and then by the civilian noninstitutional population with ages from 25 to 64, so that these nominal variables are transformed to real variables per capita. The population series is smoothed with Christiano and Fitzgerald (2003)'s band-pass filter to eliminate seasonal fluctuations and breaks due to the Census's population controls.

In addition to the series of credit supply changes, Figure 5 displays the log values of real business lending (B_t^{Data}), real consumption (C_t^{Data}), and real investment (I_t^{Data}). It is evident from the top right panel of Figure 5 that bank loans experience a sharp decline at the beginning of the Great Recession and its recovery has been slow. Consumption and investment, displayed in the bottom two panels of Figure 5, show similar patterns but with different magnitudes. In particular, the fall of investment during the Great Recession is more severe and persistent than the fall of consumption.

II.3. **Does credit supply matter?** Do disruptions to the supply of bank-intermediated credit matter to the real economy? BCDZ present robust VAR evidence that a shock to credit supply changes has a significant effect on both bank loans and aggregate output. In this section we use our own constructed series and perform a similar VAR analysis. Our findings are consistent with BCDZ's. Specifically, we first compute the log value of aggregate output as

$$\log Y_t^{\text{Data}} = y_c \log C_t^{\text{Data}} + y_i \log I_t^{\text{Data}},$$

where y_c is the average share of consumption in output and y_i is the average share of investment in output. We then estimate a 5-variable structural VAR with credit supply changes, charge-off (delinquency) rates of commercial banks, log business lending, log hours, and log output. Following BCDZ, the identification is recursive and the series of credit supply changes is ordered first. This identification is sensible and economically appealing because the series of credit supply changes is so constructed as to remove the effect of macroeconomic factors, bank-specific factors, and other demand factors.

Figure 6 reports the estimated impulse responses of business lending and aggregate output over the 5-year horizon in response to a negative one-standard-deviation shock to changes in bank-intermediated credit supply. Even though our time series are defined differently from BCDZ, the pattern and magnitude of output responses is remarkably similar. The response of business lending is procyclical: its persistent decline is concurrent with the persistent fall of output. The maximum impact is about a 1% loss of output, in line with BCDZ's estimate. This robust result should serve as a styled fact for structural models to match. The error bands indicate that the responses of both business lending and output are statistically significant.

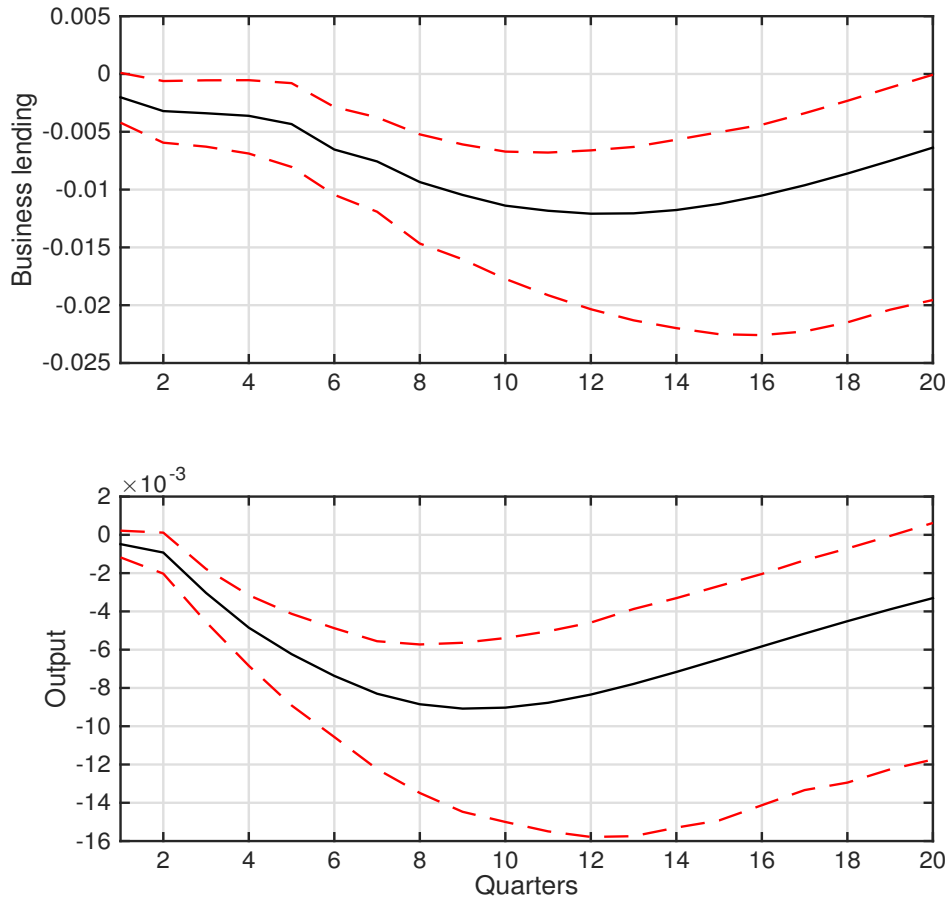

FIGURE 6. The dynamic impact on business lending and aggregate output of a negative one-standard-deviation shock to credit supply changes. The solid line represents the likelihood estimate and the two dashed lines around the solid lines contains the .90 probability bands simulated according to Sims and Zha (1999).

What is the mechanism that generates such an impact on output? And how are shocks to bank-intermediated credit supply transmitted to affect first business lending and then aggregate output. As discussed in the introduction, the theoretical literature on bank intermediation has attempted to answer these questions, but empirical evidence in favor of the theory is scant or even nonexistent. In sections that follow, we take up the important task of developing a structural model emphasized by this literature and testing its mechanism with our newly constructed data set.

III. MODEL

In this section we develop our structural model. The model economy is inhabited by an infinitely-lived representative household, a representative final goods producer, a continuum

of entrepreneurs and intermediate good producers with unit mass, and a representative capital good producer.

In each period entrepreneurs purchase intermediate goods to produce differentiated goods, the so-called "variety goods", as an input into final goods production. A competitive bank exists to provide loans to entrepreneurs to finance the purchase of intermediate goods. All entrepreneurs are subject to idiosyncratic shocks to the production technology. Realizations of these shocks are not observed and can only be verified with costs.

Given the demand for intermediate goods, producers of such goods choose capital and labor to minimize the production cost. The representative household supplies capital and labor for production of intermediate goods and is entitled to the profit of the capital producer.

III.1. **Technology.** There are a continuum of entrepreneurs indexed by $k \in [0, 1]$ and endowed with technology for producing variety goods $Y_t(k)$. For each variety k, the technology for production of differentiated variety goods is

$$Y_t(k) = A_t(k) y_t(k),$$

where $y_t(k)$ represents intermediate goods used to produce variety k and $Y_t(k)$ represents variety (differentiated) goods indexed by k. Since entrepreneurs producing different varieties are symmetric, we drop k for notational brevity whenever there is no confusion. The idiosyncratic productivity A_t takes the form $A_t = \overline{A}\xi_t$, where ξ_t is a shock to idiosyncratic productivity with the form of

$$\xi_t = \begin{cases} 1 - \sigma\sqrt{\frac{1-\pi_t}{\pi_t}} \text{ with probability } \pi_t \\ 1 + \sigma\sqrt{\frac{\pi_t}{1-\pi_t}} \text{ with probability } 1 - \pi_t \end{cases}$$

such that the unconditional mean of this shock process is 1 and the unconditional variance is σ^2. Let

$$\pi_t = \frac{\vartheta_t}{1 + \vartheta_t},$$

where ϑ_t follows a stochastic process specified as

$$\log \vartheta_t = (1 - \rho_\vartheta) \log \vartheta + \rho_\vartheta \log \vartheta_{t-1} + \sigma_\vartheta \, \epsilon_{\vartheta,t},$$

where $\epsilon_{\vartheta,t}$ is a normal random variable. Denote

$$A_{1,t} = \overline{A}\left[1 - \sigma\sqrt{\frac{1-\pi_t}{\pi_t}}\right],$$
$$A_{2,t} = \overline{A}\left[1 + \sigma\sqrt{\frac{\pi_t}{1-\pi_t}}\right].$$

The subscript 1 denotes a bad state and 2 a good state for entrepreneurs. We have $\overline{A}_t \equiv E_t(A_t) = \pi_t A_{1,t} + (1-\pi_t) A_{2,t}$ and $Var_t(A_t) = \pi_t(1-\pi_t)(A_{2,t} - A_{1,t})^2$. Accordingly, variations in π_t drive the variance of A_t while its mean remains constant. Therefore, a shock to π_t is essentially a shock to delinquency.

There is a CES technology for producing final goods by combining the differentiated varieties:

$$Y_t = \left[\int_0^1 (Y_t(k))^{\mu} dk\right]^{\frac{1}{\mu}},$$

where the elasticity of substitution is $0 < \mu < 1$. Given the specification of idiosyncratic shocks, the above expression can be rewritten as

$$Y_t = \left\{\pi_t (A_{1,t} y_t)^{\mu} + (1-\pi_t)(A_{2,t} y_t)^{\mu}\right\}^{\frac{1}{\mu}} = \left[A_t^{\mu}\right]^{\frac{1}{\mu}} y_t,$$

where

$$A_t^{\mu} \equiv \pi_t (A_{1,t})^{\mu} + (1-\pi_t)(A_{2,t})^{\mu}.$$

As in the standard model with monopolistic competition, the final goods producer chooses different varieties to maximize the profit. The first-order condition for this maximization delivers the demand function for each differentiated good:

$$P_{i,t} = \left(\frac{Y_t}{A_{i,t} y_t}\right)^{1-\mu}, i \in \{1,2\}, \tag{3}$$

where $P_{i,t}$ is the price of variety goods at state i.

III.2. **Financial contract between entrepreneur and bank.** *Before* the final goods production takes place, entrepreneurs need to purchase intermediate goods at a cost $p_t^y y_t$, where p_t^y is the price of intermediate good. Entrepreneurs can use both their net worth and external borrowing to finance the purchase of intermediate goods. Entrepreneurs' savings at the end of the last period, a_t^e, is in the form of capital and entrepreneurs' net worth is $q_t a_t^e$, where q_t is the price of capital. The gap between the purchasing cost of intermediate goods and entrepreneurs' net worth is financed by the bank, where the bank receives deposits from households.

In each period, an entrepreneur enters into a financial contract with the bank *before* idiosyncratic productivity shocks, ξ_t, are realized. Debt is repaid at the end of the period. Since the realized idiosyncratic shock is not publicly observable, payments to the bank at the end of the period are made according to the report submitted by the entrepreneur. The bank utilizes a costly-state-verification technology to verify the veracity of the report. Following Greenwood, Sanchez, and Wang (2010), the probability that the entrepreneur is

found cheating is specified as

$$P(m_t/y_t) = \begin{cases} 1 - \frac{1}{(\varepsilon_t m_t/y_t)^{\psi}} < 1, \ \psi > 0 \\ \qquad \text{for a report } \xi_t \neq \xi_{2t}, \\ 0, \quad \text{for a report } \xi_t = \xi_{2t}, \end{cases}$$

where m_t denotes the monitoring input of the project and is measured in consumption goods. The object m_t/y_t is the amount of monitoring per unit of intermediate goods, which we call the "monitoring intensity"; it captures the (unit) cost of bank intermediation.

Note that the bank will only have to verify the state when a bad state is reported. Under the assumption of $\psi > 0$, moreover, the probability of detecting a misreport depends positively on the monitoring intensity. As the size of bank loans increases, banks incur a higher cost to intermediate the loans or to maintain the same probability of detecting a misreport. To capture the exogenous variations in the efficiency of bank intermediation, we allow ε_t to affect the monitoring technology. The stochastic process for ε_t takes the following form:

$$\log \varepsilon_t = (1 - \rho_\varepsilon) \log \varepsilon + \rho_\varepsilon \log \varepsilon_{t-1} + \sigma_\varepsilon \, \epsilon_{\varepsilon,t},$$

where $\epsilon_{\varepsilon,t}$ is a normal random variable, which is a shock to the supply of bank intermediated credit. Thus, we refer to $\epsilon_{\varepsilon,t}$ as a bank intermediation shock.

The timing of the financial contract at time t is as follows. First, the bank determines the loan amount and the resources devoted to the monitoring or intermediation technology. Then, entrepreneurs use bank loans and their own net worth to purchase intermediate goods before the realization of idiosyncratic technology shocks. At the end of the period, an entrepreneurs reports the production outcome to the bank. The bank then decides whether to conduct a verification. At the final stage, output is split between an entrepreneurs and the bank based on the outcome of monitoring.

Denote the payoff to the bank at state i by b_{it} for $i \in \{1, 2\}$. Given the entrepreneur' net worth and the value of the loan contract to the entrepreneur, denoted by v_t, the optimal contract problem for the bank is to choose the quadruple $\{b_{1t}, b_{2t}, y_t, m_t\}$ to maximize the bank's expected profit. Specifically, we have

$$\max_{b_{1t}, b_{2t}, y_t, m_t} \{\pi_t b_{1t} + (1 - \pi_t) b_{2t} - (p_t^y y_t - q_t a_t^e) - \pi_t m_t\} \tag{4}$$

subject to

$$b_{1t} \leq P_{1,t} A_{1,t} y_t, \tag{5}$$

$$b_{2t} \leq P_{2,t} A_{2,t} y_t, \tag{6}$$

$$[1 - P(m_t/y_t)] \, [P_{2,t} A_{2,t} y_t - b_{1t}] \leq P_{2,t} A_{2,t} y_t - b_{2t}, \tag{7}$$

$$\pi_t (P_{1,t} A_{1,t} y_t - b_{1t}) + (1 - \pi_t)(P_{2,t} A_{2,t} y_t - b_{2t}) = v_t, \tag{8}$$

and the demand schedule (3). Constraints (5) and (6) are the limited liability constraints at each of the two states. The incentive compatibility constraint (7) for the entrepreneur dictates that when her cash flow is in a good state, the expected benefit for her to report, represented by the lefthand side of (7), is less or equal to the benefit of telling the truth. The participating constraint (8) represents the contract value for the entrepreneur. This contract defines business lending as

$$\mathcal{B}_t = p_t^y y_t - q_t a_t^e.$$

The bank's non-negative profit requires the entrepreneur's contract value v_t to satisfy

$$v_t \leq Y_t^{1-\mu} \left(\pi_t \left(A_{1,t}\right)^{\mu} + \left(1-\pi_t\right)\left(A_{2,t}\right)^{\mu}\right)\left(y_t\right)^{\mu} - \left(p_t^y y_t - q_t a_t^e\right) - \pi_t m_t. \tag{9}$$

We assume that the banking sector is competitive so that in equilibrium, the bank earns zero profit. As a result, the entrepreneur's contract value equation (9) holds with equality.

Proposition 1. There is no monitoring if and only if $Y_t^{1-\mu}\left(A_{1,t}y_t^{fb}\right)^{\mu} \geq p_t^y y_t^{fb} - q_t a_t^e$, where $y_t^{fb} \equiv \arg\max_{y_t} Y_t^{1-\mu}\left(\pi_t\left(A_{1,t}\right)^{\mu} + \left(1-\pi_t\right)\left(A_{2,t}\right)^{\mu}\right)\left(y_t\right)^{\mu} - p_t^y y_t$ subject to (3).

Proof. See Appendix E. ∎

The intuition behind Proposition 1 is straightforward. As the production scale increases, if the payoff in the bad state becomes larger than the amount of bank loans, then there is no incentive for the bank to engage in costly monitoring. Proposition 1 implies that as the firm becomes large, it relies less on bank loans to finance the purchasing of intermediate goods. Accordingly, it is optimal for the bank to have zero monitoring if the bank loan advanced to the entrepreneur is less than what the bank can seize in the bad state.

In our benchmark model, we assume that all entrepreneurs' net worth is sufficiently small so that the financial constraint is always binding. In Appendix D, we relax this assumption by introducing a second type of entrepreneurs, whose net worth is large enough for the financial constraint not to bind. We show that our results hold in this extended model.

III.3. **Intermediate goods producers' problem.** We assume that each intermediate goods producer faces the same Cobb-Douglas technology for using capital and labor. Given the entrepreneur's demand for intermediate goods y_t, the intermediate goods producer rents capital and hires labor to minimize the production cost

$$\min_{k_t, h_t} \left\{r_t k_t + w_t h_t\right\} \tag{10}$$

subject to

$$z_t \left(k_t\right)^{\alpha} \left(h_t\right)^{1-\alpha} \geq y_t,$$

where z_t a technology shock with the following stochastic process:

$$\log z_t = \rho_z \log z_{t-1} + \sigma_z \epsilon_{z,t}.$$

Note that $\epsilon_{z,t}$ is a normal random variable. The competitiveness of the intermediate goods market implies that the price of intermediate goods equals the production cost:

$$p_t^y = \frac{1}{z_t}\left(\frac{r_t}{\alpha}\right)^{\alpha}\left(\frac{w_t}{1-\alpha}\right)^{1-\alpha}.$$

III.4. **Entrepreneurs' consumption-saving problem.** In each period, after the production takes place, an entrepreneur decides how much to consume and how much to invest in physical capital a_t^e. To make our problem tractable, we assume perfect consumption insurance among entrepreneurs after they receive idiosyncratic productivity shocks. Thus, the consumption-saving problem of individual entrepreneurs can be aggregated and written as a problem faced by the representative entrepreneur. The representative entrepreneur maximizes

$$E_0\sum_{t=0}^{\infty}(\beta^e)^t\log\left(c_t^e-\varpi_e c_{t-1}^e\right) \text{ with } 0<\beta^e<1$$

subject to

$$c_t^e + q_t a_{t+1}^e = \left[q_t\left(1-\delta\right)+r_t\right]a_t^e + \left(v_t - q_t a_t^e\right).$$

We assume that $\beta^e < \beta$, where β is the household discount factor.

III.5. **Households.** The representative household has no access to the production technology, but provides physical capital and labor to intermediate goods producers in each period. The household is entitled to the profits of the capital goods producer. After the production takes place, the household makes optimal decisions on consumption, hours to work, and investment in physical capital. The representative household solves the problem

$$E_0\sum_{t=0}^{\infty}\beta^t\Theta_t\left[\log\left(c_t^h-\varpi_h c_{t-1}^h\right)-\phi_t\frac{H_t^{1+\nu}}{1+\nu}\right] \text{with } 0<\beta<1,$$

subject to

$$c_t^h + q_t a_{t+1}^h = \left[q_t\left(1-\delta\right)+r_t\right]a_t^h + w_t H_t + \Pi_t^k,$$

where a_{t+1}^h is the physical capital purchased at the end of the period t by the household, c_t^h and H_t denote the household's consumption and the total hours supplied, and Π_t^k is the profit of the representative capital producer. Let $\theta_t = \Theta_t/\Theta_{t-1}$, which follows a stochastic process as

$$\log\theta_t = (1-\rho_\theta)\theta + \rho_\theta\log\theta_{t-1} + \sigma_\theta\epsilon_{\theta,t},$$

where $\epsilon_{\theta,t}$ is a normal random variable. The labor supply shock ϕ_t also follows an AR(1) process as

$$\log\phi_t = (1-\rho_\phi)\phi + \rho_\phi\log\phi_{t-1} + \sigma_\phi\epsilon_{\phi,t},$$

$\epsilon_{\phi,t}$ is a normal random variable.

III.6. **The capital producer's problem.** In each period, after the final goods production takes place, the capital producer purchases I_t units of consumption goods from the final goods producer (and $(1-\delta)K_t$ units of physical capital from households and entrepreneurs), and produces the new capital stock to be sold to households and entrepreneurs at the end of the period.

The technology to transform new investment into the installed capital involves installation costs, $S(I_t/I_{t-1})$, which increase with the rate of investment growth. Since the marginal rate of transformation from the previously installed capital stock (after it has depreciated) to the new capital is unity, the price of the new and used capital is the same. The capital producer's period-t profit can be expressed as

$$\Pi_t^k = q_t\left[(1-\delta)K_t + \chi_t\left(1 - S\left(I_t/I_{t-1}\right)\right)I_t\right] - q_t(1-\delta)K_t - I_t,$$

where χ_t is a marginal efficiency shock to investment (MEI shock) as in Justiniano, Primiceri, and Tambalotti (2011), which has the following stochastic process:

$$\log\chi_t = (1-\rho_\chi)\chi + \rho_\chi \log\chi_{t-1} + \sigma_\chi\epsilon_{\chi,t}.$$

The capital producer solves the following dynamic optimization problem:

$$\max_{I_{t+j}} E_t\left\{\sum_{j=0}^{\infty}\beta\lambda_{t+j}\Pi_{t+j}^k\right\},$$

where λ_t is the Lagrangian multiplier for the household's budget constraint. We assume $S(1) = S'(1) = 0$ and $S''(1) > 0$. It is straightforward to show that $\Pi_t^k = 0$ at the steady state.

IV. Empirical analysis

In this section we provide empirical results for the theoretical model developed in the previous section and discuss the economic intuition behind these results.

IV.1. **Findings.** To see whether our structural model is capable of generating empirical results consistent with the data (i.e., the VAR evidence discussed in Section II.3), we fit the model to the six quarterly U.S. time series: credit supply changes ($\mathcal{L}_t^{\text{Data}}$), log real per capita business lending ($\mathcal{B}_t^{\text{Data}}$), commercial banks' charge-off rates on business loans (d_t^{Data}), log real per capita consumption (C_t^{Data}), log real per capita investment (I_t^{Data}), and log per capita hours worked (H_t^{Data}). BCDZ's VAR controls for the series of corporate bond spreads; our VAR and our structural model control for firms' charge-off and delinquency rates. Since our structural model is trend-stationary, we follow the DSGE literature and remove from all trend series the balanced linear trend defined by output growth. We apply Christiano and Fitzgerald (2003)'s band-pass filter to the series of credit supply changes in order to remove measurement errors and white noise left in the construction of this series, as we use this

series to identify the endogenous monitoring intensity directly. Specifically, the monitoring intensity is identified by the measurement equation

$$\mathcal{L}_t^{\text{Data}} = a_l + b_l \left(\hat{m}_t - \hat{y}_t\right),$$

where a_l and b_l are the parameters to be estimated jointly with other parameters in the models. The measurement equation for bank loans is

$$\log \mathcal{B}_t^{\text{Data}} = a_b + b_b \hat{\mathfrak{b}}_t.$$

Because the series of business lending includes long-term debts and unused commitments, the relationship between $\log \mathcal{B}_t^{\text{Data}}$ and $\hat{\mathfrak{b}}_t$ would not be exact. We estimate the parameters a_b and b_b jointly with the other parameters as well. The measurement equations for the rest of the variables are

$$\log C_t^{\text{Data}} = \hat{c}_t,$$
$$\log I_t^{\text{Data}} = \hat{i}_t,$$
$$\log H_t^{\text{Data}} = \log H + \hat{h}_t,$$
$$\log d_t^{\text{Data}} = \log d + \hat{\vartheta}_t.$$

In Appendix C, we give a detailed description of how our model is estimated and report the estimation results. Among other parameters, the estimates of both b_b and b_l are statistically significant, implying that the credit supply channel is well identified by these series.

There are six shocks introduced in the model. Except for the bank intermediation shock ε_t that is identified directly through the data on credit supply changes, we do not explicitly identify the other five shock processes. Because these shock processes are studied by various articles in the DSGE literature, we include them to control for the effects of these shocks for the purpose of obtaining an accurate estimate of the magnitude of the impulse responses of a shock to bank intermediation.[6]

Figure 7 reports the estimated impulse responses to a negative shock to bank intermediation. Consumption, investment, and bank loans all fall. As a result, aggregate output falls and its decline is persistent. The output responses are similar to those in the data by comparing Figure 7 to Figure 6 and by taking into account the error bands in both figures. The estimated maximum magnitude of output responses is remarkably close to the VAR estimate (about 1.0%). Even though the capital adjustment costs are set to be very low (the parameter value is 1.0), the output responses are hump-shaped—a result that is very difficult to obtain by many DSGE models in the literature (see, for example, Christiano, Motto, and Rostagno (2014)).

[6]Alternatively, one can follow Christiano, Eichenbaum, and Evans (2005) and use Hansen (1982)'s method to match the model's impulse responses to the corresponding VAR impulse responses.

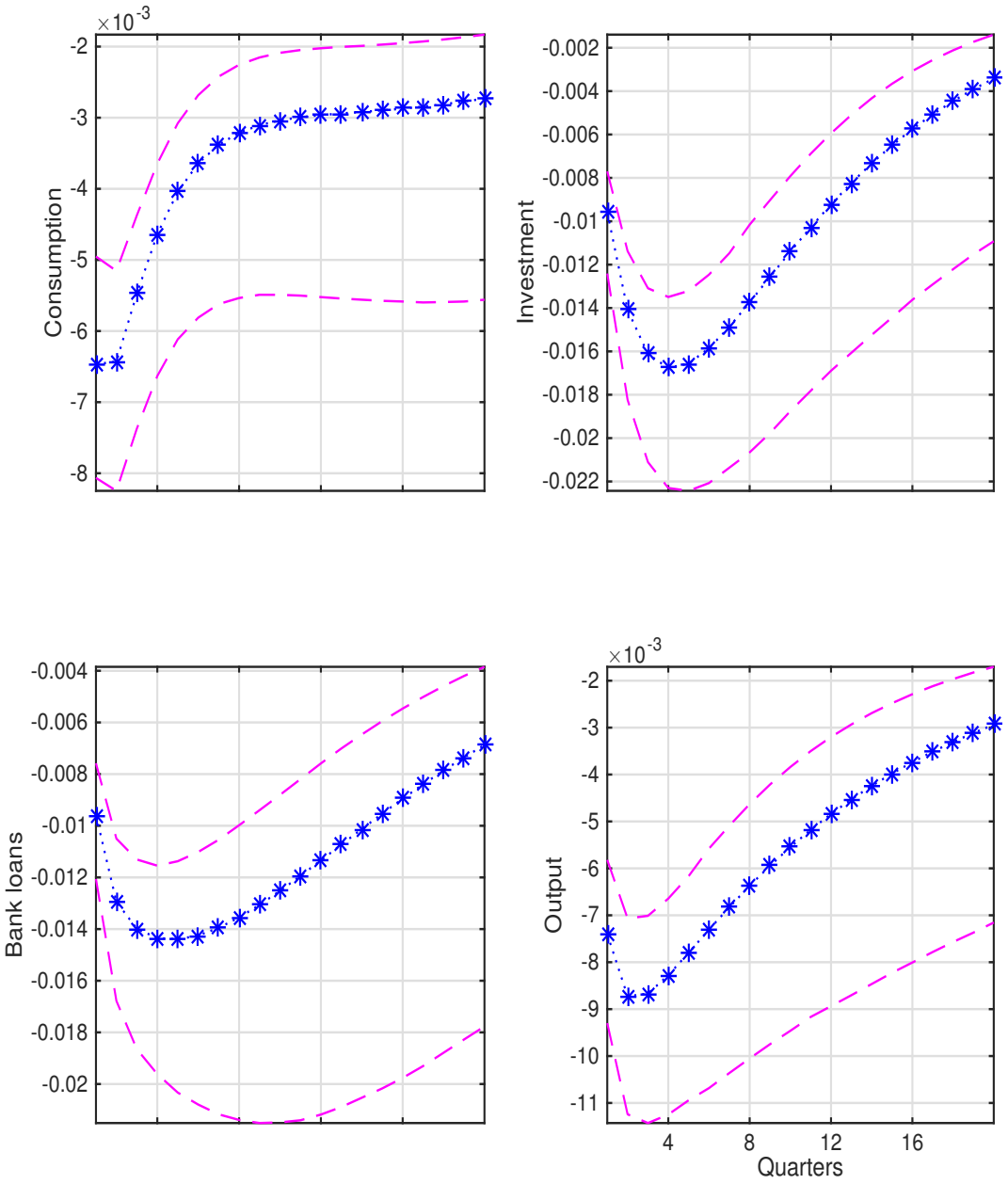

FIGURE 7. The impulse responses to a negative one-standard-deviation shock to bank intermediation. The starred line represents the posterior model estimate. The dashed lines around the solid lines represent the .90 probability error bands.

IV.2. **Understand the transmission mechanism.** What explains why the model-generated dynamic responses of bank loans and aggregate output to a bank intermediation shock are remarkably close to their empirical VAR counterparts? In this section, we explore the transmission mechanism for channeling bank intermediation shocks into fluctuations in bank loans and aggregate output and compare it to the mechanism affecting other shocks outside the

banking sector. We argue that estimation of the model's intermediation process can be disciplined by the constructed series of changes in bank-intermediated credit supply.

We begin with characterizing the optimal contract as described in Section III. The focus is on disentangling the credit supply channel from the credit demand channel in the equilibrium determination of bank loans. We then explore how bank intermediation shocks and other shocks in the model influence the equilibrium outcome of bank loans via each of these two channels.

IV.2.1. *Credit supply and credit demand.* To characterize the supply and demand channels of bank-intermediated credit, we first establish the properties of the optimal loan contract. As in the standard costly-state-verification model, the following proposition characterizes the optimal contract.

Proposition 2. Given that $Y_t^{1-\mu}\left(A_{1,t}y_t^{fb}\right)^{\mu} < p_t^y y_t^{fb} - q_t a_t$, the limited liability constraint for state 1 is binding, the limited liability constraint for state 2 is nonbinding, and the incentive compatibility constraint is always binding.

Proof. See Appendix E. ∎

With Proposition 2, we derive two equations to characterize the relationship between the cost of intermediation m_t/y_t and the amount of intermediate goods y_t: one equation describing the credit supply curve and the other the credit demand curve. A combination of the incentive compatibility constraint and the participation constraint gives

$$y_t = \left[\frac{v_t}{(1-\pi_t)Y_t^{1-\mu}\left((A_{2,t})^{\mu} - (A_{1,t})^{\mu}\right)}\left(\varepsilon_t m_t/y_t\right)^{\psi}\right]^{\frac{1}{\mu}}. \tag{11}$$

Solving the optimal contract leads to the following first order condition with respect to y_t:

$$\mu Y_t^{1-\mu} A_t^{\mu}\left(y_t\right)^{\mu-1} - p_t^y = \pi_t m_t/y_t\left(1+\frac{\mu}{\psi}\right), \tag{12}$$

where $A_t^{\mu} \equiv \pi_t\left(A_{1,t}\right)^{\mu} + \left(1-\pi_t\right)\left(A_{2,t}\right)^{\mu}$.

Both the bank and the entrepreneur take the price of intermediate goods and the entrepreneur's net worth as given when solving the contract problem. Behind the functional relationship between the cost of intermediation and the amount of intermediate goods, therefore, equations (11) and (12) also describe the relationship between the cost of intermediation and business lending (bank loans).

Equation (11) describes the credit supply function. That is, for each loan amount, it reveals what is the cost of intermediation (or monitoring activities) that the bank needs to incur in order for that particular loan amount to satisfy the incentive compatibility constraint. Intuitively, given the information asymmetry, a larger amount of bank loans and thus a larger production scale tend to increase the entrepreneur's gain of misreport when the outcome is

in the good state. This requires banks to exert a higher monitoring intensity, which incurs a higher cost of intermediation, to prevent the entrepreneur from misreporting. Since banks are competitive, such a positive relationship between bank loans and the cost of intermediation translates into a positive relationship between the amount of intermediate goods and the cost of intermediation on the credit supply side.

On the other hand, equation (12) characterizes the optimal choice of intermediate goods y_t that maximizes the contract value, which is the expected profit from the entrepreneur's project. Hence, equation (12) governs the credit demand function. It states that given the cost of intermediation and the cost of loans, what would be the demand for bank loans to finance the purchasing of intermediate goods so that the expected profit of the project is maximized. To understand the effect of intermediation costs on credit demand, note that the presence of intermediation costs—unlike in the frictionless economy—drives a wedge between the marginal revenue product of y_t and its purchasing cost p_t^y. Because a higher cost of intermediation, which eventually passes onto the entrepreneur, leads to a higher overall marginal cost of intermediate goods (as the sum of the purchasing cost and the intermediation cost). As a result, the size of project and thus the amount of of intermediate inputs have to be reduced, which in turn leads to a lower demand for bank loans. The negative relationship between loan demand and the cost of intermediation translates into the negative relationship between y_t and m_t/y_t as implied by equation (12).

A combination of equation (11) and (12), therefore, determines bank loans and the cost of loans in equilibrium or equivalently the amount of intermediate goods and the cost of intermediation in equilibrium. In standard DSGE models that assume a constant monitoring intensity and therefore a constant cost of intermediation, the credit supply curve is horizontal. This leaves credit demand as the only channel to transmit shocks by shifting the credit demand curve. By contrast, our model endogenizes the bank's decision on monitoring activities. The endogeneity allows the credit supply channel to play a role in determining bank loans in equilibrium, *in addition to the standard credit demand channel*. We show, in the next section, that allowing both demand and supply channels to operate is the key to identifying a bank intermediation shock from other shocks.

IV.2.2. *Identifying bank intermediation shocks and their transmission mechanism.* We first explore how bank intermediation shocks and other shocks transmit into fluctuations in bank loans through the credit supply and demand channels. Figures 8 and 9 plot both the upward supply curve via equation (11) and the downward demand curves via equation (12). The intersection of the two curves determines output and the cost of intermediation in equilibrium. Specifically, the two solid lines in each figure represent the credit demand and supply curves before any shock arrives. Point A, their intersection, represents the initial equilibrium. In

our model, various shocks affect the equilibrium outcome by shifting either the credit supply curve or the credit demand curve. We analyze how a particular shock shifts which curve and in which direction.

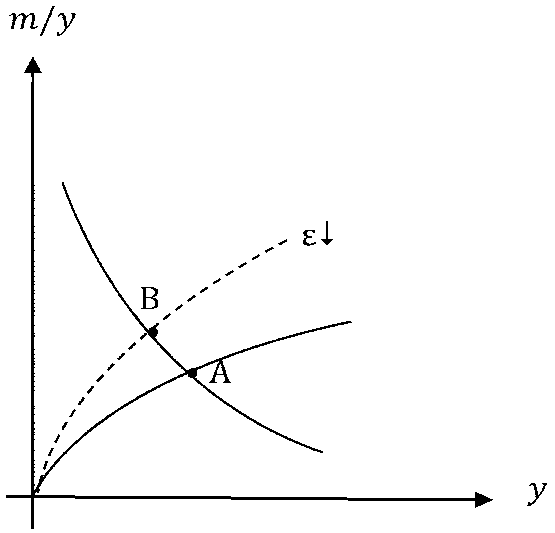

FIGURE 8. The impact of a negative shock to bank intermediation through the credit supply channel.

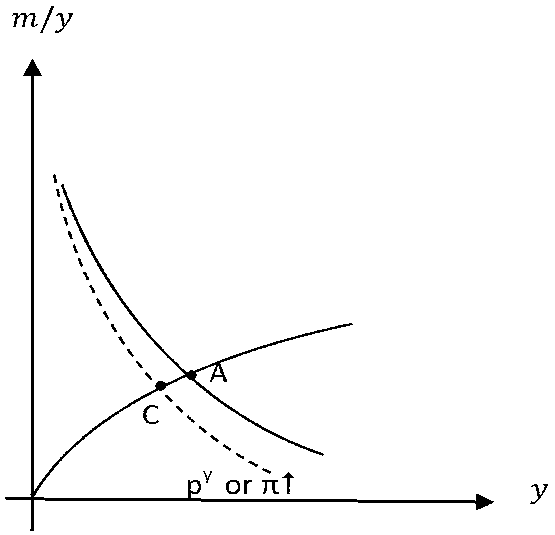

FIGURE 9. The impact of shocks outside the banking sector through the credit demand channel.

Figure 8 illustrates the impact of a negative shock to bank intermediation. Such a shock shifts the credit supply curve to the left as shown by the dotted line. Output declines as a result of a decline of bank loans, while the cost of intermediation increases. Intuitively, banks must engage in monitoring activities more intensively in response to a negative shock to the bank sector. Since the monitoring activity is costly, the negative shock raises the cost of

intermediation. This cost passes onto the cost of bank loans to entrepreneurs, which in turn reduces bank loans and thus output. The equilibrium moves from point A to point B. Thus, banks' monitoring activities and the resultant cost of intermediation are countercyclical.

The mechanism is propagated by the traditional financial accelerator channel. A fall in bank loans shrinks the production scale for intermediate goods and thus the expected profit of the project. Both the end-of-period net worth of entrepreneurs and the next-period loan contract value fall accordingly. This exacerbates the incentive problem and makes both bank loans and production shrink further. Quantitatively, such a propagation mechanism plays an important role for generating the hump shape of the dynamic responses of bank loans, investment, and aggregate output in response to a bank intermediation shock.

By contrast, other shocks outside the banking sector affect bank loans by shifting the credit demand curve as illustrated by Figure 9. Specifically, a negative shock to technology, MEI, or discount factor and a positive shock to labor supply all lead to an increase in the cost of production p_t^y directly or indirectly by increasing either wages or interest rates. This reduces the optimal size of the project and the demand for bank loans at each level of the intermediation cost. Similarly, a positive shock to the delinquency rate of bank loans (i.e., an increase in π_t) reduces the demand for intermediated goods and thus the demand for bank loans. All these shocks therefore shift the credit demand curve to the left, and the equilibrium moves from Point A to C.[7] For our model, we do not have enough data to identify each of these shocks, but we can identify them as a group of shocks that are outside the banking sector. This identification can be achieved by using the survey data on credit supply changes because the cost of bank intermediation is procyclical, *not countercyclical*, in response to any of these shocks that originate outside the banking sector.

Introduction and Section II establish the linkage between the cost of bank intermediation and the series of changes in credit supply. This new series is constructed by removing demand factors and other supply factors, thus allowing us to measure the effect of credit supply via movements in the cost of bank intermediation. Shocks outside the banking sector generate procyclcial movements of the intermediation cost, while a shock to bank-intermediated credit supply generates countercyclical movements of intermediation costs as evinced in the data work presented in Section II. From our model's perspective, it is the countercyclicality of bank intermediation costs that holds the key to our identification.

V. Conclusion

We have developed and estimated a structural model to show that the supply of bank-intermediated credit, both in theory and in practice, is an important channel in the business

[7]Moreover, a positive shock to the delinquency rate would also shift the credit supply curve to the right, further depressing the cost of intermediation.

cycle. We have isolated this channel by the micro-based survey data. In particular, our unique data help identify a shock to bank intermediation as the source of changes in credit supply. Shocks outside the banking sector play an important role through the credit demand channel but do not influence the credit supply channel.

A negative shock to bank intermediation forces banks to increase their monitoring activities, which leads to an increase in intermediation costs. The rise of these costs reduces bank loans through the credit supply channel. As a result, output contracts. By measuring the quantitative importance of this mechanism, we have shown that it is both economically and statistically significant.

Appendix A. Equilibrium conditions for the benchmark model

The equilibrium for the model described in Section III is characterized by the following system of equations:

(E1) The household's budget constraint (c_t^h):

$$c_t^h + q_t a_{t+1}^h = \left[q_t\left(1-\delta\right) + r_t\right] a_t^h + w_t H_t + \Pi_t^k. \tag{A1}$$

(E2) Intertemporal Euler equation for the household (r_t):

$$q_t MU_t^h = \beta E_t\left[\theta_{t+1} MU_{t+1}^h \left(q_{t+1}\left(1-\delta\right) + r_{t+1}\right)\right]. \tag{A2}$$

(E3) Marginal utility of consumption for the household (MU_t^h):

$$MU_t^h = \frac{1}{c_t^h - \varpi_h c_{t-1}^h} - \beta\varpi_h E_t \frac{1}{c_{t+1}^h - \varpi_h c_t^h}, \tag{A3}$$

(E4) Optimal labor decision (H_t):

$$\phi_t H_t^\nu = w_t MU_t^h. \tag{A4}$$

(E5) Final goods (Y_t):

$$Y_t = \left[A_t^\mu\right]^{\frac{1}{\mu}} y_t. \tag{A5}$$

(E6) Business lending ($\mathcal{B}_t$):

$$\mathcal{B}_t = p_t^y y_t - q_t a_t^e. \tag{A6}$$

(E7) Euler equation for the supply of credit (v_t):

$$y_t = \left[\frac{v_t}{(1-\pi_t) Y_t^{1-\mu}\left(\left(A_{2,t}\right)^\mu - \left(A_{1,t}\right)^\mu\right)}\left(\varepsilon_t m_t / y_t\right)^\psi\right]^{\frac{1}{\mu}}. \tag{A7}$$

(E8) Euler equation for the demand of credit (m_t/y_t):

$$\mu Y_t^{1-\mu} A_t^\mu \left(y_t\right)^{\mu-1} - p_t^y = \pi_t m_t / y_t \left(1 + \frac{\mu}{\psi}\right). \tag{A8}$$

(E9) The production of intermediate goods by entrepreneurs (w_t):

$$y_t = z_t \left(k_t\right)^\alpha \left(h_t\right)^{(1-\alpha)}. \tag{A9}$$

(E10) Demand for capital (and labor) by entrepreneurs (k_t):

$$k_t = h_t \frac{\alpha w_t}{\left(1-\alpha\right) r_t}. \tag{A10}$$

(E11) Competitiveness in the intermediate goods market makes the price equal to the marginal cost (p_t^y):

$$p_t^y = \frac{1}{z_t}\left(\frac{r_t}{\alpha}\right)^\alpha \left(\frac{w_t}{(1-\alpha)}\right)^{(1-\alpha)}. \tag{A11}$$

(E12) Intertemporal Euler equation for entrepreneurs (a_t^e):

$$q_t MU_t^e = \beta^e E_t\left[MU_{t+1}^e\left(r_{t+1} - q_{t+1}\delta + v_{t+1}'\left(a_{t+1}^e\right)\right)\right]. \tag{A12}$$

(E13) Definition of MU_t^e (MU_t^e):

$$MU_t^e = \frac{1}{c_t^e - \varpi_e c_{t-1}^e} - \beta^e \varpi_e E_t \frac{1}{c_{t+1}^e - \varpi_e c_t^e}. \tag{A13}$$

(E14) Entrepreneurs' budget constraint (c_t^e):

$$c_t^e + q_t a_{t+1}^e = (r_t - \delta q_t)\, a_t^e + v_t. \tag{A14}$$

(E15) The capital producer's period-t profit (Π_t^k):

$$\Pi_t^k = q_t \left[(1-\delta) K_t + \chi_t \left(1 - S\left(I_t / I_{t-1}\right)\right) I_t\right] - q_t (1-\delta) K_t - I_t. \tag{A15}$$

(E16) Optimality condition for the capital producer (q_t):

$$q_t = \frac{1 - E_t \beta \theta_{t+1} \frac{MU_{t+1}^h}{MU_t^h} \left[q_{t+1} \chi_{t+1} S'\left(I_{t+1}/I_t\right) \left(\frac{I_{t+1}}{I_t}\right)^2\right]}{\chi_t \left[1 - S'\left(I_t/I_{t-1}\right) \frac{I_t}{I_{t-1}} - S\left(I_t/I_{t-1}\right)\right]}. \tag{A16}$$

(E17) Labor market (h_t):

$$H_t = h_t. \tag{A17}$$

(E18) Capital market (K_{t+1}):

$$K_{t+1} = k_{t+1}. \tag{A18}$$

(E19) Asset market (a_{t+1}^h):

$$K_{t+1} = a_{t+1}^e + a_{t+1}^h. \tag{A19}$$

(E20) Aggregate capital accumulation (I_t):

$$K_{t+1} = (1-\delta) K_t + \chi_t \left(1 - S\left(I_t/I_{t-1}\right)\right) I_t. \tag{A20}$$

(E21) Aggregate goods market (y_t):

$$Y_t = \widetilde{Y}_t + \pi_t m_t. \tag{A21}$$

(E22) Aggregate consumption (C_t):

$$C_t = c_t^h + c_t^e. \tag{A22}$$

(E23) Aggregate output ($\widetilde{Y}_t$):

$$\widetilde{Y}_t = C_t + I_t. \tag{A23}$$

(E24) Costs in the bad state (b_{1t}):

$$b_{1t} = Y_t^{1-\mu} \left(A_{1,t} y_t\right)^{\mu}. \tag{A24}$$

(E25) Charge-off rate (d_t):

$$d_t = \pi_t \frac{\mathcal{B}_t - b_{1t}}{\mathcal{B}_t}. \tag{A25}$$

Appendix B. Log-Linearization

We log-linearize the equilibrium conditions presented in Appendix A. We denote $\hat{X}_t = \log X_t - \log X$, where X is the corresponding steady state variable of X_t, for the following log-linearized system:

(L1) From (A1),

$$a^h \hat{a}^h_{t+1} - [(1-\delta)+r]a^h \hat{a}^h_t + c^h \hat{c}^h_t - wH\hat{H}_t - \hat{\Pi}^{ke}_t + \delta a^h \hat{q}_t - r a^h \hat{r}_t - wH\hat{w}_t = 0,$$

where $\Pi^{ke}_t = e^{\Pi^k_t}$.

(L2) From (A2),

$$\hat{MU}^h_{t+1} + \beta(1-\delta)\hat{q}_{t+1} + \beta r \hat{r}_{t+1} + \hat{\theta}_{t+1} - \hat{MU}^h_t - \hat{q}_t = 0.$$

(L3) From (A3),

$$\beta\varpi_h \hat{c}^h_{t+1} - (1+\beta\varpi_h^2)\hat{c}^h_t - (1-\beta\varpi_h)(1-\varpi_h)\hat{MU}^h_t + \varpi_h \hat{c}^h_{t-1} = 0.$$

(L4) From (A4),

$$\nu\hat{H}_t - \hat{MU}^h_t + \hat{\phi}_t - \hat{w}_t = 0.$$

(L5) From (A5),

$$\frac{1}{\mu}\hat{A}^\mu_t - \hat{Y}_t + \hat{y}_t = 0.$$

Note

$$\overline{A}^\mu \hat{A}^\mu_t + (\overline{A})^\mu \left[\overline{\pi}\left(1+\sigma\sqrt{\frac{\overline{\pi}}{1-\overline{\pi}}}\right)^\mu - \overline{\pi}\left(1-\sigma\sqrt{\frac{1-\overline{\pi}}{\overline{\pi}}}\right)^\mu - \frac{\mu\sigma}{2}\sqrt{\frac{\overline{\pi}}{1-\overline{\pi}}}\left[\left(1+\sigma\sqrt{\frac{\overline{\pi}}{1-\overline{\pi}}}\right)^{\mu-1} + \left(1-\sigma\sqrt{\frac{1-\overline{\pi}}{\overline{\pi}}}\right)^{\mu-1}\right]\right]\hat{\pi}_t = 0.$$

(L6) From (A6),

$$a^e \hat{a}^e_t + \mathcal{B}\hat{\mathcal{B}}_t - p^y y \hat{p}^y_t + a^e \hat{q}_t - p^y y \hat{y}_t = 0.$$

(L7) From (A7),

$$\frac{\mu(\overline{A}_1)^\mu}{(\overline{A}_2)^\mu - (\overline{A}_1)^\mu}\hat{A}_{1,t} - \frac{\mu(\overline{A}_2)^\mu}{(\overline{A}_2)^\mu - (\overline{A}_1)^\mu}\hat{A}_{2,t} + \psi\hat{\varepsilon}_t + \psi\hat{m}_t + \frac{\overline{\pi}}{1-\overline{\pi}}\hat{\pi}_t + \hat{\upsilon}_t - (1-\mu)\hat{Y}_t - (\mu+\psi)\hat{y}_t = 0.$$

Note

$$\hat{A}_{1,t} = \frac{\frac{\sigma}{2\overline{\pi}}\sqrt{\frac{\overline{\pi}}{1-\overline{\pi}}}}{1-\sigma\sqrt{\frac{1-\overline{\pi}}{\overline{\pi}}}}\hat{\pi}_t;\ \hat{A}_{2,t} = \frac{\frac{\sigma}{2\overline{\pi}}\left(\frac{\overline{\pi}}{1-\overline{\pi}}\right)^{\frac{3}{2}}}{1+\sigma\sqrt{\frac{\overline{\pi}}{1-\overline{\pi}}}}\hat{\pi}_t;\ \hat{\pi}_t = \frac{1}{1+\overline{\vartheta}}\hat{\vartheta}_t.$$

(L8) From (A8),

$$\frac{\mu Y^{1-\mu}\overline{A}^{\mu}(y)^{\mu-1}}{\mu Y^{1-\mu}\overline{A}^{\mu}(y)^{\mu-1}-p^{y}}\hat{A}_{t}^{\mu}-\hat{m}_{t}-\hat{\pi}_{t}-\frac{p^{y}}{\mu Y^{1-\mu}\overline{A}^{\mu}(y)^{\mu-1}-p^{y}}\hat{p}_{t}^{y}$$
$$+\frac{(1-\mu)\mu Y^{1-\mu}\overline{A}^{\mu}(y)^{\mu-1}}{\mu Y^{1-\mu}\overline{A}^{\mu}(y)^{\mu-1}-p^{y}}\hat{Y}_{t}+\frac{\mu^{2}Y^{1-\mu}\overline{A}^{\mu}(y)^{\mu-1}-p^{y}}{\mu Y^{1-\mu}\overline{A}^{\mu}(y)^{\mu-1}-p^{y}}\hat{y}_{t}=0.$$

(L9) From (A9),

$$(1-\alpha)\hat{h}_{t}+\alpha\hat{k}_{t}-\hat{y}_{t}+\hat{z}_{t}=0.$$

(L10) From (A10),

$$\hat{h}_{t}-\hat{k}_{t}-\hat{r}_{t}+\hat{w}_{t}=0.$$

(L11) From (A11),

$$\hat{p}_{t}^{y}-\alpha\hat{r}_{t}-(1-\alpha)\hat{w}_{t}+\hat{z}_{t}=0.$$

(L12) From (A12),

$$E_{t}\hat{MU}_{t+1}^{e}-\beta^{e}\delta E_{t}\hat{q}_{t+1}+\beta^{e}rE_{t}\hat{r}_{t+1}+\beta^{e}v'E_{t}\hat{v}_{t+1}'-\hat{MU}_{t}^{e}-\hat{q}_{t}=0.$$

(L13) From (A13),

$$\beta^{e}\varpi_{e}E_{t}\hat{c}_{t+1}^{e}-(1+\beta^{e}\varpi_{e}^{2})\hat{c}_{t}^{e}-(1-\beta^{e}\varpi_{e})(1-\varpi_{e})\hat{MU}_{t}^{e}+\varpi_{e}\hat{c}_{t-1}^{e}=0.$$

(L14) From (A14),

$$a^{e}\hat{a}_{t+1}^{e}-(r-\delta)a^{e}\hat{a}_{t}^{e}+c^{e}\hat{c}_{t}^{e}+(1+\delta)a^{e}\hat{q}_{t}-ra^{e}\hat{r}_{t}-v\hat{v}_{t}=0.$$

(L15) From (A15),

$$I\hat{\chi}_{t}-\hat{\Pi}_{t}^{ke}+I\hat{q}_{t}=0.$$

(L16) From (A16),

$$\beta S''\hat{I}_{t+1}+\hat{\chi}_{t}-(1+\beta)S''\hat{I}_{t}+\hat{q}_{t}+S''\hat{I}_{t-1}=0.$$

(L17) From (A17),

$$\hat{H}_{t}-\hat{h}_{t}=0.$$

(L18) From (A18),

$$\hat{K}_{t+1}-\hat{k}_{t+1}=0.$$

(L19) From (A19),

$$a^{e}\hat{a}_{t+1}^{e}+a^{h}\hat{a}_{t+1}^{h}-K\hat{K}_{t+1}=0.$$

(L20) From (A20),

$$K\hat{K}_{t+1}-I\hat{\chi}_{t}-I\hat{I}_{t}-(1-\delta)K\hat{K}_{t}=0.$$

(L21) From (A21),

$$\pi m\hat{m}_{t}+\pi m\hat{\pi}_{t}-Y\hat{Y}_{t}+\widetilde{Y}\hat{\widetilde{Y}}_{t}=0.$$

(L22) From (A22),

$$C\hat{C}_t - c^e\hat{c}^e_t - c^h\hat{c}^h_t = 0.$$

(L23) From (A23),

$$C\hat{C}_t + I\hat{I}_t - \widetilde{Y}\hat{\widetilde{Y}}_t = 0.$$

(L24) From (A24),

$$\hat{b}_{1t} = (1-\mu)\hat{Y}_t + \mu\left(\hat{A}_{1t} + \hat{y}_t\right).$$

(L25) From (A25),

$$\hat{d}_t = \hat{\pi}_t - \hat{\mathcal{B}}_t + \frac{\mathcal{B}}{\mathcal{B}-b_1}\hat{\mathcal{B}}_t - \frac{b_1}{\mathcal{B}-b_1}\hat{b}_{1t} = \hat{\pi}_t + \frac{b_1}{\mathcal{B}-b_1}\left(\hat{\mathcal{B}}_t - \hat{b}_{1t}\right).$$

Appendix C. Estimation procedure

We apply the Bayesian methodology to estimation of the log-linearized structural model, using our own C/C++ code. The advantage of using our own code instead of using the Dynare is the flexibility and accuracy we have for finding the posterior mode. Our Dynare code fails to converge with any of its optimization options. The failure is partly due to the difficulty of solving the steady state and partly due to the complexity of the model the Dynare software has yet to deal with. We are in the process of collaborating with Dynare developers to make our estimation procedure available through the Dynare interface.

We use the log-linearized equilibrium conditions, reported in Appendix A, to form the likelihood function fit to the six quarterly U.S. time series from 1990Q2 to 2014Q4. We categorize the model's parameters in three groups. The first group consists of those fixed at values commonly used or calibrated by the average behavior of the data. The growth rate of aggregate output is 1.25% at an annual rate; the capital share is set to 0.35; the subjective discount factor β is set to 0.995; the elasticity-of-substitution parameter μ is set to 0.85, which implies a markup of 17.6%, consistent with the empirical evidence provided by Morrison (1992); the steady state hours is $H = 0.3$; the capital adjustment cost parameter is $S'' = 1.0$ (between 0.18 found in Liu, Wang, and Zha (2013) and 2.5 used in much of the DSGE literature); the parameter for the inverse of the Frisch elasticity of labor supply is set to $\nu = 1.0$; the delinquency parameter is $\bar{\vartheta} = 0.8\%$ so that the model's average delinquency rate is the same as the data average 0.79%; the leverage ratio $B/\tilde{Y}$ is 0.75 as in the literature on financial frictions; the intermediation-cost ratio $\bar{\pi}m^c/\tilde{Y}$ is 0.1194 at a quarterly frequency, equal to the ratio of financially intermediated services in the banking system to aggregate output, where financially intermediated services are constructed using the NPIA data following (Mehra, Piguillem, and Prescott, 2011); the ratio of output to capital is 0.126 at quarterly frequency, calculated from our quarterly data; and the ratio of investment to capital is 0.0378 at quarterly frequency, which is also calculated from our quarterly data.

TABLE 1. Prior distributions of structural parameters

Parameter	Description	Distribution	a	b	Low	High
p^y	Price of intermediate goods	Gamma(a,b)	9.387	9.952	0.5	1.5
ϖ^h	Household habit	Beta(a,b)	1.00	2.00	0.025	0.776
ϖ^c	Entrepreneur habit	Beta(a,b)	1.00	2.00	0.025	0.776
a_b	Intercept for total loans	Normal(a,b)	0.0	1.0	-1.64	1.64
b_b	Slope for total loans	Gamma(a,b)	9.387	9.952	0.5	1.5
a_l	Intercept for credit supply	Gamma(a,b)	0.0	1.0	-1.64	1.64
b_l	Slope for credit supply	Gamma(a,b)	9.387	9.952	0.5	1.5
ρ_z	Technology	Beta(a,b)	1.00	2.00	0.025	0.776
ρ_χ	MEI	Beta(a,b)	1.00	2.00	0.025	0.776
ρ_ϑ	Uncertainty	Beta(a,b)	1.00	2.00	0.025	0.776
ρ_θ	Preference	Beta(a,b)	1.00	2.00	0.025	0.776
ρ_ε	Bank intermediation	Beta(a,b)	1.00	2.00	0.025	0.776
ρ_ϕ	Labor supply	Beta(a,b)	1.00	2.00	0.025	0.776
σ_z	Technology	Inv-Gamma(a,b)	3.26e-01	1.45e-04	1.0e-04	2.0
σ_χ	MEI	Inv-Gamma(a,b)	3.26e-01	1.45e-04	1.0e-04	2.0
σ_ϑ	Uncertainty	Inv-Gamma(a,b)	3.26e-01	1.45e-04	1.0e-04	2.0
σ_θ	Preference	Inv-Gamma(a,b)	3.26e-01	1.45e-04	1.0e-04	2.0
σ_ε	Bank intermediation	Inv-Gamma(a,b)	3.26e-01	1.45e-04	1.0e-04	2.0
σ_ϕ	Labor supply	Inv-Gamma(a,b)	3.26e-01	1.45e-04	1.0e-04	2.0

Note: "Low" and "high" denotes the bounds of the 90% probability interval for each parameter.

The second group of parameters are to be estimated. Table A1 reports the prior distribution of each of these parameters, where "Inv-Gamma" stands for an inverse Gamma probability density. Most of these prior settings, agnostic in nature, are used in the literature (see Liu, Wang, and Zha (2013) for detailed discussions). We discuss the few prior settings that are specific to our model. The price of intermediate goods, p^y, is *not* a parameter but an implicit function of model parameters implied by the steady state. Solving for the steady state value p^y and other steady state variables requires solving a system of nonlinear equations, which would be costly during the estimation phase. A nonlinear system may not have a solution or its solution can be difficult to find, which is the case for our model. This difficulty is one of the main reasons that the routine Dynare package has difficulty in finding the posterior mode of this model. By finding the value of p^y first, however, we can reverse-engineer to pin down the value of the parameter $\bar{\varepsilon}$. The steady state can be solved

TABLE 2. Posterior distributions of structural parameters

		Posterior estimates		
Parameter	Description	Mode	Low	High
p^y	Price of intermediate goods	0.85	0.49	1.49
ϖ^h	Household habit	0.35	0.32	0.46
ϖ^c	Entrepreneur habit	0.75	0.71	0.79
a_b	Intercept for total loans	-0.03	-0.13	0.11
b_b	Slope for total loans	0.87	0.78	1.45
a_l	Intercept for credit supply	-0.15	-0.65	0.29
b_l	Slope for credit supply	3.48	2.88	4.23

Note: "Low" and "High" denote the bounds of the 90% probability interval for each parameter.

recursively. This advancement makes the estimation feasible, even though the steady state for our model is complicated. The prior we set for p^y is around 1.0 with the .90 probability interval between 0.5 and 1.5. We experiment with a much looser prior and our results are very robust to different prior settings. The prior settings are centered around 0 for a_b and a_l and 1 for b_b and b_l. We also change the variance of the prior and the posterior results are not materially affected since the posterior modes are similar and the impulse responses do not change much.

The posterior modes, alongside the .90 probability intervals, for the second group of parameters are reported in Tables A2 and A3. Among other parameters, the slope parameters in the measurement equations for bank loans and credit supply changes are significant and well above zero according to the .90 probability intervals. Both the persistence and shock standard deviation in the bank intermediation shock process are significant but not extremely large compared to other shock processes. In Seciton IV.1 we discuss how a bank intermediation shock affects bank loans and aggregate output.

The third group collects the remaining parameters. These parameters are obtained by solving the steady state given the parameter values in the first two groups. Since the steady state can be solved recursively, these parameter values can be calculated with little computing time.

APPENDIX D. A MODEL WITH TWO TYPES OF ENTREPRENEURS

In the benchmark model we assume all entrepreneurs are financially constrained due to insufficient net worth. According to Proposition 1, if firms are large enough, the financial constraint would be nonbinding and therefore there is no incentive for banks to engage in

TABLE 3. Posterior distributions of shock parameters

		Posterior estimates		
Parameter	Description	Mode	Low	High
ρ_z	Technology	0.9987	0.9768	0.9992
ρ_χ	MEI	0.9987	0.7543	0.9994
ρ_ϑ	Uncertainty	0.8313	0.7978	0.8860
ρ_θ	Preference	0.9967	0.9369	0.9984
ρ_ε	Bank intermediation	0.8915	0.8523	0.9521
ρ_ϕ	Labor supply	0.9221	0.8517	0.9704
σ_z	Technology	0.0359	0.0293	0.0404
σ_χ	MEI	0.2003	0.1288	0.2293
σ_ϑ	Uncertainty	0.2576	0.2268	0.2948
σ_θ	Preference	0.0042	0.0039	0.0124
σ_ε	Bank intermediation	0.0738	0.0595	0.0938
σ_ϕ	Labor supply	0.0059	0.0054	0.0085

Note: "Low" and "High" denote the bounds of the 90% probability interval for each parameter.

costly monitoring. We now extend our model to allow for the existence of unconstrained entrepreneurs representing large firms. We explore the robustness of our empirical findings in this more general framework.

Specifically, there are two types of entrepreneurs: type-c and type-u. The superscript c stands for constrained firms and u unconstrained firms. These two types differ in their utility discount factors, which govern their net worth at the steady state. We assume that one quarter of firms, in terms of the employment share, are unconstrained. Unconstrained entrepreneurs do not need bank loans to finance the purchasing of intermediate goods, but constrained entrepreneurs do.

The consumption-saving problem for each type of entrepreneur is the same as before; the only difference is that $\beta^u = \beta$, $\beta^c < \beta$. Since the representative household and the type-u entrepreneur share the same discount factor, type-u entrepreneurs' net worth at steady state satisfies

$$Y_t^{1-\mu} \left(A_{1,t}^u y_t^u\right)^\mu \geq p_t^y y_t^u - q_t a_t^u.$$

For type-c entrepreneurs, the optimal contract problem for bank loans is exactly the same as in the benchmark model. From Proposition 1 one can show that the optimal loan contract for type-u entrepreneurs is such that no bank loans are needed. In other words, bank loans are demanded by constrained entrepreneurs only. Using the same estimates as in the benchmark

TABLE 4. Prior distributions of structural and shock parameters

Parameter	Distribution	a	b	Low	High
ν	Gamma(a,b)	1.0	3.0	0.017	1.000
η	Gamma(a,b)	1.0	0.5	0.100	6.000
δ''/δ'	Gamma(a,b)	1.0	0.5	0.100	6.000
γ	Beta(a,b)	1.0	2.0	0.026	0.776
Ω	Gamma(a,b)	1.0	0.5	0.100	6.000
ρ_z	Beta(a,b)	1.0	2.0	0.026	0.776
ρ_{ν_z}	Beta(a,b)	1.0	2.0	0.026	0.776
ρ_a	Beta(a,b)	1.0	2.0	0.026	0.776
ρ_{ν_a}	Beta(a,b)	1.0	2.0	0.026	0.776
ρ_θ	Beta(a,b)	1.0	2.0	0.026	0.776
ρ_ξ	Beta(a,b)	1.0	2.0	0.026	0.776
ρ_ψ	Beta(a,b)	1.0	2.0	0.026	0.776
σ_z	Inv-Gamma(a,b)	0.3261	1.45e04	0.0001	2.0000
σ_{ν_z}	Inv-Gamma(a,b)	0.3261	1.45e04	0.0001	2.0000
σ_a	Inv-Gamma(a,b)	0.3261	1.45e04	0.0001	2.0000
σ_{ν_a}	Inv-Gamma(a,b)	0.3261	1.45e04	0.0001	2.0000
σ_θ	Inv-Gamma(a,b)	0.3261	1.45e04	0.0001	2.0000
σ_ξ	Inv-Gamma(a,b)	0.3261	1.45e04	0.0001	2.0000
σ_ψ	Inv-Gamma(a,b)	0.3261	1.45e04	0.0001	2.0000

Note: "Low" and "High" denote the bounds of the 90% probability interval for each parameter.

model, we generate the impulse responses of bank loans and output in response to a negative one-standard-deviation shock for this extended model. As shown in Figure 10, the effects are similar to those in the benchmark model; therefore, our findings are robust to allowing for a fraction of firms to be unconstrained.

APPENDIX E. PROOFS

In this appendix we prove the various propositions presented in the main text. We first establish the equivalence between our benchmark model and an alternative setup in which entrepreneurs rent capital and labor directly to produce the variety goods. We then prove Propositions 1 and 2.

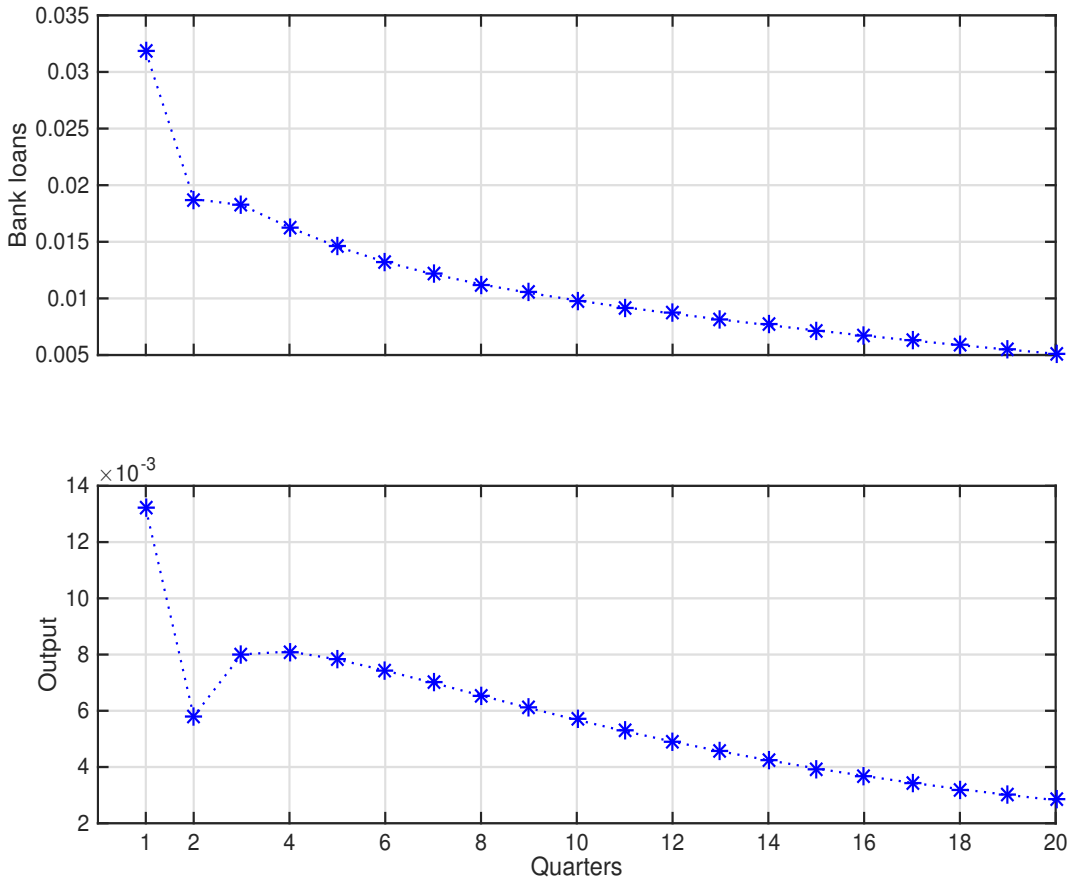

FIGURE 10. The extended model with the inclusion of unconstrained firms: the impulse responses to a one-standard-deviation shock to bank intermediation.

E.1. **The Alternative Setup.** Consider an economic environment in which entrepreneurs producing differentiated variety goods rent capital and labor directly from the factor market. As a result, the production technology for variety k becomes

$$Y_t = A_t z_t k_t^{\alpha} h_t^{1-\alpha},$$

where again we drop k for notational tractability.

Before the production takes place, the entrepreneur needs to finance the cost of inputs with either his own net worth or bank loan. Here, the total cost of production is $r_t k_t + w_t h_t$. All other elements of the model environments are similar to their counterparts in the benchmark economy. We would like to prove that this alternative setup delivers the same equilibrium outcome as our benchmark economy.

The optimal contract problem for a bank is

$$\max_{b_{1,t}, b_{2,t}, k_t, h_t, m_t} \{\pi_t b_{1,t} + (1-\pi_t)\, b_{2,t} - (r_t k_t + w_t h_t - q_t a_t^e) - \pi_t m_t\}, \tag{A26}$$

subject to

$$b_{1,t} \leq P_{1,t} A_{1,t} z_t k_t^{\alpha} h_t^{1-\alpha}, \tag{A27}$$

$$b_{2,t} \leq P_{2,t} A_{2,t} z_t k_t^{\alpha} h_t^{1-\alpha}, \tag{A28}$$

$$[1 - P(m_t/y_t)] \left[P_{2,t} A_{2,t} z_t k_t^{\alpha} h_t^{1-\alpha} - b_{1,t} \right] \leq P_{2,t} A_{2,t} z_t k_t^{\alpha} h_t^{1-\alpha} - b_{2,t}, \tag{A29}$$

$$\pi_1 (P_{1,t} A_{1,t} z_t k_t^{\alpha} h_t^{1-\alpha} - b_{1t}) + \pi_2 (P_{2,t} A_{2,t} z_t k_t^{\alpha} h_t^{1-\alpha} - b_{2,t}) = v_t. \tag{A30}$$

For notational concision, we drop the subscript t. Denote $\{b_1^*, b_2^*, k^*, h^*, m^*\}$ as the optimal solution to $(A26)$. Denote $y_t \equiv z_t k_t^{\alpha} h_t^{1-\alpha}$. The first-order conditions gives

$$k^* = \frac{y^*}{z} \left(\frac{w}{1-\alpha} \right)^{1-\alpha} \left(\frac{r}{\alpha} \right)^{\alpha-1},$$
$$h^* = \frac{y^*}{z} \left(\frac{r}{\alpha} \right)^{\alpha} \left(\frac{w}{1-\alpha} \right)^{-\alpha}.$$

Given the definition of y_t, we can reexpress the cost of inputs as

$$rk^* + wh^* = p^y y^*,$$

where $p^y \equiv \left(\frac{r}{\alpha}\right)^{\alpha} \left(\frac{w}{1-\alpha}\right)^{1-\alpha} / z$.

Similarly, we can solve the optimal contract $\left\{\widetilde{b}_1, \widetilde{b}_2, \widetilde{y}, \widetilde{m}\right\}$ from our benchmark setup, denoted with the superscript tilde. And given the demand for the intermediate goods $\widetilde{y}$, The optimal factor inputs $\left\{\widetilde{k}, \widetilde{h}\right\}$ solved under the cost minimization problem of the intermediate goods producer satisfy

$$\widetilde{k} = \frac{\widetilde{y}}{z} \left(\frac{w}{1-\alpha} \right)^{1-\alpha} \left(\frac{r}{\alpha} \right)^{\alpha-1},$$
$$\widetilde{h} = \frac{\widetilde{y}}{z} \left(\frac{r}{\alpha} \right)^{\alpha} \left(\frac{w}{1-\alpha} \right)^{-\alpha}.$$

Clearly, we have

$$r\widetilde{k} + w\widetilde{h} = p^y \widetilde{y}.$$

Now we would like to prove that $y^* = \widetilde{y}$. Denote

$$\begin{aligned} Q^* &\equiv \pi b_1^* + (1-\pi) b_2^* - (rk^* + wh^* - qa^e) - \pi m^*, \\ \widetilde{Q} &\equiv \pi \widetilde{b}_1 + (1-\pi) \widetilde{b}_2 - (p^y \widetilde{y} - qa^e) - \pi \widetilde{m}. \end{aligned}$$

Our proof consists of two steps. In step 1, we show that $Q^* = \widetilde{Q}$; in step 2, we show that the solution to (4) and $(A26)$ is unique, such that $Q^* = \widetilde{Q}$ implies $\left\{\widetilde{b}_1, \widetilde{b}_2, \widetilde{k}, \widetilde{h}, \widetilde{y}, \widetilde{m}\right\} = \{b_1^*, b_2^*, k^*, h^*, y^*, m^*\}$.

Step 1: Suppose $Q^* > \widetilde{Q}$. Then,

$$\begin{aligned} Q^* &= \pi b_1^* + (1-\pi)\, b_2^* - (rk^* + wh^* - qa^e) - \pi m^* \\ &= \pi b_1^* + (1-\pi)\, b_2^* - (p^y y^* - qa^e) - \pi m^* \\ &> \widetilde{Q}. \end{aligned}$$

Since $\{b_1^*, b_2^*, y^*, m^*\}$ satisfies (5) , (6) , (7), and (8) , we conclude that $\left\{\widetilde{b}_1, \widetilde{b}_2, \widetilde{y}, \widetilde{m}\right\}$ is not the optimal solution for the contract problem (4) in our benchmark economy. This is a contradiction.

Now suppose $Q^* < \widetilde{Q}$. Then,

$$\begin{aligned} \widetilde{Q} &= \pi \widetilde{b}_1 + (1-\pi)\, \widetilde{b}_2 - (p^y \widetilde{y} - qa^e) - \pi \widetilde{m} \\ &= \pi \widetilde{b}_1 + (1-\pi)\, \widetilde{b}_2 - \left(r\widetilde{k} + w\widetilde{h} - qa^e\right) - \pi \widetilde{m} \\ &> Q^*. \end{aligned}$$

Note that $\left\{\widetilde{b}_1, \widetilde{b}_2, \widetilde{k}, \widetilde{h}, \widetilde{m}\right\}$ satisfies the constraints $(A27)$, $(A28)$, $(A29)$, and $(A30)$. Hence, $\{b_1^*, b_2^*, k^*, h^*, m^*\}$ is not the optimal solution for the contract problem in the alternative setup $(A26)$. This again is a contradiction. Therefore, $Q^* = \widetilde{Q}$.

Step 2: For the contract problem (4) , the objective function is concave in $\{b_1, b_2, y, m\}$ and the choice set is strongly convex in $\{b_1, b_2, y, m\}$ due to the strict concavity of the demand function for the variety goods and the strict concavity of the monitoring technology in m/y. Hence, the optimal problem (4) has a unique solution.

Similarly, for the contract problem $(A26)$, the objective function is concave in $\{b_1, b_2, k, h, m\}$ and the choice set is strongly convex in $\{b_1, b_2, k, h, m\}$ because of the strict concavity of the demand function for the variety good and the strict concavity of the monitoring technology in m/y. Hence, the optimal contract problem $(A26)$ has a unique solution.

Note that $\{b_1^*, b_2^*, k^*, h^*, m^*\}$ is the optimal solution for the contract problem in the alternative economy and , and $\left\{\widetilde{b}_1, \widetilde{b}_2, \widetilde{y}, \widetilde{m}\right\}$ in the benchmark economy. With $Q^* = \widetilde{Q}$, therefore, we have $\left\{\widetilde{b}_1, \widetilde{b}_2, \widetilde{k}, \widetilde{h}, \widetilde{y}, \widetilde{m}\right\} = \{b_1^*, b_2^*, k^*, h^*, y^*, m^*\}$.

E.2. **Proof of Proposition 1.** We take two steps to prove Proposition 1. We first derive the necessary condition for the monitoring cost $m_t = 0$. We then derive its sufficient condition.

With $m_t = 0$, from the incentive compatibility constraint (7) , we have

$$P_{2,t} A_{2,t} y_t - b_{2,t} \geq P_{2,t} A_{2,t} y_t - b_{1,t}. \tag{A31}$$

Also, combining (8) with (9) , we get

$$\begin{aligned} & \left[\pi_t P_{1,t} A_{1,t} + (1-\pi_t)\, P_{2,t} A_{2,t}\right] y_t - \left[\pi_t (P_{1,t} A_{1,t} y_t - b_{1,t}) + (1-\pi_t)\, (P_{2,t} A_{2,t} y_t - b_{2,t})\right] - \pi_t m_t \\ \geq\ & p_t^y y_t - q_t a_t^e. \end{aligned} \tag{A32}$$

Plugging $(A31)$ (with equality) into $(A32)$, we obtain the necessary condition for $m_t = 0$.

$$[\pi_t P_{1,t} A_{1,t} + (1-\pi_t) P_{2,t} A_{2,t}] y_t - (1-\pi_t)(P_{2,t} A_{2,t} y_t - b_{1,t}) - \pi_t (P_{1,t} A_{1,t} y_t - b_{1,t}) \geq p_t^y y_t - q_t a_t^e$$

or

$$\begin{aligned} P_{1,t} A_{1,t} y_t &\geq P_{1,t} A_{1,t} y_t - b_{1,t} + p_t^y y_t - q_t a_t^e \\ &\geq p_t^y y_t - q_t a_t^e \end{aligned}$$

where the second inequality is obtained from the limited liability condition (5). Plugging the demand function for variety goods into the above inequality, we obtain the necessary condition for $m_t = 0$ as in Proposition 1.

To prove the sufficiency, the financial contract can be simply designed as

$$b_{1,t} = b_{2,t} = p_t^y y_t^{fb} - q_t a_t^e \tag{A33}$$

Note that the payoff at the low state, $P_{1,t} A_{1,t} y_t - (p_t^y y_t - q_t a_t^e)$, is non-negative by assumption and is thus feasible. Plugging $(A33)$ into the incentive compatibility constraint (7), we have

$$[1 - P(m_t/y_t)] \left[P_{2,t} A_{2,t} y_t^{fb} - \left(p_t^y y_t^{fb} - q_t a_t^e \right) \right] \leq P_{2,t} A_{2,t} y_t^{fb} - \left(p_t^y y_t^{fb} - q_t a_t^e \right).$$

Obviously, the above incentive compatibility constraint is always satisfied, even if no monitoring resource is used such that the probability of identifying misreport is zero (i.e,, $P = 0$). Thus, the incentive compatibility constraint can be dropped from the bank problem (4). Also, the non-negative profit condition of the bank is satisfied. Hence, it is optimal to set $m_t = 0$ and $P = 0$. Intuitively, since the bank does not monitor in either state and the entrepreneur has an incentive to misreport, it is optimal to set the payoff at both states at the value equal to the bank's finance cost.

E.3. **Proof of Proposition 2.** Using the demand function for variety goods (3) to replace $P_{1,t}$ in the optimal contract problem (4), we can write the Lagrangian as

$$\begin{aligned} L \;=\; & \pi_t b_{1,t} + (1-\pi_t) b_{2,t} - (p_t^y y_t - q_t a_t^e) - \pi_t m_t \\ & + \lambda_1 [\pi_t (Y_t^{1-\mu} (A_{1,t} y_t)^\mu - b_{1,t}) + (1-\pi_t)(Y_t^{1-\mu} (A_{2,t} y_t)^\mu - b_{2,t}) - v_t] \\ & + \lambda_2 [Y_t^{1-\mu} (A_{2,t} y_t)^\mu - b_{2,t} - (1 - P(m_t/y_t))(Y_t^{1-\mu} (A_{2,t} y_t)^\mu - b_{1,t})] \\ & + \lambda_{31} [Y_t^{1-\mu} (A_{1,t} y_t)^\mu - b_{1,t}] + \lambda_{32} [Y_t^{1-\mu} (A_{2,t} y_t)^\mu - b_{2,t}], \end{aligned}$$

where λ_1, λ_2, λ_{31}, and λ_{32} denote the Lagrange multipliers for the entrepreneur's participation constraint, the incentive compatibility constraint, and limited liability constraints in state 1 and 2, respectively.

The first-order conditions are:

$$\frac{\partial L}{\partial b_{1,t}} = \pi_t (1 - \lambda_1) + \lambda_2 (1 - P(m_t/y_t)) - \lambda_{31} = 0, \tag{A34}$$

$$\frac{\partial L}{\partial b_{2,t}} = (1-\pi_t)(1-\lambda_1) - \lambda_2 - \lambda_{32} = 0, \tag{A35}$$

$$\begin{aligned}\frac{\partial L}{\partial y_t} &= -p_t^y + \lambda_1 \mu Y_t^{1-\mu}\left[\pi_t A_{1,t}^{\mu} + (1-\pi_t) A_{2,t}^{\mu}\right](y_t)^{\mu-1} \\ &\quad + \lambda_2[\mu Y_t^{1-\mu} A_{2,t}^{\mu}(y_t)^{\mu-1} + \frac{\partial P(m_t/y_t)}{\partial y_t}(Y_t^{1-\mu}(A_{2,t}y_t)^{\mu} - b_{1,t}) - (1-P(m_t/y_t))Y_t^{1-\mu}\mu A_{2,t}^{\mu}(y_t)^{\mu-1}] \\ &\quad + \left(\lambda_{31}A_{1,t}^{\mu} + \lambda_{32}A_{2,t}^{\mu}\right) Y_t^{1-\mu}\mu(y_t)^{\mu-1}, \\ &= 0 \end{aligned} \tag{A36}$$

$$\frac{\partial L}{\partial m_t} = -\pi_t + \lambda_2 \frac{\partial P(m_t/y_t)}{\partial m_t}(Y_t^{1-\mu}(A_{2,t}y_t)^{\mu} - b_{1,t}) = 0. \tag{A37}$$

Proof. From the first-order conditions, we have the following results:

Result $1 : \lambda_1 \in (0,1)$.

Proof: From (A35), we have $\lambda_1 \in [0,1]$. Since the participation constraint is binding, $\lambda_1 \in (0,1]$.

Now we turn to prove $\lambda_1 \neq 1$.

Suppose $\lambda_1 = 1$. Then from $(A34)$ and (A35), we have $\lambda_2 = \lambda_{31} = \lambda_{32} = 0$. Therefore, (A37) implies that $\pi_t = 0, \forall t$. This leads to a contradiction.

Result $2 : \lambda_{31} > 0$; that is, the limited liability constraint for state 1 is binding.

Proof: A combination of Result 1 and (A34) gives this result immediately.

Result $3 : \lambda_2 > 0, \lambda_{32} = 0$; that is, the incentive compatibility constraint is binding and the limited liability constraint for state 2 is not binding.

Proof: Suppose $\lambda_{32} > 0$. Then, the limited liability constraint at state 2 is binding, $b_{2,t} = Y_t^{1-\mu}(A_{2,t}y_t)^{\mu}$. We thus have two cases:

Case 1: $\lambda_2 = 0$.

This implies that the incentive compatibility constraint is not binding. Therefore, a combination of Result 2 and the incentive compatibility constraint implies

$$b_{2,t} < Y_t^{1-\mu}(A_{2,t}y_t)^{\mu} - (1-P(m_t/y_t))(Y_t^{1-\mu}(A_{2,t}y_t)^{\mu} - Y_t^{1-\mu}(A_{1,t}y_t)^{\mu}) < Y_t^{1-\mu}(A_{2,t}y_t)^{\mu},$$

which contradicts $b_{2,t} = Y_t^{1-\mu}(A_{2,t}y_t)^{\mu}$.

Case 2: $\lambda_2 > 0$.

This implies that the incentive compatibility constraint is binding. Therefore, a combination of Result 2 and the incentive compatibility constraint implies

$$Y_t^{1-\mu}(A_{2,t}y_t)^{\mu} - b_{2,t} = (1-P(m_t/y_t))(Y_t^{1-\mu}(A_{2,t}y_t)^{\mu} - Y_t^{1-\mu}(A_{1,t}y_t)^{\mu}) > 0,$$

which implies $Y_t^{1-\mu}(A_{2,t}y_t)^{\mu} > b_{2,t}$, which again contradicts $b_{2,t} = Y_t^{1-\mu}(A_{2,t}y_t)^{\mu}$.

Therefore, $\lambda_{32} = 0$. With this result, a combination of Result 1 and (A35) gives us $\lambda_2 > 0$. ∎

References

Bassett, W. F., M. B. Chosak, J. C. Driscoll, and E. Zakrajšek (2014): "Changes in Bank Lending Standards and the Macroeconomy," *Journal of Monetary Economics*, 62(0), 23 – 40.

Bassett, W. F., and F. B. Covas (2013): "A New Look at the Relationship Between Capital Constraints and Bank Lending," Unpublished Manuscript, Federal Reserve Board.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999): "The Financial Accelerator in a Quantitative Business Cycle Framework," in *The Handbook of Macroeconomics*, ed. by J. B. Taylor, and M. Woodford, vol. 1C, chap. 21, pp. 1341–1393. Elsevier, Amsterdam.

Christiano, L. J., M. S. Eichenbaum, and C. L. Evans (2005): "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 113, 1–45.

Christiano, L. J., and T. J. Fitzgerald (2003): "The Band Pass Filter," *International Economic Review*, 44(2), 435–465.

Christiano, L. J., and D. Ikeda (2013): "Leverage Restrictions in a Business Cycle Model," Unpublished Manuscript.

Christiano, L. J., R. Motto, and M. Rostagno (2014): "Risk Shocks," *American Economic Review*, 104(1), 27–65.

Diamond, D. W., and P. H. Dybvig (1983): "Bank Runs, Deposit Insurance, and Liquidity," *Journal of Political Economy*, 91(3), 401–419.

Gertler, M., and P. Karadi (2011): "A Model of Unconventional Monetary Policy," *Journal of Monetary Economics*, 58(1), 17–34.

Gertler, M., and N. Kiyotaki (2010): "Financial Intermediation and Credit Policy in Business Cycle Analysis," in *Handbook of Monetary Economics*, ed. by B. M. Friedman, and M. Woodford, vol. 3, chap. 11, pp. 547–599. Elsevier B. V.

——— (Forthcoming): "Banking, Liquidity and Bank Runs in an Infinite-Horizon Economy," *American Economic Review*.

Gilchrist, S., and E. Zakrajšek (2012a): "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, 102(4), 1692–1720.

——— (2012b): "Credit Supply Shocks and Economic Activity in a Financial Accelerator Model," in *Rethinking the Financial Crisis*, ed. by A. Blinder, A. Lo, and R. Solow. Russell Sage Foundation.

Greenwood, J., J. M. Sanchez, and C. Wang (2010): "Financing Development: The Role of Information Costs," *American Economic Review*, 100(4), 1875–91.

Hansen, L. P. (1982): "Large Sample Properties of Generalized Methods of Moments Estimators," *Econometrica*, 50(4), 1029–1054.

Jermann, U., and V. Quadrini (2012): "Macroeconomic Effects of Financial Shocks," *American Economic Review*, 102(1), 238–271.

Justiniano, A., G. Primiceri, and A. Tambalotti (2011): "Investment Shocks and the Relative Price of Investment," *Review of Economic Dynamics*, 14, 101–121.

Liu, Z., P. Wang, and T. Zha (2013): "Land-Price Dynamics and Macroeconomic Fluctuations," *Econometrica*, 81(3), 1147–1184.

Mehra, R., F. Piguillem, and E. C. Prescott (2011): "Costly Financial Intermediation in Neoclasical Growth Theory," *Quantitative Economics*, 2, 1–36.

Morrison, C. J. (1992): "Unravelling the Productivity Growth Slowdown in the United States, Canada, and Japan: The Effects of Subequilibrium, Scale Economies, and Markups," *Review of Economics and Statistics*, 74, 381–393.

Quadrini, V. (2015): "Bank Liabilities Channel," Unpublished Manuscript, University of Southern California.

Sims, C. A., and T. Zha (1999): "Error Bands for Impulse Responses," *Econometrica*, 67(5), 1113–1155.

Townsend, R. M. (1979): "Optimal Contracts and Competitive Markets with Costly State Verification," *Journal of Economic Theory*, 21(2), 265 – 293.

Williamson, S. D. (1987): "Costly Monitoring, Loan Contracts, and Equilibrium Credit Rationing," *Quarterly Journal of Economics*, 102, 135–145.

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