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Macroeconomic Implications of "Deep Habits" in Banking

Recent empirical evidence shows that price-cost margins in the market for bank credit are countercyclical in the U.S. economy and that this cyclical behavior can be explained in part from the fact that switching banks is costly for customers (i.e., from a borrower hold-up effect). Our goal, in this paper, is to study the "financial accelerator" role of these countercyclical margins as a propagation mechanism of macroeconomic shocks. To do so, we apply the "deep habits" framework in Ravn, Schmitt-Grohé, and Uribe (2006) to financial markets to model this hold-up effect within a monopolistically competitive banking industry. We are able to reproduce the pattern of price-cost margins observed in the data, and to show that the real effects of aggregate total factor productivity shocks are larger the stronger the friction implied by borrower hold-up. Also, output, investment, and employment all become more volatile than in a standard model with constant margins in credit markets. An empirical contribution of our work is to provide structural estimates of the deep habits parameters for financial markets.

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An extensive literature has widely studied the macroeconomic implications of financial market imperfections. Our paper seeks to contribute to this literature by dealing with a particular type of financial market, the market for bank credit, and with a particular type of imperfection, that of endogenously cyclical banks' loan pricing policies.

Our goal, in this paper, is to study the macroeconomic effects of these pricing policies. Specifically, we seek to answer the following two questions: do countercyclical

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price-cost margins in banking (defined as the spread between the interest rates on loans and deposits) act as a "financial accelerator," working as a propagation mechanism of aggregate total factor productivity (TFP) shocks?[1] If so, do countercyclical margins in banking can help us better understand business cycles? Our hypothesis is that in our setting, where recessions trigger an increase in the cost of credit, credit-dependent firms may delay their production, employment, and investment decisions by more than in a standard model with constant price-cost margins. This, in turn, might make recessions deeper and more persistent.

The reason why in our framework recessions trigger an increase in the cost of bank credit is associated to a *borrower "hold-up"* effect. The idea is that when banks monitor borrowers, they get an "information monopoly" over their customers' creditworthiness, which creates switching costs of changing banks for borrowers (i.e., a *borrower hold-up*). In recessions, when borrowers are perceived to be in greater risk of failure, the information monopoly lets lenders hold up the borrowers for higher interest rates, giving rise to countercyclical margins in credit markets. Several studies in the banking literature along with our own findings presented below in Section 1 support this story (see Diamond 1984, Sharpe 1990, Rajan 1992, von Thadden 1995, Dell'Ariccia 2001, Santos and Winton 2008).

We model this relationship between banks' cyclical pricing policies and borrower switching costs through an application of the "deep habits" framework in Ravn, Schmitt-Grohé, and Uribe (2006) (hereafter RSGU) to financial markets. By doing so we follow their suggestion that their model can be viewed as a natural vehicle for incorporating switching costs into dynamic general equilibrium frameworks.[2] Although RSGU is not a model of informational asymmetries, their deep habits framework is a useful and tractable way to replicate the borrower hold-up effect generated by these asymmetries within a dynamic stochastic general equilibrium (DSGE) setting. The bank pricing policies in a model where borrowers exhibit deep habits in the choice of lenders are equivalent to those that would arise in an asymmetric information model where incumbent banks accumulate proprietary information on their customers creditworthiness, which allows them to build an information monopoly and gives them market power. With deep habits, it is costly for borrowers to switch to a different bank and thus banks can hold up borrowers for higher interest rates just as in an asymmetric information model.

An additional value added of our work is to provide structural estimates of the deep habits parameters for financial markets.

There are two ways in which a setup with deep habits in banking allows us to better understand business cycles. First, our model can reproduce the empirical observation that margins in the market for credit are more volatile than GDP in the

1. For studies documenting the countercyclical nature of these margins, see Dueker and Thornton (1997), Mandelman (2006), Aliaga-Díaz and Olivero (2010, Forthcoming), and Olivero (2010).

2. RSGU demonstrate the formal similarity between the deep habit model and switching costs models. Nakamura and Steinsson (2006) interpret this good specific habit model as providing a specification for the effects of switching costs.

U.S. economy. Second, our model is able to reproduce the countercyclicality of banks' price-cost margins observed in the data. Moreover, these margins are endogenously countercyclical in a way consistent with the presence of switching costs or borrowers hold-up (see empirical evidence provided in Section 1). The intuition for this result is as follows. Because of the *hold-up* effect, when choosing the interest rate on loans, banks face a trade-off between current profits and future market share: lowering interest rates lowers current profits but allows them to build a larger future market share. After a positive TFP shock hits the economy, the present value of future profits is expected to be high, which raises the lenders' incentives to lure customers that will be held up in the future. The future market share motive gains importance relative to the current profits motive, and induces banks to charge lower margins.

From the simulation analysis, we conclude that aggregate TFP shocks have larger real effects when price-cost margins are countercyclical and that these effects are larger the stronger hold-up. Also, output, investment, and employment all become more volatile than in a standard model with constant margins in credit markets. Therefore, countercyclical margins act as a financial accelerator of business cycles. The supply-side effects coming from banks' loan pricing policies in the model work to amplify the standard demand-side effects of aggregate TFP shocks.

Our results have relevant policy implications since countercyclical margins seem to provide additional grounds for stabilization policy in economies where margins are more cyclical and where the share of bank credit in total external financing is higher.

Related to our work are Bernanke and Gertler (1989) and Bernanke, Gertler, and Gilchrist (1998, 1999). They study the role of endogenously countercyclical external finance premia as an amplifier of business fluctuations. Our *borrower hold-up*, or *borrower switching costs*, story provides an alternative way to generate countercyclical external finance premia and the implied financial accelerator.

The rest of the paper is organized as follows. Section 1 presents some empirical evidence on the cyclicality of price-cost margins in banking. Section 2 develops the model. Section 3 presents the simulation results. Section 4 concludes and provides some directions for further research. The Appendix presents the results of a sensitivity analysis on the calibration of the deep habits parameters.

1. THE EMPIRICAL EVIDENCE

To provide some insight on banks cyclical pricing policies, in this section, we present empirical evidence on the cyclical behavior of price-cost margins in banking (defined as the spread between the interest rates on loans and deposits). Margins are a useful measure of the cost of external finance for borrowers since they represent the premium of the interest rate paid on loans over borrowers' opportunity cost of internal funds (as measured by the interest rate on deposits).

TABLE 1

THE CYCLICAL BEHAVIOR OF PRICE-COST MARGINS IN BANKING CORRELATION COEFFICIENTS BETWEEN MARGINS AND BUSINESS CYCLE MEASURES

	Margin 1	Margin 2	Margin 3
GDP	−0.214	−0.237	−0.306
	(0.066)	(0.029)	(0.004)
Total loans	−0.203	−0.395	−0.657
	(0.081)	(0.000)	(0.000)

NOTES: GDP = real gross domestic product. Total loans from bank-level balance sheet data for all banks regulated by the Federal Reserve System, the FDIC, and the Comptroller of the Currency. Margin 1 denotes the difference between the lending rate from the survey of terms of business lending and the federal funds rate. As standard in the banking literature, the federal funds rate is used here as a proxy for the marginal cost of funds for banks. Margin 2 is calculated as the ratio of total interest income minus total interest expenses to total assets. Margin 3 is calculated as the ratio of total interest income minus total interest expenses to loans. The *p*-values are shown in parentheses. The series were filtered using the Hodrick–Prescott filter.
SOURCE: Reports on condition and income and Board of Governors of the Federal Reserve System data for the period 1984–2005.

1.1 Countercyclical Margins in Banking

Aliaga-Díaz and Olivero (2010, Forthcoming) present detailed evidence on the cyclical properties of margins for the U.S. economy. Olivero (2010) does so for a cross-section of developed countries. We refer the reader to this work for detailed evidence on the countercyclicality of margins.

In this section, we complement their work by studying the cyclical properties of three margin measures in the United States. The first margin is obtained using posted interest rate series as the difference between the lending rate from the survey of terms of business lending and the federal funds rate. Following the standard practice in the empirical banking literature, the second and third margin measures are obtained from bank-level balance sheet and income statement data from the Call Reports on Condition and Income.[3] The second margin is calculated as the ratio of banks' interest income net of interest expenses to banks' total assets, and the third as the ratio of this net income to loans.

In Table 1, we present the sample unconditional correlations between the Hodrick–Prescott filtered series for these three alternative measures of margins and two alternative business cycle indicators: GDP and total loans. Worthy of note is that these correlations are always negative and significant, which provides preliminary evidence on the countercyclical nature of these price-cost margins.

Furthermore, the results in Aliaga-Díaz and Olivero (2010, Forthcoming) show that the comovement between margins and the level of economic activity cannot be entirely explained by countercyclical monetary policy and default risk. Thus, there seems to be enough evidence that in recessions banks are able to raise their rates by more than is justified by borrower default risk alone. This ability can be explained in part by the effect on price-cost margins of borrower hold-up and switching costs. We explore this hypothesis in the next subsection.

3. These data are available from the Federal Reserve Bank of Chicago for all banks regulated by the Federal Reserve System, the Federal Deposit Insurance Corporation, and the Comptroller of the Currency. The period covered is 1984–2005.

1.2 How Borrower Hold-Up and Switching Costs Give Rise to the Observed Countercyclicality

Santos and Winton (2008) present evidence that borrower switching costs give rise to a lasting borrower–lender relationship, which allows incumbent banks to accumulate information over time, and to eventually earn an informational monopoly over their customers. This creates a *hold-up*, or *"lock-in,"* effect that makes it costly for firms to switch lenders. Santos and Winton (2008) use microloan data and find that bank-dependent firms without accessibility to public debt markets pay significantly higher loan rates than those firms with the accessibility, implying that banks do take advantage of their information monopoly. They also show that banks seem to be able to exploit this advantage further during recessions, when borrowers are in greater risk of failure. They do so by providing evidence that in recessions, banks raise their rates more for bank-dependent borrowers than for those with access to public bond markets, and that much of this is due to informational hold-up effects.[4]

To further study how this hold-up can give rise to the observed cyclicality of margins, in this section, we measure the empirical relationship between borrowers switching costs and the degree of countercyclicality of margins using unbalanced panel data for 56 countries including developing and developed economies in North and South America, Europe, and Asia. To do so, we conduct a two-step estimation methodology. In the first step, we use time-series techniques to obtain a measure of the cyclicality of credit margins in each country. In the second step, we perform a cross-sectional analysis, and we regress the measure of cyclicality of margins from the first step on a measure of switching costs and other controls.

For the first step, we use data on lending and deposit rates and real GDP from the IMF International Financial Statistics (IFS) for this cross-section of countries. We then calculate price-cost margins as the difference between lending and deposit rates. We obtain a measure of cyclicality of margins as the unconditional correlation coefficient between Hodrick–Prescott filtered margins and GDP.

In the second step, we regress this cyclicality on a measure of switching costs in banking. Switching costs measures are from Yuan (2009) and Olivero and Yuan (2009), who obtain switching costs for a cross-section of countries by structurally estimating the model in Kim, Kliger, and Vale (2003). Yuan uses bank-level balance sheet and income statement data from Bankscope to estimate switching costs for 25 of the countries in our sample. Olivero and Yuan obtain them for the United States using data from the Call Reports on Condition and Income. For the remaining countries in our sample, we obtain the switching costs estimates as the predicted values from a regression of the switching cost measures in Yuan and in Olivero and Yuan on margins.

In the second step regression of the cyclicality of margins on these switching costs, we also control for relative country size (measured as the ratio of each country's GDP to GDP in the United States), the degree of openness in each country (proxied by the

4. Hale and Santos (2009) show that firms are able to borrow from banks at lower interest rates after they issue for the first time in the public bond market. They interpret this finding as evidence that banks do indeed price their informational monopoly.

TABLE 2

SWITCHING COSTS IN BANKING AND COUNTERCYCLICAL MARGINS

	OLS results		Median quantile regression results	
Dependent variable: ρ (margin, GDP)	(1)	(2)	(3)	(4)
SCs	−0.0020		−0.0036	
	(0.0023)		(0.0014)	
NIMs		−0.0078		−0.0065
		(0.0070)		(0.0061)
Relative country size $\frac{GDP_i}{GDP_{U.S.}}$	−0.2954	−0.2962	−0.2913	−0.3083
	(0.1635)	(0.1625)	(0.0532)	(0.0773)
$\frac{CA}{GDP}$	−0.0039	−0.0041	−0.0019	−0.0016
	(0.0037)	(0.0037)	(0.0021)	(0.0031)
Dummy OECD	−0.0287	−0.0298	−0.1348	−0.0948
	(0.0541)	(0.0535)	(0.0320)	(0.0466)
Dummy Asia–Latin America	0.0472	0.0412	0.0327	0.0244
	(0.0607)	(0.0591)	(0.0360)	(0.0526)
N	56	56	56	56
$F(6, 49)$	13.98	14.17	–	–
R^2	0.6313	0.6344	0.4525	0.4657
Adj. R^2	0.5862	0.5896	–	–

NOTES: Standard errors are shown in parentheses. SCs are the switching cost structural estimates from Yuan (2009) and Olivero and Yuan (2009). Net interest margins (NIMs) are calculated as the difference between lending and deposit rates from the International Financial Statistics of the IMF and are used as a proxy for switching costs in the regression results presented in columns (2) and (4). Columns (1) and (2) correspond to standard OLS regression. Columns (3) and (4) correspond to least absolute deviation estimations (i.e., median quantile regression), performed to obtain robust estimates even in the presence of outliers in our relatively small cross-section of countries.

GDP share of the current account), and some indicator variables to denote whether the country is an OECD economy and/or an emerging economy in Asia and Latin America. All macroeconomic data are from the International Financial Statistics of the IMF.

We also explore the idea that switching costs should be higher in countries with less competitive banking industries (i.e., those countries where margins are higher). Then, as a robustness check in a separate regression, we use margins as a proxy for switching costs.

Table 2 summarizes the results of this second step regression analysis. Columns (1) and (2) correspond to a standard OLS regression. Columns (3) and (4) correspond to a least absolute deviation estimation (i.e., median quantile regression), performed to obtain robust estimates even in the presence of outliers in our relatively small cross-section of countries. Although not always statistically significant, the coefficients on switching costs (SCs) or its proxy (net interest margins (NIMs)) are always negative, which seems to indicate that SCs in banking do indeed provide a channel for countercyclical price-cost margins.

2. THE MODEL

The model is an application of the "deep habits" framework in RSGU to the financial sector. As suggested by RSGU, their model can be viewed as a natural vehicle for incorporating SCs into a dynamic general equilibrium model.

In a context of asymmetric information on borrowers creditworthiness, banks gradually accumulate this information over time as they lend repeatedly to their customers, eventually earning an informational monopoly over these borrowers. This creates a borrower hold-up effect, which makes it costly for borrowers to switch lenders and to have to start signaling this information to a new bank. Thus, borrower hold-up gives rise to SCs. In recessions when these informational asymmetries are more pronounced and when borrowers are in greater risk of failure, incumbent banks can further exploit their advantage and raise lending rates by more than in a standard model that lacks this friction.

Although RSGU is not a model of informational asymmetries, their deep habits framework is still a useful and tractable way to replicate the borrower hold-up effect in a DSGE setting. With deep habits, it is costly for borrowers to switch to a different bank, and thus banks can hold up borrowers for higher interest rates, just as in a fully microfounded informational monopoly model. Admittedly, this is a reduced form of incorporating the effects of informational asymmetries into a DSGE model. However, a formal setup of asymmetric information in a DSGE framework would require heterogeneous agent solution methods, something that is beyond the scope of this paper.[5]

This is a closed economy with a household sector, a production sector and financial intermediaries (hereafter called banks). Households take consumption–saving and labor–leisure decisions to maximize their expected lifetime utility. Firms produce goods using labor and capital. To finance investment spending, firms use a composite of heterogeneous bank loans. Banks use household savings to provide loans in a monopolistically competitive market.

We now proceed to present the optimization problems of all agents in this economy.

2.1 *Firms*

There is a continuum of measure one of firms indexed by $j \in [0, 1]$. In each period t firm j sells output (Y_t^j) in a competitive goods market, produced using labor (h_t^j) and capital (K_t^j). To finance investment spending, firm j uses a composite (x_t^j) of imperfectly substitutable heterogeneous loans provided by a continuum of mass one of banks. Each bank is indexed by i, and firm j borrows from a subset ψ^j of them.[6]

In this setup, firms engage in multiple banking relationships by borrowing from several banks in the economy. This is in line with the rich empirical evidence

5. Aliaga-Díaz and Olivero (2008) provide such a model.

6. There is abundant evidence on the existence of product differentiation in banking that makes the financial services from different banks imperfectly substitutable from the point of view of borrowers. Banks can differentiate their loans by targeting the financial services that they provide together with a loan (i.e., firm monitoring, valuation of collateral, and investment project evaluation) toward particular sectors of economic activity. Also, banks can choose various quality characteristics to build reputation and differentiate from competitors, like equity ratios, size, loss avoidance, etc. (Kim, Kristiansen, and Vale 2005). Last, lenders use different product packages and the extensiveness and location of their branches (Northcott 2004), personalized service, accessibility to the institution's executives, hours of operation and ATM, and remote access availability (Cohen and Mazzeo 2004) to differentiate their services from those of competitors.

presented by Ongena and Smith (2000a) and references therein.[7] Fama (1985), Sharpe (1990), Rajan (1992), Petersen and Rajan (1994), Hart (1995), von Thadden (1995), Bolton and Scharfstein (1996), Detragiache, Garella, and Guiso (1999), Neuberger and Schacht (2005), and Vulpes (2005) also study various reasons for firms to borrow from multiple banks.

To model the existence of borrower hold-up effects and costs of switching banks, the loan composite x_t^j is assumed to depend on past levels of borrowing, as defined by equations (1) and (2),

$$x_t^j = \left[\int_0^{\psi^j} \left(l_{it}^j - \theta s_{it-1} \right)^{1-\frac{1}{\eta}} di \right]^{1/(1-\frac{1}{\eta})}, \tag{1}$$

$$s_{it-1} = \rho_s s_{it-2} + (1 - \rho_s) l_{it-1}, \tag{2}$$

where l_{it}^j is firm j's demand for credit from bank i in period t, and $\eta > 1$ is the elasticity of substitution across varieties. This specification for the Dixit–Stiglitz aggregator implies that each firm j borrows from a subset ψ^j of all banks in the economy.

The second term in x_t^j is intended to capture the borrower hold-up effect. s_{it-1} measures the stock of firm–bank relationships and the parameter θ measures the degree of hold-up.

The fact that $\theta > 0$ implies that the current demand for credit is a function of past borrowing levels. It will become clear later that $\theta > 0$ also implies that the interest rate elasticity of the demand for loans and, hence price-cost margins in the market for credit are cyclical, and that they exhibit a behavior consistent with the empirical evidence presented in Section 1. When $\theta = 0$ the model boils down to the benchmark version with constant interest rate elasticity of the demand for credit, pinned down by the elasticity of substitution across varieties η.

Equation (2) defines the stock s as a function of the cross-sectional average level of borrowing from bank i in period $t - 1$. This average satisfies $l_{it-1} \equiv \int_0^{\mu_i} l_{it-1}^j dj$, where μ_i is the subset of j firms that borrow from bank i. This average is taken as exogenous by each individual atomistic firm. The fact that the stock s_{it-1} is a function of the average level of borrowing implies that habits are external to the borrower.[8] This can be rationalized through banks exhibiting economies of scale in

7. According to various studies cited by Ongena and Smith (2000a), the average number of bank relationships is 15.2 in Italy; 11 in Portugal, France, and Belgium; 9.7 in Spain; 8.1 in Germany; 7.4 in Greece; 5 in Austria, Luxembourg, and the Czech Republic; 4 in Hungary; 3 in Japan, Finland, Switzerland, Denmark, the Netherlands, Poland, Ireland, and the United Kingdom; and 2 in Sweden, Norway, and the United States.

8. As in RSGU, this assumption makes the model analytically tractable, since it preserves the separation of the dynamic problem of choosing total borrowing over time from the static problem of choosing individual borrowing from each bank at any given point in time. If this was not the case, the current demand from each bank i would depend both on its current relative interest rate and on all future expected rates. Therefore, each bank would face an incentive to renege from past interest rate promises, and the problem would no longer be time consistent.

the management of informational asymmetries. Thus, the more firms bank with one bank, the larger the information monopoly for that bank.

Equation (2) gives the law of motion for the stock s, where the parameter $\rho_s \in [0, 1)$ measures the persistence or duration of the hold-up effects or, in other words, the speed of adjustment of these effects to variations in the previous period cross-sectional average l_{it-1}. The fact that $\rho_s > 0$ makes the model general enough to allow for these effects to last over several periods. When $\rho_s = 0$, hold-up effects are very short-lived and last for only one period.

In each period t, firm j chooses investment (I_t^j), employment (h_t^j), the loans composite (x_t^j) and borrowing from each bank i (l_{it}^j) to maximize the expected present discounted value of its lifetime profits. Its optimization problem is given by[9]

$$\max_{K_{t+1}^j, I_t^j, h_t^j, x_t^j, l_{it}^j} \quad E_0 \quad \sum_{t=0}^{\infty} \prod_{m=0}^{t} q_m \pi_t^j \qquad q_m = \beta^m \frac{U_{C_m}}{U_{C_{m-1}}}$$

$$s.t.$$

$$\text{eq.}(1),$$

$$\text{eq.}(2),$$

$$\pi_t^j = A_t F\left(K_t^j, h_t^j\right) - w_t h_t^j - I_t^j + x_t^j - \int_0^{\psi^j} (1 + R_{it-1}) l_{it-1}^j di + \Omega_t^j, \tag{3}$$

$$K_{t+1}^j = I_t^j + (1 - \delta) K_t^j, \tag{4}$$

$$\int_0^{\psi^j} l_{it}^j di \geq \phi I_t^j \qquad \phi \leq 1, \tag{5}$$

$$ln(A_{t+1}) = \rho ln(A_t) + \epsilon_t, \tag{6}$$

where ψ^j is the subset of i banks that firm j borrows from, and where as in RSGU $\Omega_t^j \equiv \theta \int_0^{\psi^j} \frac{(1+R_{it})}{(1+R_t)} s_{it-1} di$. Equation (3) corresponds to firm j's cash flow, where w_t is the wage rate and R_{it-1} is the interest rate contracted with bank i in period $t-1$, on loans to be repaid in period t. This equation defines firm j's profits in period t as sales revenues plus what the firm obtains from borrowing minus the sum of labor, investment, and borrowing costs.

Equation (3) is a key equation in the model, since it helps to understand how deep habits work to provide microfoundations for SC models. In that sense, what the

9. Firms in this economy are owned by households, and therefore, their discount factor q is given by the households' intertemporal marginal rate of substitution.

firms/borrowers *actually* borrow is $l_t^j \equiv \int_0^{\psi^j} l_{it}^j di$ and they repay $\int_0^{\psi^j}(1+R_{it})l_{it}^j di$ one period later. However, what they *effectively* borrow is given by the term $(x_t^j + \Omega_t^j) = [\int_0^{\psi^j}(l_{it}^j - \theta s_{it-1})^{1-1/\eta} di]^{\frac{1}{1-1/\eta}} + \theta \int_0^{\psi^j} \frac{(1+R_{it})}{(1+R_t)} s_{it-1}\, di$ in the profit function. Thus, the wedge between these two can be thought of as the cost of switching between bank i and any other rival bank. This cost is a function of the difference between the rate charged by bank i (R_i) and the market rate (R). To see this analytically, consider the case for which $\eta \to \infty$. In this case, *effective* borrowing amounts to: $\int_0^{\psi^j} l_{it}^j di - \theta \int_0^{\psi^j} s_{it-1}\frac{(R_t - R_{it})}{(1+R_t)} di$, while *actual* borrowing amounts to: $\int_0^{\psi^j} l_{it}^j di$. Therefore, the wedge between the two or SCs is represented by: $\theta \int_0^{\psi^j} s_{it-1}\frac{(R_t - R_{it})}{(1+R_t)} di$.

Notice that, as discussed in RSGU, this is still a model where there is no discrete switching when a seller raises its price, but rather a gradual loss of customers for that seller. This is important because it makes the general equilibrium model computationally tractable and suitable to explore the macroeconomic and business cycle implications of deep habits in banking. However, even without discrete switching, there is still a wedge between what firms *actually* borrow (i.e., the amount that they repay in $t+1$) and what they *effectively* borrow. This wedge is what we refer to as SCs in this model.

Equation (4) gives the standard law of motion for the firm's capital stock.

Equation (5) introduces the need for bank financing into the model, and it states that each firm needs to finance at least a fraction ϕ of its investment spending with external borrowing.[10]

Last, equation (6) describes the exogenous process followed by TFP, where ϵ_t follows an i.i.d. distribution with mean zero and standard deviation σ_ϵ.

From this problem, firm j's optimal demand for credit from bank i is

$$l_{it}^j = \left(\frac{1+R_{it}}{1+R_t}\right)^{-\eta} x_t^j + \theta s_{it-1}, \tag{7}$$

where $(1+R_t) \equiv [\int_0^{\psi^j}(1+R_{it})^{1-\eta} di]^{\frac{1}{1-\eta}}$ is the nominal price index for the loan composite.

10. With market power in banking and $(1+R_i) \geq q^{-1}$ firms will always prefer to finance investment with internal rather than with external resources, and borrowing would be zero if this condition was not imposed. In other words, ϕ would always equal 0 if it was optimally chosen by borrowers. Therefore, equation (5) always binds in equilibrium. Equation (5) is actually the opposite of a standard *borrowing constraint* that sets an upper limit on borrowing equal to a fraction of the borrower's collateral. On the contrary, this *financing constraint* sets a lower limit on external borrowing, and it is needed for banks and external credit to play a role in the model. Admittedly, it is an *ad hoc* way to incorporate meaningful financial intermediation into the model. Modeling the existence of financial intermediaries from first principles through their role in liquidity provision, monitoring of borrowers credit worthiness or management of maturity mismatches has been widely studied in the past, and it is beyond the scope of our paper. The parameter ϕ is calibrated to match the ratio of external credit to business investment in the data.

2.2 *The Banking Sector*

There is a continuum of mass one of banks indexed by $i \in [0, 1]$. Each variety of loans/financial services is produced by a bank operating in a monopolistically competitive loan market. Banks are competitive in the market for deposits.

In each period t bank i chooses its demand for deposits (D_{it}) and the interest rate charged on loans (R_{it}) to maximize the expected present discounted value of its lifetime profits. Bank i's optimization problem is given by[11]

$$\max_{D_{it}, R_{it}} E_0 \sum_{t=0}^{\infty} \prod_{m=0}^{t} q_m \Pi_{it} \qquad q_m = \beta^m \frac{U_{C_m}}{U_{C_{m-1}}}$$

$$s.t.$$

$$\Pi_{it} = D_{it} - L_{it} + (1 + R_{it-1})L_{it-1} - (1 + r_{t-1})D_{it-1} - \kappa, \tag{8}$$

$$L_{it} = D_{it}, \tag{9}$$

$$L_{it} \equiv \int_0^{\mu_i} l_{it}^j \, dj = \int_0^{\mu_i} \left[\left(\frac{1 + R_{it}}{1 + R_t} \right)^{-\eta} x_t^j + \theta s_{it-1} \right] dj, \tag{10}$$

where μ_i is the subset of j firms that borrow from bank i.

Equation (8) is the bank's cash flow in period t, where r_{t-1} is the common risk-free interest rate on deposits paid by all banks. κ denotes the fixed costs of production introduced to guarantee no entry in the monopolistically competitive banking sector. The presence of κ ensures that profits are relatively small on average, in spite of equilibrium price-cost margins being significantly positive. Equation (9) is bank i's balance sheet condition, and equation (10) shows the aggregate demand from a μ_i subset of j firms that bank i internalizes.

The Lagrangian of bank i's problem is given by

$$\ell = E_0 \sum_{t=0}^{\infty} Q_{0,t} \Bigg\{ (R_{it-1} - r_{t-1})L_{it-1} - \kappa + \nu_{it} \left[-L_{it} + \int_0^{\mu_i} \left[\left(\frac{1 + R_{it}}{1 + R_t} \right)^{-\eta} x_t^j + \theta s_{it-1} \right] dj \right] \Bigg\},$$

$$Q_{0,t} = \beta^t \frac{U_{C_t}}{U_{C_0}},$$

where the multiplier ν_{it} measures the shadow value of lending an extra dollar by bank i in period t.

11. Banks are owned by households so that their discount factor q is given by the households' intertemporal marginal rate of substitution.

The first-order conditions with respect to L_{it} and R_{it} are, respectively,

$$\nu_{it} = (R_{it} - r_t) E_t Q_{t,t+1} + \theta E_t Q_{t,t+1} \nu_{it+1} (1 - \rho_s), \tag{11}$$

$$L_{it} E_t Q_{t,t+1} = -\nu_{it} \frac{\partial L_{it}}{\partial R_{it}}. \tag{12}$$

Equation (11) states that the value of lending an extra dollar in period t is composed of two terms: the short-run returns of that operation ($(R_{it} - r_t) E_t Q_{t,t+1}$), and the future expected profits associated with the fact that a share of this lending will be held up in period $t + 1$. Equation (12) states that the marginal revenue of an increase in the interest rate (given by the discounted value of the loans $L_{it} E_t Q_{t,t+1}$) has to equal the marginal cost of that increase (given by the resulting reduction in the quantity demanded of loans $\frac{\partial L_{it}}{\partial R_{it}}$ evaluated at the shadow price ν_{it}).

We are now able to use equations (11) and (12) to formally show the equivalence between this deep habits model and a SC model á la Klemperer (1995). Let $V(L_{it-1})$ be the value of the maximized objective function for the bank for any given L_{it-1}. Then, we can represent the bank's optimization problem as

$$V(L_{it-1}) = \max_{R_{it}, L_{it}} \left\{ (R_{it-1} - r_{t-1}) L_{it-1} - \kappa + E_t Q_{t,t+1} V(L_{it}) \right\}$$

$$s.t.$$

$$L_{it} \equiv \int_0^{\mu_i} l_{it}^j \, dj = \int_0^{\mu_i} \left[\left(\frac{1 + R_{it}}{1 + R_t} \right)^{-\eta} x_t^j + \theta s_{it-1} \right] dj.$$

Using the constraint to eliminate L_{it}, the FOC with respect to R_{it} is

$$\frac{\partial \Pi_{it}}{\partial R_{it}} + E_t Q_{t,t+1} \frac{\partial V(L_{it})}{\partial L_{it}} \frac{\partial L_{it}}{\partial R_{it}} = 0.$$

This equation is analogous to equation (2′) in Klemperer (1995), where firm F's FOC is

$$\frac{\partial \pi_t^F}{\partial p_t^F} + \delta \frac{\partial V_{t+1}^F}{\partial \sigma_t^F} \frac{\partial \sigma_t^F}{\partial p_t^F} = 0,$$

where π_t^F, p_t^F, and σ_t^F denote firm F's profits, price and market share in period t, respectively. As in RSGU, the equivalence with the Klemperer (1995) model becomes obvious noting that p_t^F and σ_t^F are linearly related to R_{it} and L_{it}, respectively.

Still an important difference between the two models is the absence of discrete switching in equilibrium in the deep habits model, where each firm j can distribute its borrowing identically among a subset ψ^j of banks, and still each bank i faces a gradual loss of market share if it raises its interest rate R_i above R. This is a useful feature that facilitates numerical tractability of the DSGE model when studying macroeconomic issues.

2.3 Households

A representative household takes consumption (C_t), savings and labor supply decisions in this economy. Each household derives disutility from working and is allowed to save by accessing a competitive market for bank deposits (D_t) in each period $t \geq 0$. Firms' and banks' profits are rebated to households in a lump-sum fashion.

The optimization problem for the representative household is given by

$$\max_{C_t, h_t, D_{it}} E_0 \sum_{t=0}^{\infty} \beta^t U(C_t, h_t)$$

$$s.t.$$

$$C_t + \int_0^1 D_{it}\, di = w_t h_t + (1 + r_{t-1}) \int_0^1 D_{it-1}\, di + \int_0^1 \pi_t^j\, dj + \int_0^1 \Pi_{it}\, di, \quad (13)$$

and a no-Ponzi game constraint, taking as given initial deposit holdings and the processes for w_t, π_t^j, and Π_{it}.

2.4 Deep Habits and Price-Cost Margins in Banking

In this section, we obtain an equation for equilibrium price-cost margins in the market for bank credit, and we discuss the role that deep habits play in shaping the cyclical nature of these margins.

Working with equations (11) and (12) and using the approximation $\frac{1+R_{it}}{1+R_t} \approx e^{(R_{it}-R_t)} \approx (1 + R_{it} - R_t)$, we can derive an expression for the price-cost margin $(R_{it} - r_t)$ charged by each noncompetitive bank i in this economy as[12]

$$(R_{it} - r_t) = \left\{ \eta\, (\psi)^{\frac{1}{(1-\eta)}} \left[1 - \theta\rho_s \frac{s_{it-2}}{l_{it}} - \frac{\theta(1-\rho_s)}{\gamma_t} \right] \right\}^{-1} - \theta(1-\rho_s) \frac{E_t Q_{t,t+1} \nu_{it+1}}{E_t Q_{t,t+1}}, \quad (14)$$

where $\gamma_t \equiv \frac{l_{it}}{l_{it-1}}$ denotes the growth rate of loans at time t.

The expression $\{\eta(\psi)^{\frac{1}{(1-\eta)}} [1 - \theta\rho_s \frac{s_{it-2}}{l_{it}} - \frac{\theta(1-\rho_s)}{\gamma_t}]\}$ gives the short-run interest rate elasticity of the demand for credit faced by bank i. It is easily seen that the margin between R_{it} and r_t is inversely related to this elasticity. An increase in the level

12. The approximation error tends to cancel out since the same transformation is performed on the numerator and the denominator of the original expression. The details on this derivation are presented in a mathematical appendix available at https://faculty.lebow.drexel.edu/OliveroM/.

of economic activity (reflected in an increase in l_t and γ_t) raises the elasticity and lowers the margin. The intuition is the following: as a result of the *hold-up effect*, when choosing the interest rate on loans banks face a trade-off between current profits and future market share: lowering interest rates lowers current profits but allows them to build larger future market shares. With autocorrelated TFP shocks, an increase in the current demand for credit implies that the present value of future profits is high, which raises lenders' incentives to lure customers that will be held up in the future. The future market share motive dominates over the current profits motive. Thus, banks start charging lower margins to lure customers and to increase their current market share. A higher market share today implies more customers for the future. Therefore, the optimal price-cost margin for each bank is diminishing in the level of current demand.

The spread also depends negatively on the value of future perunit profits discounted to period $t+1$ (as measured by ν_{t+1}).[13] The intuition here is that an increase in future expected profits raises the value of a higher future market share. Thus, banks have an incentive to lower margins today to gain a higher customer base in the future, even if this implies giving up current profits.

Last, notice that if $\theta = 0$, then $(R_{it} - r_t) = \frac{1}{\eta}(\psi^j)^{-\frac{1}{(1-\eta)}}$, and the model collapses to the benchmark version with no borrower hold-up and constant price-cost margins pinned down by the inverse of the elasticity of substitution across varieties.

It is important to highlight that we obtain this hold-up effect in equilibrium even in a model where agents are forward looking. These agents do anticipate that they might be being currently lured with lower interest rates and that this might be happening at the expense of higher future rates. However, even in this case, these forward-looking agents cannot avoid higher rates because hold-up is modeled as *external* in this framework. In other words, habits are modeled at the cross-sectional sector level instead of at the individual borrower's level, and borrowers have no control over the external component of habits.

This intuition is also evident from the model's FOCs. In our framework of *external* habits, the demand for loans in equation (7) is only a function of current relative prices and the stock of habits. Conversely, the current demand for a particular variety depends also on all future expected relative prices when habits are *internal*.[14] Therefore, in a model with forward-looking agents and *internal habits*, that is, in a model where demand is a function of both current and future prices, banks may be less able to charge lower interest rates today to lure borrowers at the expense of higher future rates.[15]

13. It can be shown that ν_t is the present discounted value of expected future perunit profits induced by a unit increase in current lending.

14. See Section 4.3 of RSGU for the internal habits extension of their model.

15. Notice that in the internal habits model, the problem is no longer time consistent; since then, monopolists have the incentive to renege from price promises made in the past. Thus, this statement is conditional on banks not reneging from their past promises. Special thanks to one of the referees for pointing out the need for this analysis and how it relates to the external habits formulation of the model.

TABLE 3

BENCHMARK CALIBRATION

Preference parameters		
$\beta = 0.99$	$\sigma = 2$ $\omega = 0.2$	
Financing parameters $\theta = 0.72$ $\rho_s = 0.85$	$\eta = 190$	$\phi = 0.42$
Production parameters $\alpha = 0.64$	$\delta = 0.018$	
TFP process $\sigma_\epsilon = 0.007$	$\rho = 0.95$	

3. MODEL SOLUTION

3.1 Calibration

The model is calibrated at a quarterly frequency to the U.S. economy following the standards in the RBC literature.

Preferences are assumed to be isoelastic and of the constant relative risk aversion type. The utility function is $U(C, h) = \frac{(C^{\omega}(1-h)^{1-\omega})^{1-\sigma}}{(1-\sigma)}$, where $\sigma > 1$ is the inverse of the intertemporal elasticity of substitution. The parameter σ is set to 2, and ω to 0.2.

The production function is of the Cobb–Douglas type $F(K, h) = AK^{1-\alpha}h^{\alpha}$ and it is assumed to exhibit constant returns to scale. The labor share in GDP α is set to 0.64. The depreciation rate δ is set to 0.018 to match the 0.076 investment to capital ratio for annual data in Cooley and Prescott (1995). ϕ is set to 0.42 to match the mean ratio of credit market instruments to nonresidential gross fixed investment for nonfinancial businesses in the U.S. Flows of Funds Accounts data for the period 1946–2008.[16]

The discount factor β is set to match the average quarterly 10-year interest rate on U.S. government Treasury bills. We take this rate as a measure of the long-run cost of funds for banks and, therefore, as a measure of the steady-state interest rate on deposits.

The parameters describing the exogenous process followed by TFP are set following Cooley and Prescott (1995).

Table 3 shows all parameter values used for the calibration of the model.

3.2 Estimation of Deep Habits Parameters in Banking

Since no estimates exist for the elasticity of substitution across varieties in the demand for financial services η and for the deep habits parameter θ in banking, we obtain these parameters from the structural estimation of the model using GMM.

16. The minimum value of the ratio in this period was 0.23 and the maximum, 0.61.

TABLE 4

GMM ESTIMATES OF STRUCTURAL PARAMETERS

	Total loans BAA bond rate	Total loans BP loan rate	C&I loans BAA bond rate	C&I loans BP loan rate
θ	0.7164*	0.8089*	0.7159*	0.6445*
	(0.0865)	(0.0356)	(0.1009)	(0.2985)
η	245.51*	143.0795*	254.9107*	140.085*
	(10.5876)	(5.7063)	(11.3757)	(5.4101)
N	218	218	218	218
Determinant residual covariance	0.1630	0.2645	0.1766	0.1872
J-statistic	0.1010	0.1076	0.0991	0.1029

NOTES: C&I loans stands for commercial and industrial loans. BP loan rate is the bank prime rate. BAA bond's rate is Moody's bond rate. Estimates are based on quarterly U.S. data for the period 1954 Q3 to 2008 Q4. Standard errors shown in parentheses. *Significant at 10% level.

Thus, we contribute to the deep habits literature by providing structural estimates of the habit parameters for financial markets.

The equation we estimate is equation (15), derived from the supply side of the model by working with the first-order conditions of the banking sector problem, equations (11) and (12):

$$0 = E_t Q_{t,t+1} \frac{\gamma_t^L}{\left(\gamma_t^L - \theta\right)} - \eta(\mu_t - 1) - \theta E_t Q_{t,t+1} Q_{t+1,t+2} \frac{\gamma_{t+1}^L}{\left(\gamma_{t+1}^L - \theta\right)}, \qquad (15)$$

where $\mu_t \equiv \frac{(1+R_t)}{(1+r_t)}$, $E_t Q_{t+z,t+i}$ is the discount factor between periods $t+z$ and $t+i$, given by the Euler equation governing households savings, and γ_{t+1}^L denotes the gross growth rate of aggregate lending between periods t and $t+1$, that is, $\gamma_{t+1}^L \equiv \frac{L_{t+1}}{L_t}$.

To estimate this system, μ is calculated in two alternative ways as the ratio of the gross bank prime loan rate to the gross Treasury bill rate or the ratio of the gross Moody's BAA bond rate to the gross Treasury bill rate. γ^L is calculated using data on both total and commercial and industrial (C&I) loans. For the equation involving total (C&I) loan growth, as instruments we use several lags of μ, several lags of total (C&I) loan growth, and the contemporaneous growth rates for consumption, GDP, and the volume of industrial production.

We use quarterly data for the United States for the period 1954–2008. Data on total loans and C&I loans are from the Call Reports on Condition and Income. Last, data on interest rates and all macroeconomic data are from the Board of Governors of the Federal Reserve System.

Table 4 presents four sets of estimation results for the two alternative measures of loan growth γ^L and the two alternative measures of the markup μ introduced above.

The average values for θ and η across these four alternative specifications imply a steady-state price-cost margin of $(R - r) = 0.0168$ and a cost of the hold-up friction of 0.2% of GDP (as measured by the ratio $\frac{(R-r)L}{Y}$). The estimated value of the deep habits parameter θ is 0.72 on average, somewhat lower than the estimated value of 0.86 for goods markets in RSGU. This indicates that habit formation in credit markets seems to be weaker than in goods markets. Also important is that the estimated elasticity of substitution ($\eta = 190$ on average) is higher than that obtained by RSGU. This makes sense. Although differentiated, banking products and credit from different sources are still highly substitutable with each other, significantly more than different categories of goods in goods markets.[17]

The average of θ and η across the four specifications presented in Section 3.2 are used as a benchmark. Sensitivity analyses on the values of the parameters θ and η are presented in Tables A1 and A2 of the Appendix. Following RSGU, the persistence parameter ρ_s is set to 0.85 in the benchmark version of the model. A sensitivity analysis on the value of this parameter is conducted later in Table 6.

3.3 Results

The stationary competitive equilibrium for our model economy is defined as a set of allocations $\{C_t, h_t, x_t, s_t, \nu_t, I_t, K_{t+1}, l_t, D_t, L_t\}$ and prices $\{w_t, r_t, R_t\}$ satisfying a system of 13 equilibrium conditions. We solve the model by computing a log-linear approximation of this set of equations in the neighborhood of the deterministic steady state.

Table 5 shows the dynamic properties for both a standard model with constant price-cost margins in banking (i.e., a model where $\theta = 0$) and one where borrower hold-up effects generate countercyclical margins, and compares them to the data.

Introducing hold-up or SCs helps us better understand two features of business cycles in the United States. First, it reproduces the fact that the volatility of margins exceeds that of output. Second, and more importantly, it allows us to reproduce the countercyclicality of price-cost margins in banking, in a way consistent with the empirical evidence presented in Section 1. Notice that these results come at no cost in terms of still reproducing the cyclical patterns of consumption, output, investment, and employment.

The simulation results indicate that as the degree of hold-up increases (i.e., as θ rises from 0 to 0.72), output, investment, and employment all become more volatile both in absolute terms and relative to output. On the contrary, the standard deviation of consumption falls as margins become countercyclical. Thus, allowing for $\theta > 0$ works further in favor of reproducing the stylized facts that consumption is less volatile than output and that investment is more volatile than output.

Regarding the persistence of macroeconomic aggregates, the autocorrelation coefficients in Table 5 show that when margins are countercyclical output, investment, and employment all become slightly less persistent than in the standard model. This provides a major difference relative to the framework of Bernanke, Gertler, and Gilchrist

17. Also, notice that the markup (price/marginal cost) equation for goods markets in RSGU is different from our margin (price–marginal cost) equation for credit markets.

TABLE 5

Dynamic Properties of the Simulated Economies: Sensitivity to θ

	Data	$\theta = 0$	$\theta = 0.72$
Standard deviations $\sigma(x)$			
Y	–	0.0141	0.0145
C	–	0.0041	0.0038
I	–	0.0402	0.0431
h	–	0.0083	0.009
Relative standard deviations $\sigma(x)/\sigma(Y)$			
C	0.8	0.292	0.2639
I	2.61	2.856	2.9684
h	0.88	0.5903	0.6217
w	0.9514	0.4173	0.391
R	0.5596	0.021	0.0937
r	0.7721	0.0211	0.0332
$(R - r)$	2.0925	0	7.814
A	0.68	0.6253	0.6054
Autocorrelation coefficients $\rho(x_t, x_{t-1})$			
Y	0.8651	0.6803	0.6764
C	0.8206	0.717	0.7521
I	0.9275	0.6764	0.6679
h	0.4321	0.6759	0.6656
w	–	0.697	0.7107
R	0.95	0.6764	0.6084
r	0.9462	0.6764	0.6475
$(R - r)$	0.8118	0.9934	0.6084
A	–	0.6782	0.6782
Correlation with output $\rho(x, Y)$			
C	0.8734	0.9646	0.93
I	0.9245	0.9966	0.9953
h	0.5494	0.9941	0.9916
w	0.602	0.9885	0.9791
R	0.2185	0.9828	−0.8299
r	0.3526	0.9828	0.9668
$(R - r)$	−0.2002	–	−0.8691
A	0.96	0.6687	0.6715
Steady-state values			
$(R - r)$	0.01	0.0053	0.0168
$\frac{(R-r)L}{Y}$	–	0.0006	0.002

Notes: Data moments based on quarterly data for 1947–2008. GDP, personal consumption expenditures, gross private domestic investment and wages and salary accruals in billions of chained 2000 dollars from the Bureau of Economic Analysis. Number of hours, index 2002 = 100, from the Bureau of Labor Statistics. $(R - r)$ calculated as the difference between lending and deposit rates from the International Financial Statistics of the IMF. Moments calculated based on 100 simulations of length 150 each.

(1998, 1999). There, impulse response functions display an extra persistence under the friction imposed by a countercyclical external finance premium. This is explained because their mechanism works through the effects on net worth, and net worth is slow to revert to trend.

Figure 1 shows the impulse response functions to an exogenous 1% negative shock to TFP. Under borrower SCs (i.e., when $\theta = 0.72$), banks raise margins after a negative shock. The intuition is that after a negative shock, future profits are expected to be low, such that gaining future market share is not a priority.

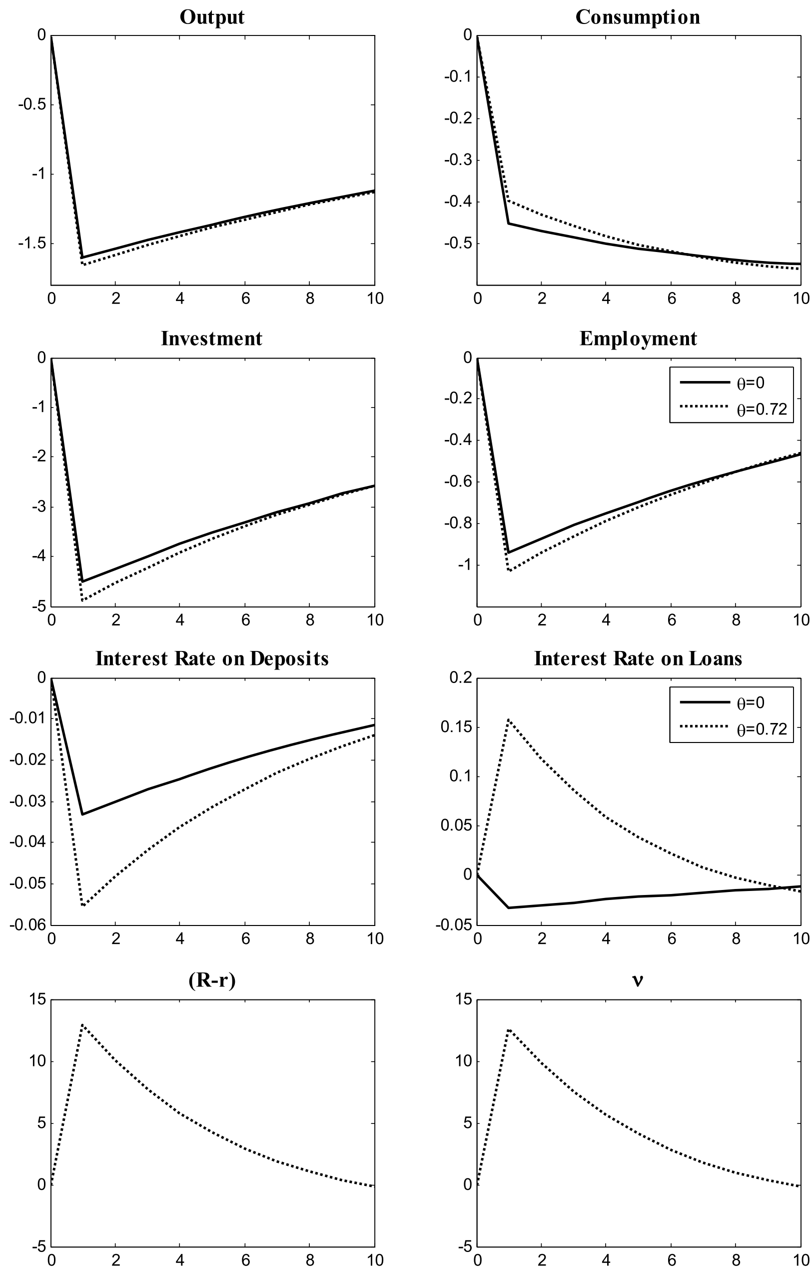

FIG. 1. Impulse Response Functions: Sensitivity to θ.

NOTE: Values are percentage deviations from the steady state.

TABLE 6

Dynamic Properties of the Simulated Economies: Sensitivity to Persistence of Habits as Measured by ρ_s

	Data	Persistence			
		None $\rho_s = 0$	Low $\rho_s = 0.5$	Intermediate $\rho_s = 0.85$	High $\rho_s = 0.95$
Standard deviations (σ)					
Y	–	0.0143	0.0143	0.0145	0.0146
C	–	0.004	0.004	0.0038	0.0037
I	–	0.0415	0.0418	0.0431	0.0437
h	–	0.0087	0.0087	0.009	0.0092
Relative standard deviations $\sigma(x)/\sigma(Y)$					
C	0.8	0.2815	0.2785	0.2639	0.2549
I	2.61	2.9078	2.9204	2.9684	2.9885
h	0.88	0.6073	0.6086	0.6217	0.6267
w	0.9514	0.4058	0.4037	0.391	0.3842
R	0.5596	0.0631	0.0637	0.0937	0.1085
r	0.7721	0.0716	0.0423	0.0332	0.0287
$(R - r)$	2.0925	33.7558	8.5896	7.814	8.0926
A	0.68	0.6155	0.6141	0.6054	0.602
Autocorrelation coefficients $\rho(x_t, x_{t-1})$					
Y	0.8651	0.6563	0.6677	0.6764	0.6797
C	0.8206	0.7844	0.7664	0.7521	0.7398
I	0.9275	0.6249	0.65	0.6679	0.6747
h	0.4321	0.6095	0.6426	0.6656	0.6741
w	–	0.7302	0.7189	0.7107	0.7048
R	0.95	−0.1295	0.3296	0.6084	0.666
r	0.9462	−0.0623	0.4402	0.6475	0.6735
$(R - r)$	0.8118	−0.155	0.31	0.6084	0.6625
A	–	0.6782	0.6782	0.6782	0.6782
Correlation with output $\rho(x, Y)$					
C	0.8734	0.9354	0.9386	0.93	0.9353
I	0.9245	0.9951	0.9954	0.9953	0.9958
h	0.5494	0.9908	0.9914	0.9916	0.9928
w	0.602	0.9796	0.9808	0.9791	0.9813
R	0.2185	−0.1152	−0.3837	−0.8299	−0.9659
r	0.3526	0.6454	0.8728	0.9668	0.983
$(R - r)$	−0.2002	−0.3703	−0.6087	−0.8691	−0.9541
A	0.96	0.6705	0.671	0.6715	0.6702
Steady-state values					
$(R - r)$	0.01	0.0053	0.0121	0.0168	0.0181
$\frac{(R-r)L}{Y}$	–	0.0006	0.0014	0.002	0.0021

Notes: Data moments based on quarterly data for 1947–2008. GDP, personal consumption expenditures, gross private domestic investment, and wages and salary accruals in billions of chained 2000 dollars from the Bureau of Economic Analysis. Number of hours, index 2002 = 100, from the Bureau of Labor Statistics. $(R - r)$ calculated as the difference between lending and deposit rates from the International Financial Statistics of the IMF. Simulations performed for a value of $\theta = 0.72$ and $\eta = 190$. Moments calculated based on 100 simulations of length 150 each.

The current profits motive dominates over the future market share motive and banks raise margins to increase their current revenues (they are able to do so because the short-run interest rate elasticity of the demand for credit falls with anegative shock). Therefore, the cost of credit increases, and investment falls by more than in the standard model with $\theta = 0$. Because of the negative effect of this reduction in investment on the stock of capital and on the marginal productivity of labor,

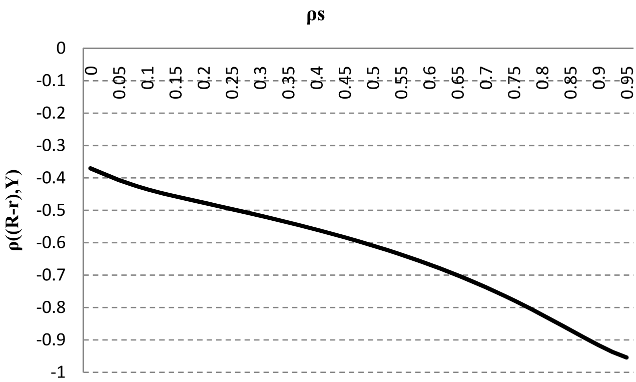

FIG. 2. Cyclicality of Margins and the Persistence of Hold-Up.

NOTES: Correlation coefficients between margins and output computed from 100 model simulations of length 150 each for each value of the persistence parameter ρ_s measured on the horizontal axis.

employment and output also fall by more under hold-up than in the standard model. Resources are reallocated away from investment into consumption, such that the negative effect on the latter is smaller when margins are countercyclical.

Thus, we provide a positive answer to the question of whether introducing a countercyclical wedge in the market for credit implies the presence of a financial accelerator. That is, endogenous developments in credit markets, in the pricing policies of banks in particular, amplify and propagate the standard effects of aggregate TFP shocks. Countercyclical price-cost margins make aggregate shocks have larger real effects than in a model that lacks this friction, and the variables of interest display more amplitude. Therefore, the friction introduced by borrower hold-up effects can be interpreted as an alternative to the financial accelerator in Bernanke, Gertler, and Gilchrist (BGG) (1998, 1999). While their accelerator originates in the demand side of the market for credit (it is caused by a friction related to the value of borrowers' collateral), our accelerator is related to the supply side of the market in the sense that deep habits lead to banks' pricing policies that are optimally countercyclical.

In Table 6 and Figures 2 and 3, we study the sensitivity of the dynamic properties of the model to changes in the duration of the hold-up effects, as measured by the parameter ρ_s. From this exercise, we can conclude that the dynamic properties of the model are monotonic in ρ_s. Figure 2 shows that as ρ_s increases, margins become more countercyclical. The degree of countercyclicality of margins observed for U.S. data can be reproduced in the presence of the estimated SCs and for a very low persistence of the borrower hold-up effect (i.e., for $\theta = 0.72$ and $\rho_s \to 0$).

The impulse responses to a 1% negative TFP shock in Figure 3 also show that countercyclical margins work as an amplifier of macroeconomic shocks, with the real effects of these shocks being larger the more sensitive margins are to GDP. Although the difference in the responses of variables among alternative values

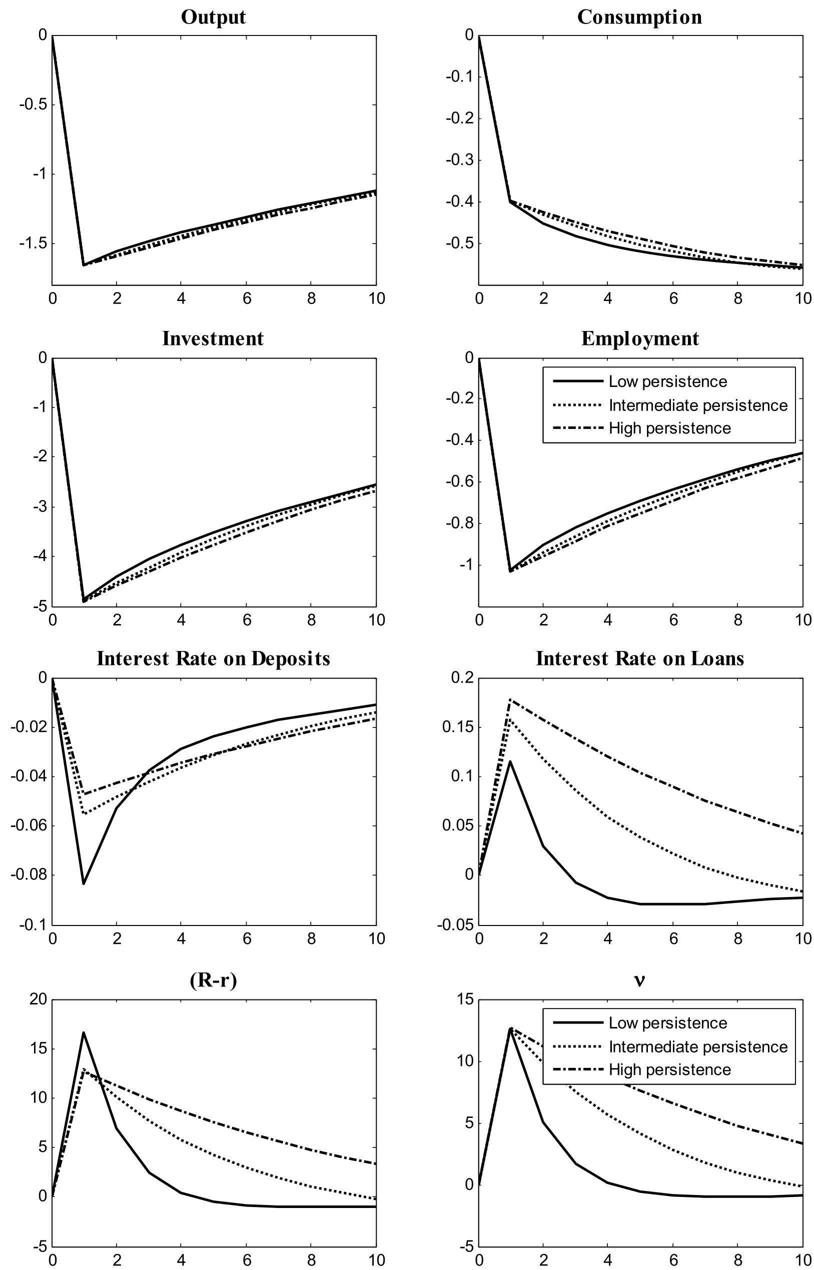

FIG. 3. Impulse Response Functions: Sensitivity to ρ_s.

NOTE: Values are percentage deviations from the steady state.

of the persistence parameter ρ_s is not quantitatively large, it is still qualitatively important.

The intuition for this result is as follows. As the persistence of firm–bank relationships (as measured by ρ_s) increases, the hold-up becomes stronger and SCs rise. Banks know that the customers that they are able to lure today will become "locked" in that relationship for several periods (for longer the larger ρ_s). Therefore, they face stronger incentives to change margins after an aggregate shock, and the resulting change in the cost of credit is larger. Consequently, the responses of consumption, investment, employment, and output are all increasing in ρ_s.

All results are qualitatively robust to the choice of parameter values in the specific sense that $\theta > 0$ always allows us to reproduce the countercyclicality of margins observed in the data and that countercyclical margins always act as a financial accelerator that amplifies and propagates the effects of aggregate shocks (i.e., it is always the case that in the simulated economies macroeconomic variables are more volatile than with constant margins). In Tables A1 and A2 of the Appendix we present consistent results obtained for several values of θ and η. Notice that the degree of countercyclicality falls as θ rises. We would initially expect more strongly cyclical margins as the size of the friction increases. However, it is also evident from the results in Table A1 that the level of margins themselves rises with θ, and it is a known feature of models with imperfect competition that the countercyclicality of margins is decreasing in their level. This is also evident from the sensitivity analysis on η. As η rises, margins fall at the same time that they become increasingly countercyclical (see Table A2). Results for alternative parametrizations of the model are available from the authors upon request.

4. CONCLUSIONS

In this paper, we study the macroeconomic consequences of endogenously cyclical price-cost margins in banking. In particular, we assess their "financial accelerator" role as a propagation mechanism of macroeconomic shocks. Building on recent empirical evidence, we model this cyclicality as arising from a borrower hold-up effect and borrower SCs by developing an application of the deep habits model of RSGU to financial markets.

Our model allows us to reproduce two important features of business cycles that models that lack this friction are unable to address: the countercyclicality of credit margins and the fact that their volatility exceeds that of output.

Furthermore, in the simulated economies, aggregate TFP shocks trigger a change in the cost of credit, and this gives rise to two main results. First, aggregate TFP shocks have larger real effects the stronger the friction implied by borrower SCs. Second, output, investment, and employment all become more volatile than in a standard model with constant margins in credit markets. These results allow us to conclude that countercyclical price-cost margins act as a financial accelerator in the U.S. economy.

Our results have interesting policy implications since they indicate that SCs in banking and borrower hold-up provide additional grounds for stabilization policy in economies where the countercyclicality of margins is stronger and where the share of bank credit in total external financing is larger. Further research should assess the optimality of those policies.

An interesting extension of our research would be to endogenize borrower hold-up effects through the existence of informational asymmetries between borrowers and lenders, and information monopolies gained by incumbent banks over their rivals.

APPENDIX

TABLE A1

Dynamic Properties of the Simulated Economies: Sensitivity to θ

	Data	$\theta = 0.6$	$\theta = 0.65$	$\theta = 0.72$	$\theta = 0.75$	$\theta = 0.8$	$\theta = 0.85$
Relative standard deviations $\sigma(x)/\sigma(Y)$							
C	0.8	0.2804	0.2756	0.2639	0.2557	0.2344	0.209
I	2.61	2.9033	2.9219	2.9684	3.0028	3.1045	3.3615
h	0.88	0.6028	0.6081	0.6217	0.6318	0.6624	0.7406
w	0.9514	0.4067	0.4022	0.391	0.3829	0.3595	0.3092
R	0.5596	0.0274	0.046	0.0937	0.1291	0.2335	0.4888
r	0.7721	0.0258	0.0279	0.0332	0.0373	0.0504	0.09
$(R-r)$	2.0925	4.3435	5.452	7.814	9.3621	13.6756	29.4714
A	0.68	0.6174	0.614	0.6054	0.599	0.5802	0.5338
Autocorrelation coefficients $\rho(x_t, x_{t-1})$							
Y	0.8651	0.6788	0.6781	0.6764	0.6749	0.6701	0.6536
C	0.8206	0.7298	0.7357	0.7521	0.7658	0.8131	0.9296
I	0.9275	0.673	0.6716	0.6679	0.665	0.6557	0.6278
h	0.4321	0.6718	0.6701	0.6656	0.6622	0.6516	0.6208
w	–	0.7021	0.7044	0.7107	0.7159	0.7338	0.7976
R	0.95	0.6221	0.6129	0.6084	0.6061	0.5984	0.5728
r	0.9462	0.6624	0.6577	0.6475	0.641	0.6248	0.5897
$(R-r)$	0.8118	0.6152	0.6133	0.6084	0.6043	0.5889	0.4517
A	–	0.6782	0.6782	0.6782	0.6782	0.6782	0.6782
Correlation with output $\rho(x, Y)$							
C	0.8734	0.9529	0.9472	0.93	0.9142	0.8493	0.5301
I	0.9245	0.9961	0.9959	0.9953	0.9949	0.9935	0.9892
h	0.5494	0.9931	0.9927	0.9916	0.9907	0.988	0.9804
w	0.602	0.9852	0.9836	0.9791	0.9751	0.9595	0.8841
R	0.2185	−0.7176	−0.7864	−0.8299	−0.8395	−0.8479	−0.847
r	0.3526	0.9758	0.9731	0.9668	0.9626	0.9521	0.9344
$(R-r)$	−0.2002	−0.8758	−0.874	−0.8691	−0.865	−0.8494	−0.7248
A	0.96	0.6698	0.6703	0.6715	0.6724	0.6751	0.6812
Steady-state values							
$(R-r)$	0.01	0.012	0.0136	0.0168	0.0187	0.0232	0.0306
$\frac{(R-r)L}{Y}$	–	0.0014	0.0016	0.002	0.0022	0.0027	0.0036

Notes: Data moments based on quarterly data for 1947–2008. GDP, personal consumption expenditures, gross private domestic investment and wages and salary accruals in billions of chained 2000 dollars from the Bureau of Economic Analysis. Number of hours, index 2002 = 100, from the Bureau of Labor Statistics. $(R-r)$ calculated as the difference between lending and deposit rates from the International Financial Statistics of the IMF. Simulations performed for a value of $\eta = 190$. Moments calculated based on 100 simulations of length 150 each.

TABLE A2

DYNAMIC PROPERTIES OF THE SIMULATED ECONOMIES: SENSITIVITY TO η

	Data	$\eta = 130$	$\eta = 150$	$\eta = 170$	$\eta = 190$	$\eta = 210$	$\eta = 230$	$\eta = 250$
Relative standard deviations $\sigma(x)/\sigma(Y)$								
C	0.8	0.2521	0.257	0.2609	0.2639	0.2665	0.2686	0.2704
I	2.61	3.0261	3.0015	2.9829	2.9684	2.9568	2.9473	2.9394
h	0.88	0.6369	0.6304	0.6255	0.6217	0.6186	0.6161	0.614
w	0.9514	0.379	0.3841	0.388	0.391	0.3935	0.3956	0.3973
R	0.5596	0.1478	0.1248	0.1074	0.0937	0.0827	0.0737	0.0662
r	0.7721	0.0396	0.0368	0.0348	0.0332	0.0319	0.0309	0.0301
$(R-r)$	2.0925	7.9953	7.9176	7.8593	7.814	7.7779	7.7483	7.7236
A	0.68	0.5959	0.5999	0.603	0.6054	0.6073	0.6089	0.6102
Autocorrelation coefficients $\rho(x_t, x_{t-1})$								
Y	0.8651	0.6741	0.6751	0.6758	0.6764	0.6768	0.6771	0.6774
C	0.8206	0.7735	0.764	0.7572	0.7521	0.7481	0.745	0.7424
I	0.9275	0.6633	0.6653	0.6667	0.6679	0.6687	0.6695	0.67
h	0.4321	0.6603	0.6626	0.6643	0.6656	0.6667	0.6675	0.6682
w	–	0.7188	0.7153	0.7127	0.7107	0.7092	0.708	0.707
R	0.95	0.6049	0.6064	0.6075	0.6084	0.6091	0.6098	0.6104
r	0.9462	0.6378	0.6418	0.6449	0.6475	0.6497	0.6515	0.6531
$(R-r)$	0.8118	0.604	0.6059	0.6073	0.6084	0.6092	0.6099	0.6105
A	–	0.6782	0.6782	0.6782	0.6782	0.6782	0.6782	0.6782
Correlation with output $\rho(x, Y)$								
C	0.8734	0.9049	0.9164	0.9242	0.93	0.9343	0.9377	0.9404
I	0.9245	0.9946	0.9949	0.9952	0.9953	0.9955	0.9956	0.9957
h	0.5494	0.9902	0.9908	0.9912	0.9916	0.9918	0.9921	0.9922
w	0.602	0.9727	0.9756	0.9776	0.9791	0.9802	0.9811	0.9818
R	0.2185	−0.8423	−0.8387	−0.8345	−0.8299	−0.8249	−0.8194	−0.8135
r	0.3526	0.9604	0.963	0.9651	0.9668	0.9682	0.9694	0.9704
$(R-r)$	−0.2002	−0.8665	−0.8676	−0.8684	−0.8691	−0.8696	−0.87	−0.8704
A	0.96	0.6729	0.6723	0.6719	0.6715	0.6712	0.671	0.6708
Steady-state values								
$(R-r)$	0.01	0.0245	0.0213	0.0188	0.0168	0.0152	0.0139	0.0128
$\frac{(R-r)L}{Y}$	–	0.0029	0.0025	0.0022	0.002	0.0018	0.0016	0.0015

NOTES: Data moments based on quarterly data for 1947–2008. GDP, personal consumption expenditures, gross private domestic investment and wages and salary accruals in billions of chained 2000 dollars from the Bureau of Economic Analysis. Number of hours, index 2002 = 100, from the Bureau of Labor Statistics. $(R-r)$ calculated as the difference between lending and deposit rates from the International Financial Statistics of the IMF. Simulations performed for a value of $\theta = 0.72$. Moments calculated based on 100 simulations of length 150 each.

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