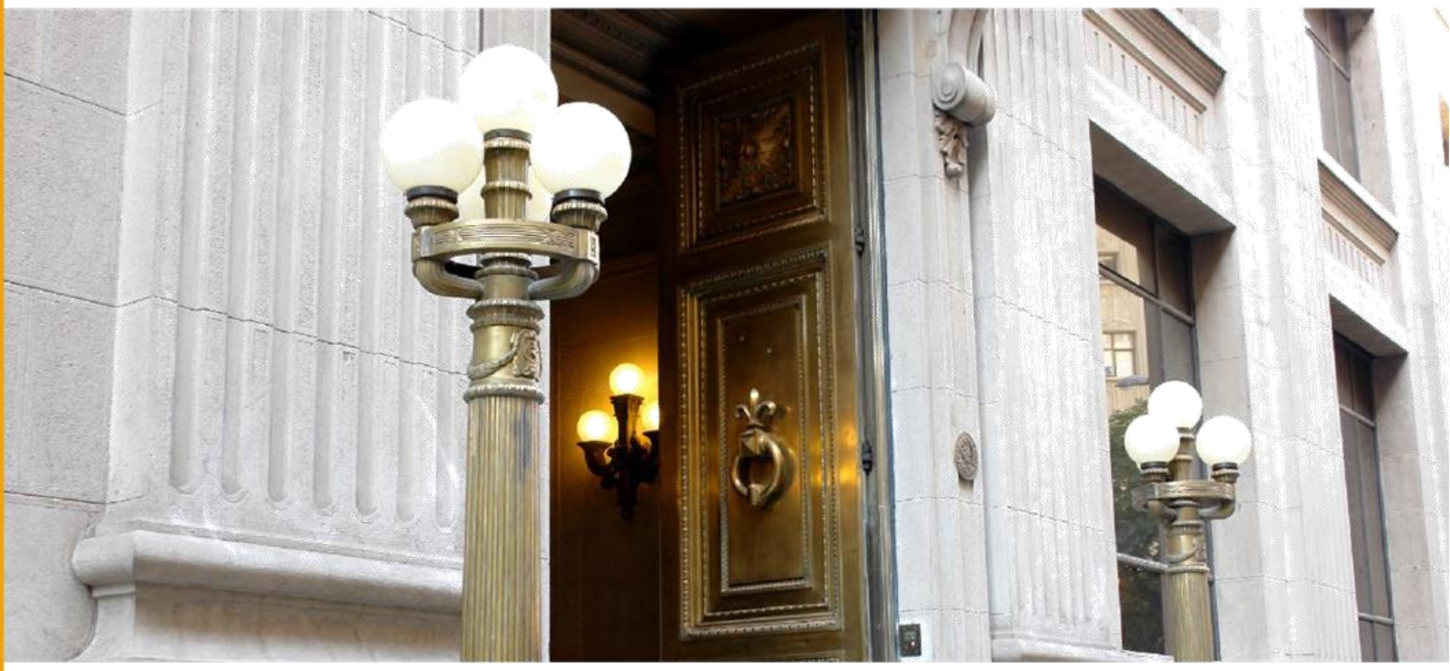
DOCUMENTOS DE TRABAJO

Relationship Lending: Characteristics and Real Effects

Miguel Acosta-Henao
Sangeeta Pratap
Manuel Taboada

N° 999 Noviembre 2023 (actualizado en enero 2024)
BANCO CENTRAL DE CHILE



Documentos de Trabajo del Banco Central de Chile
Working Papers of the Central Bank of Chile
Agustinas 1180, Santiago, Chile
Teléfono: (56-2) 3882475; Fax: (56-2) 38822311

Documento de Trabajo N° 999

Working Paper N° 999

Relationship Lending: Characteristics and Real Effects*

Miguel Acosta-Henao†
Central Bank of Chile

Sangeeta Pratap‡
Hunter College &
CUNY Graduate Center

Manuel Taboada§
Central Bank of Chile

Abstract

We evaluate the mechanisms behind relationship lending and its macroeconomic consequences. Loan and firm level data in Chile show that closer bank relationships give firms easier and cheaper access to credit. More productive firms select into relationships. We build and calibrate a dynamic model where firms choose their relationship status along with investment and borrowing. Borrowing in relationships allows for screening and monitoring, provides implicit guarantees to other creditors and substitutes for physical collateral. Counterfactual experiments indicate that extending the benefits of relationships results in an increase of 30 percent in output, capital and TFP.

Resumen

Evaluamos los mecanismos detrás de las relaciones crediticias entre firmas y bancos y sus consecuencias macroeconómicas. Datos de préstamos y firmas en Chile muestran que relaciones más cercanas con los bancos le dan a las firmas mayor y más barato acceso a créditos. Firmas más productivas se seleccionan a tener relaciones con bancos. Construimos y calibramos un modelo dinámico donde las firmas escogen tanto el estatus de su relación con el banco cómo su inversión y endeudamiento. Endeudarse dentro de una relación con el banco permite que haya filtración y monitoreo, provee garantías implícitas a otros prestamistas y sustituye el colateral físico. Experimentos contrafactuales indican que extender los beneficios de las relaciones entre firmas y bancos a todas las firmas resulta en un incremento de 30% en el PIB, el capital y la PTF.

*We are grateful to Eugenia Andreasen, Sofia Bauducco, Takeo Hoshi, Todd Keister, Miguel Faria-e-Castro, Alberto Martin, Juan Sanchez, Lucciano Villacorta, and seminar participants at the University of Birmingham, Fordham, CUNY Graduate Center, Kyoto University, University of Tokyo, Hitotsubashi Uni-versity, GRIPS, PUC Chile, Universidad de Chile, the Central Bank of Chile, Universidad de los Andes, Banco de la República, the May 2023 Midwest Macro Meetings and the 2023 SED Meetings for helpful comments. Part of this research was conducted while Pratap was visiting the University of Tokyo, whose hospitality and support are gratefully acknowledged, as is the financial support from the PSC-CUNY Re-search Award Program. The views expressed in this paper are those of the authors and do not necessarily represent the views of the Central Bank of Chile or its board members.

†E-mail: macosta@bcentral.cl

‡E-mail: spratap@hunter.cuny.edu

§E-mail: mtaboada@bcentral.cl

1 Introduction

Relationships, or interactions between borrowers and lenders are known to influence the terms of contracts and firms' access to credit.[1] The mechanisms behind these outcomes and more generally, the macroeconomic consequences of relationship lending are less well understood. In this paper, we explore the channels through which relationships influence loan contracts and the allocation of credit, and evaluate their impact on the aggregate economy.

We consider three salient characteristics of relationships. First, relationships could facilitate the screening and monitoring of borrowers. Second, relationships with banks may provide implicit guarantees to other creditors of the firm and third, relationships can potentially alter the need for physical collateral. We build a dynamic model of firm behavior which incorporates these mechanisms. Heterogeneous firms make investment and borrowing decisions under uncertainty, and simultaneously choose whether to borrow in a relationship or in an arms-length transaction. Debt contracts are characterized by monitoring, which influences the probability of default and interest rates. Firms also face working capital constraints which limit the amount they can borrow from suppliers and physical collateral constraints on bank debt. The extent of monitoring and the strength of the constraints vary depending on the type of relationship.

We use a unique data set that encompasses the universe of loans from financial intermediaries in Chile from 2012 to 2019, merged with tax data on value added, labor and capital of firms to establish a set of empirical regularities about the properties of loan contracts in relationships, and the characteristics of firms that have closer bank relationships.[2] We calibrate the differences in debt contracts to match the differences between firms that borrow

[1]For reviews of these effects, see Degryse et al. (2009), Kysucky and Norden (2016) and Duqi et al. (2018).

[2]Disclaimer: This study was developed within the scope of the research agenda conducted by the Central Bank of Chile (CBC) in economic and financial affairs of its competence. The CBC has access to anonymized information from varius public and private entities, by virtue of collaboration agreements signed with these institutions.

within relationships and those that borrow in arms-length transactions from banks. This allows us to conduct counterfactual experiments to understand the role of each of the channels through which relationship lending affects firms' outcomes as well as the macroeconomic effects on output, investment and TFP in the aggregate. To the best of our knowledge, ours is the first work to do so.

We measure the closeness of a relationship between a firm and a bank based on the history of loans the firm has taken from the bank. Our measure also takes the age, frequency and timing of the loans into account.[3] We find that closer relationships result in larger loan amounts and lower interest rates. These results hold after controlling for observed and unobserved characteristics of firms and banks which could influence the formation of relationships. We also find that firms with bank relationships are larger in terms of output, capital and labor and have higher TFP. In the aggregate, about 31 percent of all firms in the economy can be characterized as having close bank relationships.

Calibrating the model to match the Chilean data reveals important differences between contracts within relationships and in arms-length transactions. Relationship lending is associated with a greater degree of monitoring and screening, which induces more productive firms to select into relationships, reduces the probability of default[4] and allows for larger loans at lower interest rates. Relationships also serve as implicit guarantees to suppliers, which allow firms to reduce their reliance on costly trade credit, implying a weaker working capital constraint.[5] This results in a more efficient use of inputs and a higher measured aggregate TFP. Finally relationships can also partially substitute for physical collateral, although the measured effects are small.

Our counterfactual experiments suggest that extending the benefits of relationship lend-

[3]We take these measures of relationship closeness from previous work (Acosta-Henao et al., 2023) and describe them in detail in the next section.

[4]Schoar (2012) documents that personal interactions between bank officers and debtors result in higher loan repayment rates. Puri et al. (2017) find that relationships reduce default rates in Germany.

[5]Petersen and Rajan (1994) find that firms with relationships need less trade credit.

ing to the remaining 70 percent of firms in the economy produces quantitatively important benefits. An increased ability to borrow, coupled with a looser working capital constraint allows firms to increase their capital stock, resulting in a 30 percent larger output in steady state. These benefits are driven by a combination of the increased monitoring in relationships which allows for larger amounts of borrowing, and the extension of the implicit guarantee to suppliers which relaxes the working capital constraint. In other words, relationships with banks are a valuable asset for firms which allow for a more efficient allocation of resources.

Related literature. An extensive empirical literature has documented the effects of relationship lending on debt contracts, notably loan amounts and interest rates.[6] Closer relationships between borrowers and lenders are associated with a greater availability of funds for firms (Petersen and Rajan, 1994; Cole, 1998; Elsas and Krahnen, 1998; Machauer and Weber, 2000) and lower interest rates (Berger and Udell, 1995; Degryse and Van Cayseele, 2000). Some of these benefits can be vitiated by bank monopoly power, or exclusive reliance on one or a few credit sources. Weinstein and Yafeh (1998) find that firms with a main bank in Japan have higher costs of capital and Machauer and Weber (2000) show that firms with only one bank relationship post more collateral. Santos and Winton (2008) find that firms with alternative sources of finance such as bond market access face lower interest rates from banks and Beatriz et al. (2018) document lower interest rates for firms with multi-bank relationships.[7]

The terms of debt contracts in relationships also vary over the business cycle and in response to monetary policy shocks. Acosta-Henao et al. (2023) find that relationships with banks insulate firms against fluctuations and changes in monetary policy. Similarly, Dempsey and Faria-e Castro (2022) find that high customer capital reduces the interest rate elasticity of loan demand and Hachem (2011) shows that the transmission of monetary policy

[6]For comprehensive reviews of the literature, see Degryse et al. (2009), Kysucky and Norden (2016) and Duqi et al. (2018).

[7]In contrast, Cahn et al. (2020) show that central bank liquidity injections associated with unconventional monetary policy are transmitted to single bank firms, rather than to multi-bank firms.

is vitiated by firm-bank relationships.

The effects of relationship lending on the real economy are less well understood. On one hand, Banerjee et al. (2021) and Beck et al. (2018) find that longer relationships are beneficial for firms in recessions and in times of financial stress. On the other hand, the phenomenon of evergreening (i.e. banks lending to firms that are more likely to default) in relationships and its role in creating "zombie firms" has also been well documented, in particular for Japan (see for example Hoshi 2006 and Caballero et al. 2008).[8] Caballero et al. (2008) find that zombie lending can crowd out lending to healthy firms, leading to lower sectoral output and TFP, and Faria-e-Castro et al. (2022) find that evergreening leads to negative aggregate effects on TFP due to credit misallocation.

Our results in context. Our paper makes two key contributions: First, given the broad data coverage and the long panel we can characterize both the types of firms that select into relationships and the effects of relationships on debt contracts, accounting for a rich set of firm and bank characteristics. These facts enable us to construct a model to unpack the black box of relationship lending, and to understand the mechanisms that generate the allocation and the cost of credit in relationships. Given these insights, our second contribution lies in the quantification of the aggregate real effects of relationship lending. To the best of our knowledge, this is the first paper to do so.

We expect the results of this exercise to have broader applicability beyond Chile. As one of the most financially developed emerging economies with a well functioning capital market, Chile also has a substantially smaller informal sector than other emerging economies (Medina and Schneider, 2018), ensuring that our data is more reliable and representative of aggregate

[8] Peek and Rosengren (2006) show that a Japanese firm's main bank is more likely to evergreen loans, especially if it is a member of the same business group as the firm. Steinkamp et al. (2021) document higher levels of evergreening in Europe in countries facing banking distress and in the Euro area, which are negatively related to growth. Faria-e-Castro et al. (2022) document that banks that own a larger share of a firm's debt in the U.S. provide distressed firms with relatively more credit at lower interest rates, resulting in evergreening. However, Favara et al. (2022) find that zombie firms are not a prominent feature of the U.S. economy and banks are more likely to break relationships with such firms.

activity.[9] On average, the total value added of the firms in our sample is 74 percent of GDP. Coverage improves in the more recent years of the sample, but it is never less than 60 percent of GDP.[10] We expect therefore that our results represent the aggregate economy, and the lessons from Chile are valuable for other economies.

The rest of the paper is organized as follows: In section 2, we describe our data and construct measures of relationships. We use these measures to document the characteristics of firms in relationships and estimate the effects of relationships on loan contracts. Section 3 describes the model and calibrates it to the data. In section 4 we present policy experiments to disentangle the effects of various aspects of relationship lending and quantify their effects. Given the importance of the monitoring function of relationship lending, in section 5 we explore some alternative specifications of monitoring. Section 6 concludes.

2 Empirical Analysis

In this section we document two salient features of relationship lending. First, firms with stronger bank relationships enjoy better credit contracts: notably lower interest rates and larger loan amounts. Second, larger and more productive firms tend to have closer relationships with banks.

We first describe our data and sample selection method. Then, based on our previous work (Acosta-Henao et al., 2023), we construct various measures to capture the closeness of the relationship between a firm and a bank. Controlling for a rich set of observed and unobserved firm and bank characteristics, firm, bank and time effects, and the degree of bank monopoly power in each firm-bank relationship, we use these measures to estimate how the state of a relationship affects the terms of debt contracts (i.e. loan amounts and loan interest

[9]The IMF Financial Development Index Database assigns an overall rating of 0.61 to Chile's financial institutions. For comparison, the score for the US is 0.88, for China 0.62 and for Mexico 0.47.

[10]Figure 5 in Appendix A illustrates the wide coverage of our sample.

rates).[11] We also estimate how the characteristics of firm-bank relationships correlate with firm-level characteristics, including TFP.

2.1 Data

2.1.1 Sample Selection and Descriptive Statistics

We merge five anonymized datasets to build our sample.[12] These are: 1) the credit registry database from the Chilean Financial Markets Commission, which has information on each borrower-lender interaction through a new loan, with data on each loan's interest rate, amount, and type, 2) firms' monthly tax declarations to the Chilean IRS, which contain information on sales, expenditures on intermediate goods and capital expenditures,[13] 3) labor records of each firm, reported to the Chilean IRS, documenting the number of workers and wages of each worker in the firm each period, 4) data on each firm's stock of domestic debt held by the financial system from the Chilean Financial Markets Commission combined with each firm's bond issuance data built at the Central Bank of Chile, 5) data on foreign capital flows built by the Central Bank of Chile which contains the external-debt stock of each firm. All data is at a monthly frequency.

We retain firms in the sample that report all variables of interest, including their 2-digit industry, and exclude financial intermediaries and public-administration firms. We perform basic consistency checks and drop firms with capital stock of less than 10,000 Chilean Pesos (or about 11 US dollars), negative nominal interest rates, interest rates greater than 70 percent, firms whose value added over the past 12 months is negative, and firms with a

[11]By monopoly power we mean the relative importance of each bank as a lender for a particular firm.

[12]Disclaimer: To secure the privacy of workers and firms, the CBC mandates that the development, extraction and publication of the results should not allow the identification, directly, indirectly, of natural or legal persons. Officials of the Central Bank of Chile processed the disaggregated data. All the analysis was implemented by the authors and did not involve not compromise the Chilean IRS or the Chilean Financial Markets Commission.

[13]Disclaimer: The information contained in the databases of the Chilean IRS is of tax nature originating in self-declarations of taxpayers presented to the Service; therefore, the veracity of the data is not the responsibility of the Service.

capital to output ratio or debt to sales ratio greater than 1,000.[14] Finally, we winsorize the sample and eliminate the bottom and top percentile of three specific ratios (capital to sales, worker to sales and intermediate goods to sales). Our final sample consists of 47,688 firms and 600,982 loans between April 2012 and September 2019.[15] Further details of sample selection and data definitions can be found in Appendix A.

Table 1 shows summary statistics for all variables of interest. The average loan size is 1,300 million CLP (roughly equivalent to 1.5 million USD), although the median is considerably smaller at about 71.76 million CLP (80,000 USD). The average real interest rate is about 8 percent. Firm sales average around 2200 million CLP (2.5 million USD), while the median firm has sales of about 76 million CLP (85,000 USD) per year. Our sample represents a wide variety of firms, as the large standard deviations of capital, number of workers, sales and value added reveal.[16]

Table 1: Descriptive Statistics

	Mean	Median	SD
Loan amount	1301.56	71.76	26205.48
Real interest rate	0.08	0.08	0.06
Capital stock	832.48	21.37	23086.67
Value added	681.99	29.77	15567.22
Sales	2211.43	76.19	33329.21
Intermediate goods	1529.44	38.72	21836.25
Wage bill	502.71	69.64	3380.83
Number of workers	20.2	1.5	174.16
Number of Firms	47,688		

Note: All variables (except interest rates) are in millions of 2020 CLP. The real interest rate is calculated by subtracting the previous one-year inflation rate from each nominal interest rate. Sales, value added (computed as sales less intermediate goods expenditures), expenditures on intermediate and the wage bill are sums of the last 12 months. Number of workers is the sum of the last 12 months divided by 12.

Table 2 breaks down loans by firm size, where the groups represent micro, small, medium,

[14] All USD equivalents are calculated using the average nominal exchange rate in November of 2022 of 900 pesos per dollar.

[15] We end the sample at September 2019, before the contraction caused by internal political unrest and the subsequent pandemic.

[16] For confidentiality reasons, we are prohibited from presenting the maximum or minimum, or top and bottom percentiles of any variable.

and large firms, respectively.[17] The table shows that while most firms are small or medium sized (more than 65 percent), most loans are taken by large firms (42 percent of the sample). The fourth column shows that, on average, the number of loans per micro and small firm is relatively similar but substantially smaller than that for medium and large firms. The last column shows that the average number of banks per firm follows a similar pattern. Medium and large sized firms have relationships with more banks than small and micro firms. Table 12 in Appendix B shows further heterogeneity in lending behavior across 2-digit industries.

Table 2: Descriptive Statistics by Firm Size

	Fraction of				
	Firms	Loans	Loan amt	Loans/firm	Banks/ firm
Micro	0.24	0.12	0.04	6.49	1.66
Small	0.42	0.21	0.03	6.21	1.53
Medium	0.21	0.25	0.05	15.1	2.18
Large	0.13	0.42	0.89	39.92	3.54
All	47,688	600,982†	334,945††	12.6	1.96

Note: Loan amounts are in 2020 CLP. Micro-enterprises are defined as those with yearly sales of up to 70,000 USD, small firms with sales of 70,000 - 1 million USD. Medium sized firms have sales of 1-4 million USD. Firms with sales over 4 million USD are large firms. †: Total number of loans. ††: Total loan amounts (billions of 2020 CLP).

2.1.2 Relationship Measures

We construct three measures of the closeness of relationships between firm i and bank j at time t, using the methodology we develop in Acosta-Henao et al. (2023). In what follows, we describe each type of measure briefly. Define

$$d1_t^{i,j} = \frac{t - t_1^{i,j} + 1}{T_t}$$

where $t_1^{i,j}$ is the time at which the first loan taken by firm i from bank j is observed in our

[17] These categories come from the Chilean tax office, where micro-enterprises are classified as those with yearly sales of up to 70,000 USD, and small firms with sales between 70,000 and 1 million USD. Medium sized firms are defined as those with yearly sales between 1 and 4 million USD. Firms with sales over 4 million USD are considered large firms.

sample and T_t is the time elapsed since the beginning of the sample period. Therefore, $d1_t^{i,j}$ is simply the duration of a relationship normalized to deal with left censoring, a measure commonly used in the literature (see Berger and Udell 1995, Petersen and Rajan 1994 and Beatriz et al. 2018, among others).

To account for the frequency of interaction, or the number of loans a firm has taken from a bank over the sample period, we define the number of loans to firm i from bank j up to time t by $l_t^{i,j}$. Thus, the second measure of closeness is defined as

$$d2_t^{i,j} = l_t^{i,j} d1_t^{i,j},$$

and interacts the duration of the relationship with the number of loans the firm took from the bank up to the current period t, capturing the fact that firms borrow more frequently from a particular bank with which they have a closer relationships.

Finally, we define a third measure of relationship closeness as

$$d3_t^{i,j} = \sum_{k=1}^{t} \frac{\iota_k^{i,j}}{t - t_k^{i,j} + 1}$$

where $\iota_k^{i,j}$ takes is equal to one if firm i takes a loan from bank j at time k, and zero otherwise. This measure differentiates between firms with similar duration and interaction measures by the age of the interactions, and is designed to capture the idea that more recent loans provide more current information about firms.

While these three measures are proxies of the closeness of a relationship between a firm and a bank each period of time, they do not account for how concentrated or important a particular bank relationship is to a firm. In other words, while a firm could have a close relationship with a bank in period t, that bank could be the only one that lends to the firm. This could lead to the hold-up problem documented in the literature (Petersen and Rajan, 1994). Indeed, as shown in Acosta-Henao et al. (2023), more concentrated relationships are associated with higher interest rates and smaller loan amounts for firms.

Therefore, for each of the three measures above, we control for a corresponding measure of relationship concentration in our estimations. We define them as

$$ck_t^{i,j} = \frac{dk_t^{i,j}}{\sum_j dk_t^{i,j}}$$

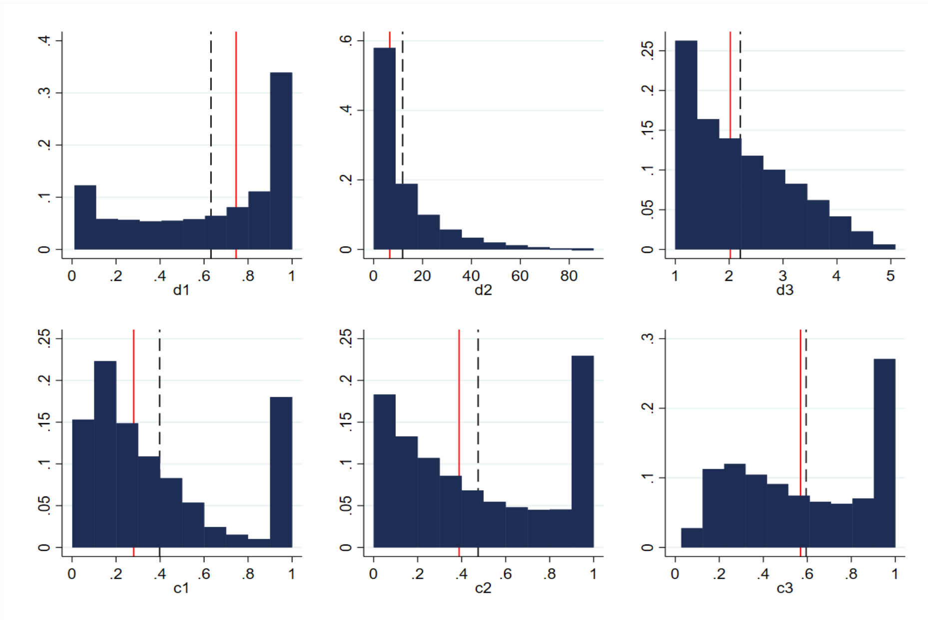
for $k = 1, 2, 3$.

These measures quantify the importance of the closeness measure between firm i and bank j, relative to the closeness of a relationship between firm i and all the banks from which it borrows. We refer to this measure of concentration as bank monopoly power. If a firm only borrows from one bank, $ck_t^{i,j}$ takes the value of one, indicating a completely concentrated relationship.[18]

Figure 1 shows the distribution of the relationship measures, along with their means and medians. The top panel shows the distribution of the closeness measures. About 30 percent of firms took their first loan during the first year of the sample as the spike at $d1 = 1$ indicates. However, weighting this by the number of loans ($d2$), or the timing of the loans ($d3$) reveals a more dispersed distribution. Similarly, the bottom panel shows that more than 20 percent of firms borrow from a single bank, although the average magnitude of the concentration measures is between 0.4 and 0.6 depending on the measure.

[18]While we follow the majority of the literature in quantifying firm-bank relationships based on their borrowing history, this is by no means the only criterion for measuring the closeness of a firm-bank relationship. Fisman et al. (2017) use measures of cultural proximity between borrowers and bank loan offices and Puri et al. (2017) look at the scope of relationships, namely the number of products a firm buys from a bank. Some studies use the geographical distance between the firm and the bank (Degryse and Ongena, 2005) or the proximity of a firm to a bank with a self reported business model based on relationship banking (Beck et al., 2018) as a proxy for closeness in relationships. Data to compute these measures is typically hard to find, so we follow the literature in using chronological measures as a proxy.

Figure 1: Distribution of Closeness and Concentration Measures



Note: Each panel shows the histogram of the corresponding closeness and concentration measures. The solid red line corresponds to the median and the dashed black line to the mean.

2.2 Relationship Lending and Terms of Credit

To study the effects of firm-bank relationships on the terms of loan contracts we estimate the following specification

$$Z_t^{i,j} = \alpha_i + \gamma_j + \lambda_t + \beta_1 dk_t^{i,j} + \beta_2 ck_t^{i,j} + \Gamma_1 X_t^i + \Gamma_2 X_t^j + \epsilon_t^{i,j} \tag{1}$$

for each closeness measure, i.e. $k = 1, 2, 3$. $Z_t^{i,j}$ denotes the outcome variable of interest which is either the (log) loan amount or the interest rate on a loan that firm i takes from bank j at time t. We focus on the coefficient β_1, which captures the marginal effects of closer relationships for each of the three measures. For each measure of closeness, we control for its corresponding measure of relationship concentration. X_t^i and X_t^j denote time varying characteristics of firms and banks respectively and include sales, leverage, capital stock and labor for firms, and sales and leverage for banks.[19] We include firm and bank fixed effects,

[19]Data definitions and details of the construction of each variable are provided in Appendix A.

as well as a time trend, to account for unobserved heterogeneity.

Table 3 shows the results of the estimation with loan amounts (in logs) as the dependent variable. The first three columns of the table correspond to estimates for Equation 1 for each closeness measure. Accounting for fixed and time-varying firm and bank characteristics, a stronger relationship between banks and firms is associated with larger loans. We observe the strongest effect in the measure that takes both the frequency and timing of previous loans into account, $d3_t^{i,j}$. A unit increase in this measure, all else equal, increases loan amounts by about 3 percent.[20]

Table 3: Relationships and Loan Size

	Loan Amount (in logs)				
d1	0.0094				
	(0.40)				
d2		0.0046***			
		(9.55)			
d3			0.0295**	0.2220***	0.2263***
			(2.39)	(13.80)	(29.61)
Firm Controls	Yes	Yes	Yes	No	No
Bank Controls	Yes	Yes	Yes	Yes	No
Concentration	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	No
Firm FE	Yes	Yes	Yes	No	No
Bank FE	Yes	Yes	Yes	Yes	No
Firm-Month FE	No	No	No	Yes	Yes
Bank-Month FE	No	No	No	No	Yes
N	588,639	588,639	588,639	251,733	251,618
R^2	0.716	0.716	0.716	0.782	0.784

Note: T Statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Loan amounts are in 2020 CLP. Standard errors are clustered using the combinations of the fixed effects. Firm and bank variables are measured in logs. Concentration refers to the measures of bank monopoly power discussed earlier.

Table 4 shows the analogous results for interest rates. As before, the cost of credit is lower for close relationships, with largest effects for $d3_t^{i,j}$. A unit increase in $d3$ lowers the interest rate by almost 50 basis points.

[20] Recall that for a semi log specification, the marginal effect of a unit change in an independent variable is $e^{\beta} - 1$ where β is the coefficient on that variable.

Table 4: Relationships and the Cost of Credit

	Real Interest Rate				
d1	−0.0041				
	(-1.33)				
d2		−0.0008**			
		(−2.40)			
d3			−0.0049***	−0.0035***	−0.0035***
			(−9.51)	(−3.96)	(−14.75)
Firm Controls	Yes	Yes	Yes	No	No
Bank Controls	Yes	Yes	Yes	Yes	No
Concentration	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	No	No
Firm FE	Yes	Yes	Yes	No	No
Bank FE	Yes	Yes	Yes	Yes	No
Firm-Month FE	No	No	No	Yes	Yes
Bank-Month FE	No	No	No	No	Yes
N	588,639	588,639	588,639	251,733	251,618
R^2	0.669	0.670	0.673	0.747	0.751

Note: T-statistics in parentheses. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered using the combinations of the fixed effects. Firm and bank variables are measured in logs. Concentration refers to the measures of bank monopoly power discussed earlier.

Even though we control for firm fixed effects as well as time varying firm characteristics in our estimations, one concern with our estimates is that of bias due to selection into relationships. It is possible that higher quality firms simultaneously choose to be in relationships and procure better terms of credit or that banks select directly what type of firms they develop a relationship with, potentially biasing our estimate of β_1. To deal with those concerns, we follow Khwaja and Mian (2008) and estimate an additional specification with time varying firm effects, and show the results for for $d3_t^{i,j}$ in the fourth column of Tables 3 and 4.[21] Moreover, we also follow Amiti and Weinstein (2018) and estimate a specification with both time varying firm effects and time varying bank effects.[22] The results for $d3_t^{i,j}$ are shown in the last column of Tables 3 and 4 respectively. The results with these two

[21]While this specification is based on Khwaja and Mian (2008), it is not quite the same. A full implementation of their framework would also require an exogenous shock to the bank which also affects firms differentially according to their exposure to the shock.

[22]The framework in Amiti and Weinstein (2018) does not require identifying an exogenous shock to the bank as in Khwaja and Mian (2008).

additional specifications reveal that the effects of relationships on the terms of contracts are robust to the inclusion of time varying firm and bank heterogeneity.[23] A shortcoming of these methodologies is that it requires firms to have relationships with more than one bank and therefore shrinks our sample by more than half. Our results indicate that even if on average better firms end up with closer bank relationships, within this group, firms with closer relationships get better terms of credit.

Tables 13 and 14 in Appendix B estimate the effects of relationships without any time varying controls, and find the effects of concentration to be strongly negative. However these effects are rendered insignificant, or their signs reversed as we account for firm characteristics in Tables 15 and 16, indicating that these negative effects are, at least in part, explained by the characteristics of firms that have relationships with fewer banks. The latter two tables also show that the effects of relationships on loan contracts are comparable to those of physical capital.

It is important therefore to study the characteristics of firms that select into relationships to understand the macroeconomic consequences of relationship lending. We now turn to documenting these characteristics.

2.3 Relationship Lending and Firm Characteristics

Table 5 presents correlations between firm characteristics and the measures of closeness. The former are averaged across time for each firm and the latter are time-averaged maximums across banks for each firm. To estimate firms' TFP we use a simple Cobb Douglas specification following the methodology of Aguirre et al. (2022). This methodology is robust to the presence of financial frictions, which are expected in an economy where relationships act as collateral.[24]

As Table 5 shows, firms with closer bank relationships are older and larger in terms

[23]Results for the other measures of closeness are very similar and available on request.

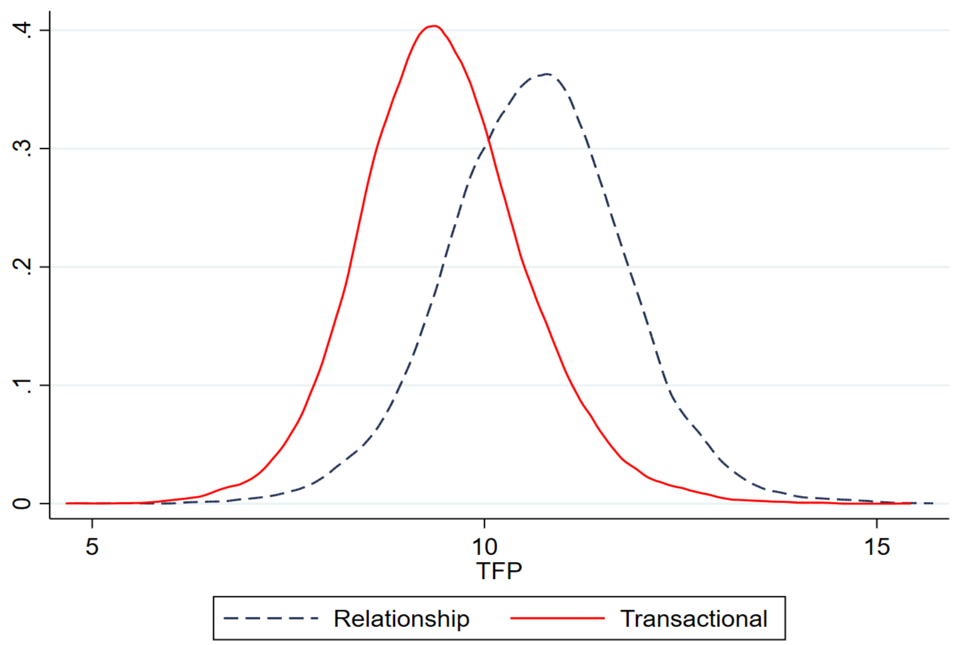
[24]We describe the production function estimation in greater detail in Appendix C.

Table 5: Relationships and Firm Characteristics - Correlations

	d1	d2	d3
Sales	0.42	0.60	0.65
Value Added	0.37	0.55	0.60
Labor	0.25	0.35	0.36
Capital	0.30	0.33	0.30
Value Added/Worker	0.26	0.42	0.50
Capital/Worker	0.17	0.12	0.08
Firm Age	0.37	0.33	0.22
TFP	0.25	0.45	0.55

Note: All firm characteristics are are in logs. The cross correlations are taken at the cross-sectional level after averaging for each firm across all years.

Figure 2: TFP Distribution



Note: The figure displays Kernel density of the log of TFP estimated using Aguirre et al. (2022) for transnactional (solid red) and relationship firms (dashed blue).

of sales, value added, labor, and capital stock.[25] These firms are also more productive as measured by value added per worker and TFP. The largest correlation is with our most comprehensive relationship measure $d3$. Figure 2 shows kernel densities of TFP for rela-

[25] The correlations are robust to alternative TFP estimation methods based on Ackerberg et al. (2015), Levinsohn and Petrin (2003), and Olley and Pakes (1996).

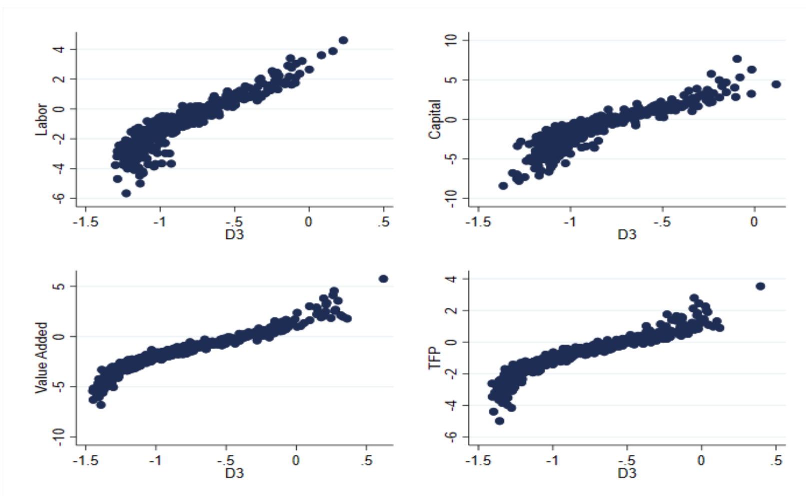
tionship lending firms, defined as firms with $d3$ greater than the average across firms, and transactional firms, illustrating that more productive firms tend to select into relationships.

To isolate the possible effects of any underlying time trend on these correlations, we isolate the fixed component of each variable $\hat{\eta}_i$ where

$$W_t^i = \eta_i + \lambda_t + \epsilon_t^i \tag{2}$$

for $W = \{d3, Labor, Capital, VA, TFP\}$. We regress the estimates of the fixed effect of each firm variable against the fixed effect of $d3$.

Figure 3: Fixed effects - Relationship Lending ($d3$) vs Firm Characteristics



Note: The figure displays scatters plot of d3, defined in the main text, with the respective firm characteristic. Each variable corresponds to the firm level fixed effect $\hat{\eta}_i$ from Equation 2. Each one of the 500 dots represents the average of approximately 80 firms.

Figure 3 shows the scatter plots from this exercise.[26] The positive relationship between the closeness of a relationship and firm size and productivity still holds. Table 6 shows that the same pattern is true for the other measures of relationships as well.

Closer firm-bank relationships do not therefore seem to be associated with unsuccessful

[26]To comply with the confidentiality agreements, each dot in the scatter plot represents an average of 80 points in its neighborhood.

Table 6: Relationships and Firm Characteristics: Fixed Effects

	Labor			Value Added		
$d1$	1.305***			2.205***		
	(58.67)			(81.63)		
$d2$		0.0408***			0.0738***	
		(61.75)			(97.38)	
$d3$			0.801***			1.627***
			(70.99)			(133.56)
N	35414	35414	35414	35414	35414	35414
R^2	0.089	0.104	0.143	0.158	0.213	0.367

	Capital			TFP		
$d1$	2.152***			0.952***		
	(63.52)			(50.86)		
$d2$		0.0626***			0.0362***	
		(62.30)			(71.14)	
$d3$			1.081***			0.940***
			(62.16)			(121.84)
N	35414	35414	35414	35414	35414	35414
R^2	0.102	0.104	0.110	0.069	0.120	0.286

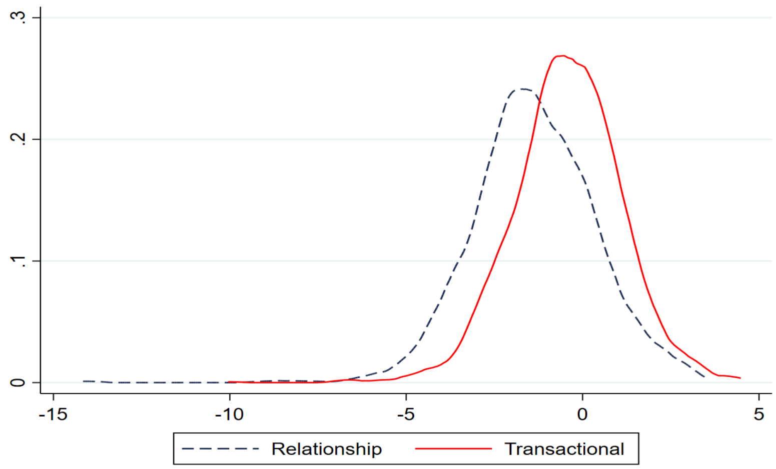
Note: The dependent and independent variables corresponds to the firm level fixed effect $\hat{\eta}_i$ from Equation 2.

firms, suggesting that the practice of "evergreening", or renewing loans for unproductive firms (that are more likely to default) in long term relationships with banks leading to the creation of "zombie" firms, does not seem to be a systematic issue in Chile. Firms in relationships not only are on average more productive but also less likely to have non-performing loans, a proxy of debt default, as shown in Figure 4.

Taken together our evidence points to the following facts: 1) Firms with closer relationships with banks get better contracts in terms of larger loan amounts and lower interest rates. These effects are the strongest for firms with multiple and more recent loans from the same lender over time. 2) Larger and more productive firms have closer bank relationships.

We use these findings to build and discipline our model in the next section. Firms make production, investment and borrowing decisions jointly with the decision to borrow in relationships or not. The properties of the debt contracts are such that more productive and

Figure 4: Non-Performing Loans to Sales Distribution



Note: The figure displays the Kernel density of the log of non-performing loans to sales ratio, for transactional (solid red) and relationship firms (dashed blue).

larger firms select into relationships, which further reinforce their ability to invest and use variable inputs efficiently. Calibrating this model to match the characteristics of firms that borrow in relationships relative to transactional borrowers allows us to conduct counterfactual exercises to evaluate the macroeconomic effects of relationships, and to understand which aspects of relationships are more important than others.

3 The Model

We build a dynamic partial equilibrium model of heterogeneous firms to study the implications of relationship lending.[27] Infinitely lived firms make investment and borrowing decisions each period to maximize the sum of their discounted stream of dividends. They also decide whether to borrow from a bank with whom they have a previous relationship or start afresh with a new bank.

As our empirical results indicate, debt contracts and firm outcomes in relationships are very different from those in arms length transactions. Our modeling strategy, accordingly,

[27] The partial equilibrium feature does not imply any significant loss of generality in a small open economy where we assume an infinitely elastic supply of funds to banks at the risk free rate.

allows for variations in contracts in three dimensions. First, we allow for differences in the working capital constraint for the purchase of intermediate goods. If relationships indeed provide an implicit guarantee to other creditors of a firm, we would expect this constraint to be weaker for firms that borrow within relationships. Second, we allow the physical collateral constraint to vary across contracts to allow for the possibility that relationships can play the same role as collateral. Finally, to capture variations in screening and monitoring, we allow the fraction of firm assets that the bank is able to repossess in case of default to vary by relationship status. As the model specifies below, a larger fraction both reduces the probability of default and ensures that more productive firms select into the contract, serving the purposes of monitoring and screening.

3.1 The Environment

Consider an infinitely lived firm that uses a production technology to produce output y_t using capital k_t and labor n_t at time t which can be represented as

$$y_t = z_t f(k_t.n_t) \tag{3}$$

where z_t is the current realization of an idiosyncratic productivity shock.

A fraction $\phi(d_t)$ of the wage bill is financed by trade credit at an interest rate $i > \rho$, the risk free rate. The variable d_t is binary and takes the value 1 if the current loan was taken from a lender with whom the firm has a previous relationship and 0 if it is an arm's length transaction.[28] As documented by Petersen and Rajan (1994), we would expect $\phi(0) > \phi(1)$, that is, firms with relationships rely less on expensive trade credit.

[28] For simplicity we abstract from the variations in debt contracts arising from the degree of closeness of a relationship.

The firm's gross asset position at time t is defined as

$$\hat{\Omega}(k_t, d_t, z_t) = \max_{n_t} y_t - (1 + \phi(d_t)i)w_t n_t + (1 - \delta)k_t \tag{4}$$

where w is the wage rate and δ is the depreciation rate of capital.[29]

The firm's current liabilities are given by b_t. If a firm is unable to repay its debt, the bank is able to repossess a fraction $\lambda(d_t)$ of its gross assets. This fraction varies by relationship status, and is a parsimonious way of capturing an important issue. The literature has emphasized the monitoring and the screening function of relationship lending (see for example, Boot and Thakor 2000, Hauswald and Marquez 2000, Puri et al. 2017, Agarwal and Hauswald 2021). These are costly technologies which produce private information for banks and allow them to assess credit risk accurately. Our empirical exercises suggests that these costs are not passed on as higher interest rates to borrowers. It seems reasonable to believe that the bank recoups these costs in some way, which we model here as a higher fraction of firm assets in case of non-repayment.[30] If $\lambda(1) > \lambda(0)$, this modeling strategy delivers a lower default probability and lower interest rates for relationship firms, both features that are observed in the data.[31] It also ensures that higher productivity firms select into relationships, as we describe in the next subsection.

It follows then that the firm's net asset position can be defined as

$$\Omega(k_t, z_t, b_t, d_t) = \max\{\hat{\Omega}(k_t, d_t, z_t) - b_t, (1 - \lambda(d_t))\hat{\Omega}(k_t, d_t, z_t)\} \tag{5}$$

The terms of a debt contract $(R_{t+1}, d_{t+1}, b_{t+1})$ are determined by a zero profit condition for banks. Let z^* denote the value of the idiosyncratic shock at which firms are indifferent

[29] Note that the total cost of labor is $(1 - \phi(d_t))w_t n_t + \phi(d_t)(1 + i)w_t n_t = (1 + \phi(d_t)i)w_t n_t$.

[30] In Section 5, we explore alternative forms of monitoring costs.

[31] Heitz et al. (2023) show that the bank loans in the construction industry are larger and carry lower interest rates, if they are accompanied by on-site monitoring of construction projects.

between repaying their debt and defaulting. In other words

$$\hat{\Omega}(k_{t+1}, d_{t+1}, z^*) - b_{t+1} = \hat{\Omega}(k_{t+1}, d_{t+1}, z^*)(1 - \lambda(d_{t+1}))$$

Then a zero profit condition for banks that can access funds at a risk free rate ρ, implies that the contractual interest rate R_{t+1} must satisfy the following equation:

$$\begin{aligned} \int_{z^*}^{\infty} b_{t+1} dF(z_{t+1}|z_t) + \int_{-\infty}^{z^*} \lambda(d_{t+1})\hat{\Omega}(k_{t+1}, d_{t+1}, z_{t+1}) dF(z_{t+1}|z_t) \\ = (1+\rho)\frac{b_{t+1}}{R_{t+1}} \end{aligned} \tag{6}$$

The first term in Equation 6 is the expected return to the bank in case of full repayment and the second term is the expected return in case the firm cannot pay its debt in full. The sum of these must equal the opportunity costs of funds for the bank, which we assume has access to an elastic supply of funds at the risk free rate ρ.

Finally a collateral constraint limits the fraction of new debt that needs to be collateralized. Hence

$$\psi(d_{t+1})b_{t+1} \leq k_{t+1} \tag{7}$$

If $\psi(0) > \psi(1)$, relationships require a smaller amount of physical collateral.

We can therefore define the firm's problem as

$$\max_{(k_{t+1}, b_{t+1}, d_{t+1})_0^\infty} E_0 \sum_{t=0}^{\infty} \left(\frac{1}{1+\iota}\right)^t \left(\Omega(k_t, z_t, b_t, d_t) - k_{t+1} + \frac{b_{t+1}}{R_{t+1}}\right) \tag{8}$$

subject to

$$\Omega(k_t, z_t, b_t, d_t) - k_{t+1} + \frac{b_{t+1}}{R_{t+1}} \geq 0. \tag{9}$$

and the constraints described in Equations 6 and 7. Equation 9 is a dividend constraint which limits the amount of equity a firm can issue and ι is the firm's discount rate.

The timing of events is as follows: At the beginning of period t, given their capital stock k_t, debt b_t and relationship lending status d_t, the firm observes its idiosyncratic shock z_t. It makes production decisions n_t and default decisions, which determine the value of its net assets $\Omega(k_t, z_t, b_t, d_t)$. The firm then makes its investment, borrowing and relationship decisions, subject to the constraints described above.

3.2 Solution

3.2.1 Functional Forms

We assume a Cobb Douglas production technology with

$$y_t = z_t k_t^\alpha n_t^\gamma$$

and decreasing returns to scale ($\alpha + \gamma < 1$). The idiosyncratic productivity shock z_t follows an AR(1) process with

$$\log z_{t+1} = \rho_z \log z_t + \epsilon_{t+1}$$

where $0 < |\rho_z| < 1$ and $\epsilon \sim N(0, \sigma^2)$ is a white noise shock.

The firm's choice of labor, n_t^* can be derived from its static first order condition

$$\max_{n_t^*} z_t k_t^\alpha n_t^\gamma - (1 + \phi(d_t) i) w_t n_t$$

and

$$n_t^* = \left(\frac{\gamma z_t k_t^\alpha}{(1 + \phi(d_t) i) w_t} \right)^{\frac{1}{1-\gamma}} \tag{10}$$

Note that the working capital constraint $\phi(d_t)$ drives a wedge between the marginal product of labor and the wage, leading to a sub-optimal allocation of labor. This wedge is larger for arms length relationships if $\phi(0) > \phi(1)$.

We can therefore express the firm's gross and net asset position respectively as

$$\hat{\Omega}(k_t, d_t, z_t) = (1-\gamma)\left(\frac{\gamma}{(1+\phi(d_t)i)w_t}\right)^{\frac{\gamma}{1-\gamma}} (z_t k_t^{\alpha})^{\frac{1}{1-\gamma}} + (1-\delta)k_t$$

and

$$\Omega(k_t, d_t, z_t, b_t) = \max\left(\hat{\Omega}(k_t, d_t, z_t) - b_t(d_t), (1-\lambda(d_t))\hat{\Omega}(k_t, d_t, z_t)\right)$$

The firm repays its debt if the realization of the shock $z_t \geq z^*$, where the cutoff value z^* is defined as

$$z^*(k_t, b_t, d_t) = \frac{(b_t/\lambda(d_t) - (1-\delta)k_t)^{1-\gamma}((1+\phi(d_t)i)w_t)^{\gamma}}{(1-\gamma)^{1-\gamma}\gamma^{\gamma}k_t^{\alpha}} \tag{11}$$

Finally we define the contractual interest rate from the zero profit condition of banks as

$$R(k_t, b_t, d_t, z_t) = \frac{(1+\rho)b_t}{\int_{z^*}^{\infty} b_t dF(z_t|z_{t-1})dz_t + \int_0^{z^*} \lambda(d_t)\hat{\Omega}(k_t, d_t, z_t)dF(z_t|z_{t-1})dz_t} \tag{12}$$

If $\lambda(1) > \lambda(0)$ and $\phi(1) < \phi(0)$, Equation 11 implies that the cutoff z^* is smaller for firms who choose to borrow in relationships for a given level of capital and debt. In other words, all else equal, firms in relationships have a higher probability of repaying their debt, as documented by Schoar (2012) in an experimental context and by Puri et al. (2017) for German firms. On the other hand, given the persistence of the idiosyncratic shock, firms with a low realization of z would, all else equal, have a lower probability of attaining the cutoff level z^* next period. Given diminishing returns, lower productivity firms would therefore select into arms length transactions to limit downside risk, as observed in the data.

The model is solved by formulating the firm's problem in recursive form and value function iteration. Further details of the solution and aggregation are given in Appendix D.

3.2.2 Calibration

Since the decision to be in a relationship with a bank is a binary choice in our model, we divide our sample into firms that borrow within relationships and those that do not. We define $d3_t^i$ for a firm as the average $d3_t^{i,j}$ across all banks and compare it to the cross sectional mean of the sample, $D3$. Firms with a value of $d3_t^i$ higher than $D3$ for 50 percent or more of the sample are classified as relationship firms. Based on this definition, 31 percent of all firms are categorized as relationship borrowers.

Table 7: Relationship and Transactional Borrowers

	Sales	Value Added	Loan Amount	Interest Rate	TFP	No. of Workers	Capital Stock
Transactional lending (T)	348.64	132.27	240.14	0.09	11,159	4.45	310.60
Relationship lending (R)	6,426.42	1925.85	3,703.25	0.05	29,436.8	55.85	2,013.34
Total lending	2211.43	681.99	1301.56	0.08	15,063	20.20	832.48
R/T	18.43	14.56	15.42	0.56	3.37	12.55	6.48
Observations	47,688	47,688	47,688	47,688	47,688	47,688	47,688

Note: A firm is defined as a relationship firm if it has a value of bank averaged $d3$ higher than the sample average for more than 50 percent of the sample peroiod. Sales, value added, loan amounts, and capital stock are in 2020 millions CLP. All variables are are averages across firms and time.

Table 7 shows the characteristics of firms defined as relationship borrowers according to this definition. As in the previous section, relationship borrowers are larger, borrow more, and at lower interest rates. The last line of the table gives us the value of each variable for relationship borrowers relative to that for transactional borrowers. These ratios form the basis of our calibration targets.

Table 8 shows the calibrated parameters. The risk free rate ρ and the depreciation rate δ are taken from the XMas model (extended structural model for analysis and simulation) of the Chilean Economy (García et al., 2019).[32] The production function parameters α and γ are estimated using the methodology of Aguirre et al. (2022) for each of the eleven 2-digit sectors, and then averaged across sectors using the relative value added of each sector as

[32]The nominal yearly risk free rate of 4.55 percent is taken from the calibration of the XMas model used for policy scenarios. Since the annual inflation rate in this period was 3 percent, this results in an annual real risk free rate of 1.55 percent.

weights. The parameters for the idiosyncratic shock are estimated from the log residuals of the production function estimation.[33]

The premium on working capital debt over the risk free rate is 15 percent and taken from Meza et al. (2019).[34] Finally the discount factor is set to correspond to a discount rate of half a percentage point less than the risk free rate to prevent firms from accumulating debt indefinitely and the wage rate is normalized to 1.

Table 8: Calibration: Targets and Parameters

Parameter		Value
Risk Free rate	ρ	0.015
Depreciation Rate	δ	0.10
Trade Credit Rate	i	ρ+0.15
Production function	α	0.34
	γ	0.40
Wage rate	w	1.00
Targeted Moments		
$x(1)/x(0)$	Data	Model
Capital	6.48	4.92
Value Added	14.56	8.45
Debt	15.42	17.96
Labor	12.55	9.49
TFP	3.37	2.00
Interest Rate	0.56	0.56
Parameters		
$\lambda(0) = 0.157$	$\phi(0) = 0.990$	$\psi(0) = 1.000$
$\lambda(1) = 0.977$	$\phi(1) = 0.221$	$\psi(1) = 0.044$
$\rho_z = 0.69$	$\sigma = 0.37$	
Untargeted Moments		
Correlations between	Data	Model
(k, d)	0.27	0.70
(b, d)	0.33	0.84
(TFP, d)	0.40	0.50
Interest Rate, d	-0.34	-0.78
Fraction of RL Firms	0.31	0.32

Note: $x(1)/x(0)$ refers to the average value of the each variable for firms with relationships relative to those without. Firms with relationships are defined as those who have a value of average (across banks) $d3$ higher than sample average in that particular period, in more than half of the sample periods.

The second panel of the table shows our calibration targets from the data as described

[33] Further details of the estimation are provided in Appendix C.

[34] Meza et al. (2019) suggest that this is a conservative value, since the data suggests an annualized rate of 34 percent for the US (Klapper et al., 2012) and 80 percent in Mexico.

above, and the panel below shows the the parameters that match these targets.[35] As our model conjectures, $\phi(1)$ is less than $\phi(0)$ to match the higher labor input of relationship firms. A smaller value of this parameter also implies that the wedge between the wage and marginal product is smaller for relationship firms, reflected in the higher value of their TFP.

The fraction of assets that can be repossessed in relationships, $\lambda(1)$ is substantially higher than $\lambda(0)$. As Table 8 shows, firms in relationships pay, on average, an interest rate which is about half of those in arms length transactions, and the value of their loans is 15 times higher. A higher value of λ implies a higher probability of repayment and therefore an ability to borrow more at lower interest rates.[36] This allows us to simultaneously match the lower interest rates and higher levels of debt for relationship firms. Together, these parameters also deliver a higher value of physical capital for firms in banking relationships. As expected, low productivity firms select into arms-length contracts, given their lower probability of repayment. These contracts limit downside risk and imply lower levels of capital and debt for these firms.

The collateral constraints for transactional firms is 1, suggesting that borrowing needs to be fully collateralized. In contrast, relationship firms have almost no collateral constraint.

3.2.3 Goodness of Fit

The bottom panel of Table 8 computes untargeted moments for the model and compares them with the data. Most importantly, our model is successful in generating the magnitude of relationship lending present in the data. The model predicts that 32 percent of all firms borrow within relationships, as compared to 31 percent in the data. Further, capital stock,

[35] We calibrate the model by choosing parameters which minimise the sum of the percentage distance of each model moment from the corresponding target moment. We restrict the parameters such that the fraction of either type of lending is always greater than 0.001 percent. We also restrict the λ and ϕ parameters to lie between 0 and 1 and the ψ parameters to be non negative. We do not impose any restrictions on the relative sizes of the parameters in relationship contracts and arms length contracts.

[36] This high value of $\lambda(1)$ is contingent on the firm being unable to pay its debt. The ex-ante expected cost of default is 2 percent of gross assets for relationships firms and 0.5 percent of gross assets in arms length transactions.

Table 9: Comparative Statics

		% RL	Output	Capital	Labor	TFP	Debt	Int. rate
(1)	Baseline Model	0.321	1.000	1.000	1.000	1.000	1.000	1.000
(2)	$\lambda(1) = \lambda(0) = 0.977$	1.000	1.292	1.250	1.320	1.234	1.270	0.518
(3)	$\phi(1) = \phi(0) = 0.221$	0.311	1.013	0.996	1.035	1.005	1.034	1.003
(4)	$\psi(1) = \psi(0) = 0.044$	0.321	1.000	1.000	1.000	1.000	1.000	1.000
(5)	$\lambda(1) = \lambda(0) = 0.977$ $\phi(1) = \phi(0) = 0.221$	0.578	1.284	1.247	1.312	1.206	1.252	0.518
(6)	$\lambda(1) = \lambda(0) = 0.977$ $\psi(1) = \psi(0) = 0.044$	1.000	1.292	1.250	1.320	1.234	1.271	0.518
(7)	$\phi(1) = \phi(0) = 0.221$ $\psi(1) = \psi(0) = 0.044$	0.311	1.013	0.996	1.035	1.005	1.034	1.003
(8)	$\lambda(1) = \lambda(0) = 0.977$ $\phi(1) = \phi(0) = 0.221$ $\psi(1) = \psi(0) = 0.044$	—	1.292	1.250	1.320	1.234	1.270	0.518

Note: The values for Output, Capital, Labor, TFP, Debt and the Interest Rate in row (1), the Baseline Model, are normalized to 1. The values of these variables in experiments (2)-(8) are relative to their respective normalized baseline.

debt and TFP are all positively correlated with the relationship dummy, as in the data.[37] The interest rates and the relationship dummy are negatively correlated, in both the data and in the model.

4 Policy Experiments

Our model contains three features that distinguish relationship lending from arms length transactions. In this section we disentangle the effects of each features and in doing so, evaluate the overall effect of relationship lending on the economy. Table 9 shows the results of our comparative statics exercises. The results of our baseline model, with aggregates normalized to 1, are shown in the first row.

[37]These correlations are different from those reported in Table 5 since d is a binary variable here.

4.1 Monitoring and Screening

Row (2) shows the effects of extending monitoring to all firms by setting $\lambda(0) = \lambda(1)$. Since low productivity firms no longer get the benefit of the lower $\lambda(0)$ in arms length transactions, they switch to relationships to enjoy the advantage of a weaker working capital constraint. The combination of these two effects produces substantial benefits. The greater ability to borrow at lower interest rates allows firms to increase their debt by 27 percent. The lower working capital constraint results in an increase in labor and a higher aggregate TFP. Capital stock increases, both due to higher earnings and the improved ability to borrow. As a result, steady state output is almost 30 percent higher.

4.2 Working Capital and Collateral Constraints

Row (3) extends the implicit guarantee provided by banking relationships to suppliers by setting $\phi(0) = \phi(1)$. This produces modest results. About 1 percent of firms, with intermediate levels of idiosyncratic productivity z switch away from relationship lending, which leads to a small decline in capital stock. The looser working capital constraint allows for a 3.5 percent increase in labor use and a small increase in TFP. Since the production function coefficient on labor is relatively small, output increases by a modest 1.3 percent.

In contrast, row (4) shows that the effects of the collateral constraints are essentially zero. Although the value of $\psi(0)$ is much larger than $\psi(1)$, a reduction in this value does not alter the capital stock. This suggests that the collateral constraint is not binding. Firms in arms-length transactions have lower productivity, and the larger increases in interest rates as debt increases is the immediate constraint. A relaxation of the collateral constraint is therefore ineffective in inducing firms to expand debt.

4.3 Combined Effects

Row (5) shows the combined effects of extending the benefits of monitoring and reducing the necessity of working capital simultaneously. Since all firms now enjoy these benefits, the results are almost identical to those of Row (1) where all firms switch to relationship. Although the fraction of firms in relationships is higher than (3), all firms enjoy the benefits of monitoring and as a result, higher levels of borrowing at lower interest rates.

Rows (6) and (7) confirm that the additional effects of relaxing the collateral constraint are negligible. Relaxing that constraint, along with increased monitoring for all firms (row (6)) yields the same results as row (2) which describes the results for monitoring only. Similarly the results in row (7) which show the combined effects of reducing dependence on both trade credit and collateral are very similar to those of row (3), which captures the effects of trade credit only.

Finally row (8) shows the results of extending all the properties of relationship lending contracts to all firms. An increase in λ allows firms to increase their borrowing by 27 percent in the aggregate, without a corresponding increase in interest rates. This increases investment and capital stock by 25 percent. TFP increases by 23 percent due to the ability of firms to reduce their dependence on trade credit, and the output increases by 30 percent.[38]

Our results suggest extending the benefits of relationship lending can result in significant gains in output. The most important driver of these gains is the monitoring function performed by banks, which ensures that firms have a lower probability of default and hence a greater availability of funds at a lower interest rate.

[38] Notice that in this case, since all firms have the benefits of being in a relationship, d is not a relevant choice for the firm anymore. Therefore, the share of firms with relationship lending is not defined.

5 Alternative Specifications of Monitoring Costs

As the previous section indicates, the role of monitoring is central in relationships and the main driver of the benefits to relationship lending. In our baseline specification we have assumed that monitoring costs are state contingent: firms pay a higher fraction of their assets to banks in relationships only in case of default. This formulation ensures that firms in relationships have a lower probability of default, and firms with higher idiosyncratic productivity select into relationships.

It is worth exploring alternative specifications to understand the role of monitoring costs. In this section we introduce upfront monitoring costs, and assume that debt contracts in relationships carry an upfront cost $c(d) > 0$ if $d = 1$ and 0 otherwise. We consider two specifications: the first is a fixed cost and the second is a monitoring cost as a fraction of new debt. In what follows, we show that neither specification is a convincing explanation of the data.

5.1 Scale Invariant Monitoring Costs

Define $c(d_t)$ as a fixed cost that a firm pays to enter into a debt contract under relationships, which is paid upfront. We also assume that the fraction of assets that bank can repossess in case of default is λ and does not depend on d.

We can therefore define the firm's problem as

$$\max_{(k_{t+1},b_{t+1},d_{t+1})_0^\infty} E_0 \sum_{t=0}^{\infty} \left(\frac{1}{1+\iota}\right)^t \left(\Omega(k_t, z_t, b_t, d_t) - k_{t+1} + \frac{b_{t+1}}{R_{t+1}} - c(d_{t+1})\right) \tag{13}$$

The dividend constraint and the collateral constraint are given by

$$\Omega(k_t, z_t, b_t, d_t) - k_{t+1} + \frac{b_{t+1}}{R_{t+1}} - c(d_{t+1}) \geq 0$$

and

$$\psi(d_{t+1})b_{t+1} \leq k_{t+1}$$

We define a firm's net assets as

$$\max\{\hat{\Omega}(k_t, d_t, z_t) - b_t, (1-\lambda)\hat{\Omega}(k_t, d_t, z_t)\}$$

where λ is now the same in relationship and arms-length transactions. As before, gross assets are given by

$$\hat{\Omega}(k_t, d_t, z_t) = \max_{n_t} y_t - (1 + \phi(d_t)i)w_t n_t + (1-\delta)k_t$$

The zero profit condition for banks now implies

$$\begin{aligned}\int_{z^*}^{\infty} b_{t+1} dF(z_{t+1}|z_t) + \int_{-\infty}^{z^*} \lambda\hat{\Omega}(k_{t+1}, d_{t+1}, z_{t+1}) dF(z_{t+1}|z_t) \\ = (1+\rho)\left(\frac{b_{t+1}}{R_{t+1}} - c(d_{t+1})\right)\end{aligned} \tag{14}$$

and the cut off value z^* is given by

$$\hat{\Omega}(k_t, d_t, z^*) - b_t = (1-\lambda)\hat{\Omega}(k_t, d_t, z^*)$$

Given a Cobb Douglas specification as before, it is straightforward to compute

$$z^* = \frac{(b_{t+1}/\lambda - (1-\delta)k_{t+1})^{1-\gamma}((1+\phi(d_{t+1})i)w)^{\gamma}}{(1-\gamma)^{1-\gamma}\gamma^{\gamma}k_{t+1}^{\alpha}}$$

Note that the difference in the probability of default between relationships and arms-length transactions only comes from the working capital constraint. Finally, the interest rate can be expressed as

$$R_{t+1} = \frac{(1+\rho)b_{t+1}}{\int_{z^*}^{\infty} b_{t+1} dF(z_{t+1}|z_t) + \int_{-\infty}^{z^*} \lambda\hat{\Omega}(k_{t+1}, d_{t+1}, z_{t+1}) dF(z_{t+1}|z_t) + (1+\rho)c(d_{t+1})}$$

For $c(1) > 0$, monitoring costs reduce interest rates in relationships without affecting the probability of default. The results of calibrating this model are shown in the top panel of Table 10.

Table 10: Upfront Monitoring Costs

Scale Invariant				
Parameters		Target Ratios	Model	Data
λ	0.378	Capital	2.04	6.48
$\phi(0)$	0.993	Debt	13.38	15.42
$\phi(1)$	0.293	Output	2.00	14.56
$\psi(0)$	0.030	Labor	2.22	12.55
$\psi(1)$	0.090	Int Rate	0.55	0.56
$c(1)$	68.18	TFP	1.14	3.37
% RL			0.99	0.31
Scale Varying				
Parameters		Target Ratios	Model	Data
λ	0.349	Capital	5.68	6.48
$\phi(0)$	0.030	Debt	18.61	15.52
$\phi(1)$	0.030	Output	10.73	14.56
$\psi(0)$	3.551	Labor	10.73	12.55
$\psi(1)$	3.510	Int Rate	1.00	0.56
$c(1)$	0.000	TFP	2.30	3.37
% RL			0.0007	0.31

Note: The table shows the result of calibrating each alternative model (Scale Invariant and Scale Varying Monitoring Costs) to match as close as possible each target ratio in the data.

As the table shows, the model generates an implausibly high level of relationship lending.[39] An upfront monitoring cost reduces interest rates, and can be repaid from borrowed funds. The level of monitoring costs are implausibly high, about half of aggregate borrowing and about 2.5 times the value of gross assets. This fits the interest rate differential between relationship and transactional firms, but since almost all firms borrow in relationships, in-

[39]Our calibration algorithm prevents 100 percent of firms from borrowing in a relationship.

cluding low productivity firms, the relative levels of output and inputs are very far from their data counterparts.

5.2 Scale Varying Monitoring Costs

Substituting the monitoring costs of the previous section with scale varying costs $c(d_{t+1})b_{t+1}$ for $d = 1$ implies the same z^* as before but with interest rates now expressed as

$$R_{t+1} = \frac{(1+\rho)b_{t+1}}{\int_{z^*}^{\infty} b_{t+1} dF(z_{t+1}|z_t) + \int_{-\infty}^{z^*} \lambda\hat{\Omega}(k_{t+1}, d_{t+1}, z_{t+1}) dF(z_{t+1}|z_t) + (1+\rho)c(d_{t+1})b_{t+1}}$$

The bottom panel in Table 10 shows that this specification also produces unconvincing results. Since our algorithm does not allow for zero or 100 percent relationship lending, it matches the data by eliminating all differences between relationship and non relationship firms and counterfactually selecting the top 0.07 percent of firms, those with the highest productivity, into relationships to match the targets but the differences are driven by idiosyncratic productivity.[40]

It seems reasonable to conclude that state contingent monitoring costs in relationships, which lower interest rates through a lower probability of default are a more convincing explanation of the data. Although the ex-post value of $\lambda(1)$ is high, given the lower probability of default, the ex-ante expected cost of default is on average 2 percent of gross assets in relationships. In contrast, our calibration implies implausibly large upfront scale invariant monitoring costs (more than half of total debt and 2.5 times gross assets), and zero upfront scale varying costs. Most importantly, neither specification can generate a realistic amount of borrowing in relationships.

[40] An exception is the interest rate differential.

6 Conclusion

While the idea that relationships between firms and banks result in more favorable debt contracts for firms is not new, the underlying mechanisms behind them and their implications for the allocation of credit and aggregate outcomes are less well understood. In this paper we provide a first evaluation of this question.

Using data from Chile, we build a comprehensive data set which merges matched borrower lender credit registry data with data on firm and bank characteristics and establish that even after controlling for observed and unobserved firm and bank attributes, firms that have closer relationships with banks get larger loans at lower interest rates. The effects of relationships are comparable to those of physical collateral, suggesting that relationships are a form of firm-bank specific capital that confer valuable benefits. We also find that firms with closer bank relationships tend to be larger and more productive.

We build a model of relationship lending where firms that are heterogeneous in their productivity choose investment and borrowing. They also simultaneously decide whether to borrow within an existing relationship with a bank or in an arms-length transaction. We evaluate three mechanisms through which relationships can alter the terms of debt contracts. First, relationships imply monitoring and screening, which our model captures as the bank's ability to claim a higher fraction of the firm's assets in case of default. This reduces the probability of default, and also ensures that more productive firms select into relationships. Second, relationships provide implicit guarantees to other creditors, and reduce firms' reliance on costly trade credit. Finally, relationships can substitute for physical collateral to a small extent.

Counterfactual experiments show that the effects of these features of relationship lending are large. Extending the benefits of relationship lending to all firms implies a gain in output and capital of about 30 percent. The lion's share of this effect comes from the ability of banks to monitor and screen borrowers.

Our results suggest that relationship lending is a significant driver of credit allocation and growth in the economy. They also have important policy implications for fostering relationship lending. While firms select into relationships in our model, there is a small literature that shows that policy actions can be important in encouraging relationships. For example, Mullins and Toro (2018) show that credit guarantee schemes in Chile not only allow small and medium enterprises to increase their borrowing, but also foster new bank relationships, laying the foundation for potential future benefits. Puri et al. (2017) show that holding a checking account is an important advantage in getting a loan from that bank. In other words, the benefits of financial inclusion are larger than previously understood, and efforts to promote such inclusion are likely to enhance growth to a larger extent.

While the effects of relationship lending may vary across countries and across time, our model and calibration exercise provide a methodology to evaluate their effects, which we expect to be applicable more generally.

References

Ackerberg, Daniel A.; Caves, Kevin, and Frazer, Garth. Identification Properties of Recent Production Function Estimators. *Econometrica*, 83:2411–2451, November 2015.

Acosta-Henao, Miguel; Pratap, Sangeeta, and Taboada, Manuel. Four facts about relationship lending: The case of chile 2012-2019. *Journal of Corporate Finance*, 80:102415, 2023.

Agarwal, Sumit and Hauswald, Robert. Information Disclosure and the Choice between Arms-Length and Inside Debt. *Journal of Monetary Economics*, 117(1):1008–1022, 2021.

Aguirre, Alvaro; Tapia, Matias, and Villacorta, Luciano. Productivity, Investment and Wealth Dynamics Under Financial Frictions: An Empirical Investigation of the Self Financing Channel. *mimeo*, 2022.

Amiti, Mary and Weinstein, David E. How much do idiosyncratic bank shocks affect investment? evidence from matched bank-firm loan data. *Journal of Political Economy*, 126(2): 525–587, 2018.

Banerjee, Ryan; Gambacorta, Leonardo, and Sette, Enrico. The real effects of relationship lending. *Journal of Financial Intermediation*, 48:1–14, 2021.

Beatriz, Mikael; Coffinet, Jérôme, and Nicolas, Théo. Relationship lending and SMEs' funding costs over the cycle: why diversification of borrowing matters. *Journal of Banking & Finance*, page 105471, 2018.

Beck, Thorsten; Degryse, Hans; De Haas, Ralph, and Van Horen, Neeltje. When arm's length is too far: Relationship banking over the credit cycle. *Journal of Financial Economics*, 127(1):174–196, 2018.

Berger, Allen N and Udell, Gregory F. Relationship lending and lines of credit in small firm finance. *Journal of Business*, pages 351–381, 1995.

Boot, Arnoud W.A. and Thakor, Anjan V. Can Relationship Banking Survive Competition. *Journal of Finance*, 55(2), 2000.

Caballero, Ricardo J.; Hoshi, Takeo, and Kashyap, Anil K. Zombie Lending and Depressed

Restructuring in Japan. *American Economic Review*, 98(5):1943–1977, 2008.

Cahn, Christophe; Duquerroy, Anne, and Mullins, William. Unconventional Monetary Policy and Bank Lending Relationships. 2020.

Cole, Rebel A. The importance of relationships to the availability of credit. *Journal of Banking & Finance*, 22(6-8):959–977, 1998.

Degryse, Hans and Ongena, Steven. Distance, lending relationships, and competition. *Journal of Finance*, 60(1):231–266, 2005.

Degryse, Hans and Van Cayseele, Patrick. Relationship lending within a bank-based system: Evidence from European small business data. *Journal of Financial Intermediation*, 9(1): 90–109, 2000.

Degryse, Hans; Kim, Moshe, and Ongena, Steven. *Microeconometrics of banking: methods, applications, and results*. Oxford University Press, USA, 2009.

Dempsey, Kyle and Faria-e Castro, Miguel. A quantitative theory of relationship lending. *FRB St. Louis Working Paper*, (2022-33), 2022.

Duqi, Andi; Tomaselli, Angelo, and Torluccio, Guiseppe. Is Relationship Lending still a Mixed Blessing? A Review of Advantages and Disadvantages for Lenders and Borrowers. *Journal of Economic Surveys*, 32:1446–1482, 2018.

Elsas, Ralf and Krahnen, Jan Pieter. Is relationship lending special? Evidence from credit-file data in Germany. *Journal of Banking & Finance*, 22(10-11):1283–1316, 1998.

Faria-e-Castro, Miguel; Paul, Pascal, and Sanchez, Juan M. Evergreening. Working paper series, Federal Reserve Bank of San Francisco, July 2022.

Favara, Giovanni; Minoiu, Camellia, and Perez-Orive, Ander. Zombie Lending to U.S. Firms. Technical report, March 2022.

Fisman, Raymond; Paravisini, Daniel, and Vig, Vikrant. Cultural Proximity and Loan Outcomes. *American Economic Review*, 107(2):457–492, 2017.

García, Benjamin; Guarda, Sebastián; Kirchner, Marcus, and Tranamil, Rodrigo. XMas: An extended model for analysis and simulations. *Documentos de Trabjo, Banco Central* *de Chile*, (833), 2019.

Hachem, Kinda. Relationship lending and the transmission of monetary policy. *Journal of Monetary Economics*, 58(6-8):590–600, 2011.

Hauswald, Robert and Marquez, Robert. Relationship banking, loan specialization and competition. Technical Report 695, Federal Reserve Bank of Chicago, 2000.

Heitz, Amanda; Martin, Christopher, and Ufier, Alex. Bank monitoring with on-site inspections. FDIC Center for Financial Research Paper 2022-09, January 2023.

Hoshi, Takeo. Economics of the Living Dead. *The Japanese Economic Review*, 57(1):30–49, 2006.

Khwaja, Asim Ijaz and Mian, Atif. Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–1442, 2008.

Klapper, Leora; Laeven, L, and Rajan, R. Trade Credit Contracts. *Review of Financial Studies*, 25(3):838–867, 2012.

Kysucky, Vlado and Norden, Lars. The Benefits of Relationship Lending in a Cross-Country Contest: A Meta-Analysis. *Management Science*, 62(1):90–110, 2016.

Levinsohn, James and Petrin, Amil. Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*, 70(2):317–341, 2003.

Machauer, Achim and Weber, Martin. Number of bank relationships: An indicator of competition, borrower quality, or just size? Technical report, CFS Working Paper, 2000.

Medina, Leandro and Schneider, Friedrich. *Shadow economies around the world: what did we learn over the last 20 years?* International Monetary Fund, 2018.

Meza, Felipe; Pratap, Sangeeta, and Urrutia, Carlos. Credit, misallocation and productivity growth: A disaggregated analysis. *Review of Economic Dynamics*, 34:61–86, 2019.

Mullins, William and Toro, Patricio. Credit Guarantees and New Bank Relationships. Working papers central bank of chile, Central Bank of Chile, 2018.

Olley, G. Steven and Pakes, Ariel. The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):1263–1297, 1996.

Peek, Joe and Rosengren, Eric S. Unnatural Selection: Perverse Incentives and the Misallocation of Credit in Japan. *American Economic Review*, 95(4):1144–1166, 2006.

Petersen, Mitchell A and Rajan, Raghuram G. The benefits of lending relationships: Evidence from small business data. *Journal of Finance*, 49(1):3–37, 1994.

Puri, Manju; Rocholl, Jörg, and Steffen, Sascha. What do a Million Observations have to say about Loan Default? *Journal of Financial Intermediation*, 31:1–31, 2017.

Santos, Joao AC and Winton, Andrew. Bank loans, bonds, and information monopolies across the business cycle. *Journal of Finance*, 63(3):1315–1359, 2008.

Schoar, Antoinette. The Personal Side of Relationship Banking. Technical report, Innovations for Poverty Action, 2012.

Steinkamp, Sven; Tornell, Aaron, and Westermann, Frank. Evergreening in the Euro Area: Evidence from Survey Data and a Conceptual Framework. *CESifo Economic Studies*, 67 (1):1–34, 2021.

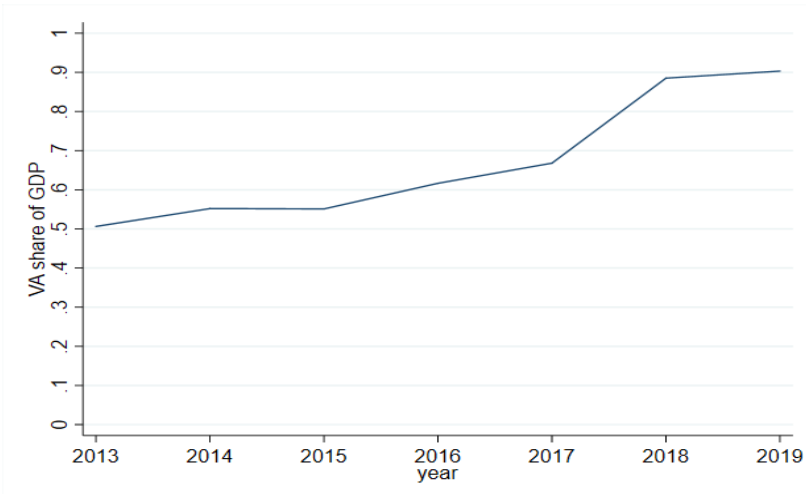
Weinstein, David E. and Yafeh, Yishay. On the Costs of a Bank-Centered Financial System: Evidence from the Changing Main Bank Relations in Japan. *Journal of Finance*, 53: 635–672, 1998.

Appendix

A Data

A.1 Coverage

Figure 5: Sample Value Added and GDP



Note: The figure displays the ratio of total value added from our sample to GDP, averaging 74%. Firms with negative value added are dropped before aggregating.

A.2 Sample Selection

Table 11: Sample Selection

	No. of obs.	No. of Firms
Original Sample	735,871	53,763
Eliminate Firms with		
Value Added <0 for $\geq$12 mths	111,395	3,805
K $<$ 1000 CLP or K/Y $>$ 1000	673	105
Leverage $>$ 1000	692	56
Top and Bottom pctile of ratios*	22,129	2,109
Final Sample	600,982	47,688

Note: The original sample consists of firms with data on all the variables of interest and excludes financial intermediaries and public administration. Firms in the bottom and top percentile of the ratios of capital to sales, worker to sales and intermediate goods to sales are dropped.

A.3 Data Definitions

The definitions of all variables used in our analysis are given below. Unless otherwise specified, all variables are deflated by the consumer price index (2020=100).

Firm Variables

1. **Loan amounts:** (monthly frequency, at the firm-bank-time level) Total value of new loans a firm takes from a particular bank in a particular month. If a firm takes more than one loan from a particular bank in a month, the amounts are aggregated.

2. **Interest rates:** (monthly frequency, at the firm-bank-time level) Interest rate on each new loan the firm takes from a bank in a particular month. Interest rates of multiple loans from a bank in the same month are computed as the loan weighted average of rates. Real rates are calculated as the difference between nominal rates and the inflation rate calculated as yearly percentage changes of the CPI.

3. **Sales:** The sum of sales over the past 12 months.

4. **Value added:** Sales less intermediate goods.

5. **Wage bill:** The sum of the wage bill over the past 12 months.

6. **Number of workers:** The sum of number of monthly workers over the past 12 months, divided by 12.

7. **Capital stock:** Constructed by the Central Bank of Chile using the initial value of capital stock, investment flow and depreciation.

8. **Total debt:** The sum of the stock of total debt outstanding from banks, value of internal and external bonds.

9. **Firm leverage:** Total debt divided by Value added.

10. **Firm wealth:** Total assets net of Total liabilities.

Bank Variables

1. **Bank sales:** Total loans given for the past 12 months.

2. **Bank leverage:** The sum of the total stock of outstanding debt, including internal and external bonds, divided by Bank sales.

B Additional Tables

Table 12: Statistics by Sector

	Firms	Number of loans	Loan amount	Loans per firm	Banks per firm
Agriculture	6.6%	5.0%	2.8%	9.49	1.83
Mining	0.7%	0.8%	3.2%	13.07	2.08
Manufacturing	16.8%	23.0%	21.3%	17.23	2.23
EGW	0.7%	0.8%	1.3%	14.04	2.38
Construction	13.4%	12.6%	7.6%	11.87	1.89
Commerce	36.6%	38.9%	21.6%	13.4	1.99
Transport	9.5%	6.7%	4.8%	8.94	1.76
Other financial activities	1.4%	1.3%	31.6%	11.41	1.9
Real estate	1.3%	0.6%	1.4%	5.71	1.49
Business services	10.5%	8.9%	3.4%	10.67	1.88
Personal services	2.5%	1.5%	1.0%	7.64	1.63
Total	47,688	600,982†	332,164††	12.6	1.96

Note: Loan amounts are in 2020 CLP. †: Total number of loans. ††: Total loan amounts (billions of 2020 CLP).

Table 13: Loan Amount Regressions

Dependent Variable: Log Loan Amounts			
c1	-0.129***		
	(-5.42)		
d1	0.0997***		
	(3.73)		
c2		-0.0777***	
		(-4.08)	
d2		0.00477***	
		(11.22)	
c3			-0.206***
			(-12.19)
d3			0.0834***
			(7.19)
N	588,639	588,639	588,639
R^2	0.712	0.712	0.712

Note: t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each specification includes a set of firm and bank fixed effects, as well as a time trend. Loan amounts are in logs. Standard errors are clustered using the combinations of the fixed effects.

Table 14: Interest Rate Regressions

Dependent Variable: Real Interest Rate			
c1	0.0106***		
	(5.29)		
d1	-0.00791**		
	(-2.34)		
c2		-0.00318	
		(-1.68)	
d2		-0.0000933***	
		(-2.97)	
c3			0.00117
			(1.35)
d3			-0.00729***
			(-10.69)
N	588,639	588,639	588,639
R^2	0.666	0.666	0.670

Note: t-statistics in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each specification includes a set of firm and bank fixed effects, as well as a time trend. Real interest rates are calculated ex post using the one-year realized inflation at the date of the loan. Standard errors are clustered using the combinations of the fixed effects.

Table 15: Relationships and Loan Size

	Loan Amount (in logs)				
d1	0.00939				
	(0.40)				
d2		0.00461***			
		(9.55)			
d3			0.0295**	0.222***	0.2263***
			(2.39)	(13.80)	(29.61)
c1	0.0330				
	(1.22)				
c2		−0.0339*			
		(−1.74)			
c3			0.0790***	−1.142***	−1.1689***
			(2.86)	(−12.60)	(−21.24)
Sales	0.145***	0.143***	0.138***		
	(13.73)	(14.75)	(10.94)		
Leverage	0.0800***	0.0803***	0.0810***		
	(5.87)	(5.87)	(6.01)		
Labor	0.152***	0.155***	0.157***		
	(15.02)	(15.25)	(15.43)		
Capital	0.0235***	0.0254***	0.0244***		
	(3.87)	(3.88)	(3.83)		
Bank sales	0.00388	0.0135	0.00630	0.0558**	
	(0.29)	(0.88)	(0.46)	(2.68)	
Bank leverage	-0.0181	-0.0146	-0.0185	-0.000306	
	(-1.40)	(-1.06)	(-1.40)	(-0.03)	
Month FE	Yes	Yes	Yes	Yes	No
Firm FE	Yes	Yes	Yes	No	No
Bank FE	Yes	Yes	Yes	Yes	No
Firm-Month FE	No	No	No	Yes	Yes
Bank-Month FE	No	No	No	No	Yes
N	588,639	588,639	588,639	251,733	251,618
R^2	0.716	0.716	0.716	0.782	0.784

Note: T Statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Loan amounts are in 2020 CLP. Standard errors are clustered using the combinations of the fixed effects. Firm and bank variables are measured in logs.

Table 16: Relationships and the Cost of Credit

	Real Interest Rate				
d1	-0.00405				
	(-1.33)				
d2		-0.000796^{**}			
		(-2.40)			
d3			-0.00487^{***}	-0.0035^{***}	-0.0035^{***}
			(-9.51)	(-3.96)	(-14.75)
c1	0.00433^{*}				
	(2.07)				
c2		-0.00465^{**}			
		(-2.31)			
c3			-0.0100^{***}	-0.0381^{***}	-0.0385^{***}
			(-6.98)	(-7.09)	(-18.88)
Sales	-0.00678^{***}	-0.00713^{***}	-0.00586^{***}		
	(-7.45)	(-8.29)	(-6.07)		
Leverage	-0.00146^{***}	-0.00159^{***}	-0.00169^{***}		
	(-3.67)	(-4.00)	(-4.21)		
Labor	-0.00317^{***}	-0.00333^{***}	-0.00393^{***}		
	(-5.75)	(-6.03)	(-7.11)		
Capital	-0.00110^{*}	-0.00131^{**}	-0.00139^{**}		
	(-2.08)	(-2.26)	(-2.50)		
Bank sales	0.00198	0.00187	0.00166	-0.000232	
	(1.11)	(1.02)	(0.94)	(-0.27)	
Bank leverage	0.00162	0.00165	0.00176	0.000211	
	(1.05)	(1.05)	(1.07)	(0.32)	
Month FE	Yes	Yes	Yes	Yes	No
Firm FE	Yes	Yes	Yes	No	No
Bank FE	Yes	Yes	Yes	Yes	No
Firm-Month FE	No	No	No	Yes	Yes
Bank-Month FE	No	No	No	Yes	Yes
N	588,639	588,639	588,639	251,733	251,618
R^2	0.669	0.670	0.673	0.747	0.751

Note: T-statistics in parentheses. $^*p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. Standard errors are clustered using the combinations of the fixed effects. Firm and bank variables are measured logs

C Production Function Estimation

We estimate the parameters α and γ of the Cobb Douglas production technology following Aguirre et al. (2022). This methodology considers the presence of financial frictions and consists of implementing a proxy approach, as in Olley and Pakes (1996) or Levinsohn and Petrin (2003). These frameworks use, respectively, investment and expenditure on materials as instruments for productivity. However, as Aguirre et al. (2022) argue, as long as financial frictions affect either investment or the demand for materials these methodologies yield biased estimates of the production function parameters, since they attribute variations in these variables to variations in TFP, and ignore the differences in investment or input use that firms with similar TFP but different collateral constraints may exhibit.[41]

Intuitively, this methodology extends the proxy approach by considering financial frictions by controlling for the firm's wealth in estimation. Since wealth is a state variable that determines the dynamics of future investment in the presence of financial frictions, it lends itself as a natural control to obtain unbiased estimates of the production function coefficients. In what follows, we describe the approach briefly and show our estimates.

Consider a Cobb Douglas production function in logs, where output y_{it} is produced using labor n_{it} and capital k_{it} and

$$y_{it} = \alpha k_{it} + \gamma n_{it} + z_{it}$$

where z_{it} is an idiosyncratic productivity shock which follows a first order Markov process of the form $z_{it} = \rho_z z_{it-1} + \epsilon_{it}$, and ϵ_{it} is a white noise disturbance. In a dynamic model of heterogeneous firms with financial frictions, self financing plays an important role in investment, and a policy function for investment can be expressed as

[41] The same issue arises in Ackerberg et al. (2015) who extend the proxy function frameworks of Olley and Pakes (1996) and Levinsohn and Petrin (2003) to account for the endogeneity of labor to the productivity shock.

$$i_{it} = h(a_{it}, k_{it}, n_{it}, z_{it})$$

where a_{it} represent the firms' net assets.

Assuming that the function h_t is monotonic in z_{it}, we can invert it to recover productivity as a function of observed variables. This yields:

$$z_{it} = h^{-1}(a_{it}, k_{it}, n_{it}, z_{it})$$

Notice that, as in Ackerberg et al. (2015), we consider labor endogenous to productivity but chosen before investment. Therefore, we include n_{it} in the estimation. By replacing z_{it} in the production function, we obtain:

$$y_{it} = \alpha k_{it} + \gamma n_{it} + h^{-1}(a_{it}, k_{it}, n_{it}, i_{it}) = \Phi(a_{it}, k_{it}, n_{it}, i_{it})$$

Approximating the Φ function with a third order polynomial with interaction terms[42] and estimating it, we can recover an estimate of the productivity shock as

$$\hat{z}_{it} = \hat{\Phi}(a_{it}, k_{it}, n_{it}, i_{it}) - \alpha k_{it} - \gamma n_{it}$$

Substituting this in the Markov process for z_{it} we have

$$z_{it} = \rho(\hat{\Phi}(a_{it-1}, k_{it-1}, n_{it-1}, i_{it-1}) - \alpha k_{it-1} - \gamma n_{it-1}) + \epsilon_{it}$$

[42] Estimations with lower order polynomials produce similar results.

and the production function can be expressed as

$$y_{it} = \alpha k_{it} + \gamma n_{it} + \rho(\hat{\Phi}(a_{it-1}, k_{it-1}, n_{it-1}, i_{it-1}) - \alpha k_{it-1} - \gamma n_{it-1}) + \epsilon_{it}$$

In the second stage of our estimation, we estimate this equation using the following three moment conditions:

$$E(\epsilon_{it}\hat{\Phi}(a_{it-1}, k_{it-1}, n_{it-1}, i_{it-1})) = 0; \quad E(\epsilon_{it}k_{it-1}) = 0; \quad \text{and} \quad E(\epsilon_{it}n_{it-1}) = 0;$$

These moment conditions allow us to jointly identify α, γ, and ρ_z, delivering consistent estimates of these parameters. Naturally, this also allows us to estimate the volatility of productivity, σ, given the assumed AR(1) process.

Implementing this method requires data on firms' wealth. We use firms' balance sheet data, which is reported yearly to the Chilean tax authority. For firms, we apply the same filters detailed in the section on sample selection. We also require 4 or more consecutive observations, more than three monthly workers, $K/Y > 0.05$, and positive investment and wealth. Considering these filters, and the fact that not all firms in the original sample report their balance sheet yearly, the final sample consists of 19,284 observations for 2,989 firms. Table 17 shows the results of the estimation. The left hand side column (Economy) shows our estimates for the whole sample, and the right column (Sectors) shows the results of doing the estimation by sector and then calculating the sector value-added weighted average of the parameters.

Table 17: Production Function Parameters

	Economy	By Sectors
α (capital)	0.33	0.34
γ (labor)	0.39	0.40
ρ_z	0.68	0.69
σ	0.39	0.37

Note: The production function coefficients are obtained following Aguirre et al. (2022). The second column is estimated within each of the 11 2-digit sectors, and then averaged across sectors using the relative value added of each sector as weights. ρ and σ are the persistence and the standard deviation from the AR(1) process for TFP.

D Solution of the Model

The firm's problem in recursive form can be written as

$$V(k,b,d,z) = \max_{k',b',d'} \Omega(k,b,d,z) - k' + \frac{b'}{R'} + \beta \int_{z'} V(k',b',d',z')dF(z'|z)dz'$$

subject to the constraints

$$\Omega(k,b,d,z) - k' + \frac{b'}{R'} \geq 0$$
$$\psi(d')b' \leq k'$$

where

$$R' = \frac{(1+\rho)b'}{\int_{z^*}^{\infty} b'dF(z'|z) + \int_0^{\infty} \lambda(d')\hat{\Omega}(k',d',z')df(z'|z)}$$

We solve this problem numerically, by discretizing the state space and iterating on the value function. This yields the policy rules

$$k' = g_k(k,b,d,z)$$
$$b' = g_b(k,b,d,z)$$
$$d' = g_d(k,b,d,z)$$

Finally we define the measure $\mu(k, b, z, d)$ as the distribution of firms in the economy. The distribution of firms evolves according to the operator T, such that $\mu' = T\mu$ and

$$\mu'(k', b', z', d') = \int_{\Theta} Pr(z'|z) d\mu(k, b, d, z)$$

where

$$\Theta = \{k', b', d' | k' = g_k(k, b, d, z), b' = g_b(k, b, d, z), d' = g_d(k, b, d, z)\}$$

The stationary distribution of firms is defined as $\mu^*(k, b, d, z)$, which satisfies the property $\mu^* = T\mu^*$. We use this distribution to compute the model moments matched to calibration targets that we describe below. So the average capital stock of firms in relationships is computed as

$$K(1) = \int_k k\mu_k^*(k|d = 1)dk$$

and that of firms in arms length transactions is

$$K(0) = \int_k k\mu_k^*(k|d = 0)dk$$

where the conditional distribution $\mu_k^*(k|d)$ is derived from the joint stationary distribution μ^*. Debt, labor, output and TFP are also computed analogously, with TFP defined as $\frac{y}{k^\alpha n^\gamma}$.

Documentos de Trabajo **Banco Central de Chile**	**Working Papers** **Central Bank of Chile**
NÚMEROS ANTERIORES	PAST ISSUES
La serie de Documentos de Trabajo en versión PDF puede obtenerse gratis en la dirección electrónica: www.bcentral.cl/esp/estpub/estudios/dtbc. Existe la posibilidad de solicitar una copia impresa con un costo de Ch$500 si es dentro de Chile y US$12 si es fuera de Chile. Las solicitudes se pueden hacer por fax: +56 2 26702231 o a través del correo electrónico: bcch@bcentral.cl.	Working Papers in PDF format can be downloaded free of charge from: www.bcentral.cl/eng/stdpub/studies/workingpaper. Printed versions can be ordered individually for US$12 per copy (for order inside Chile the charge is Ch$500.) Orders can be placed by fax: +56 2 26702231 or by email: bcch@bcentral.cl.

DTBC – 999
Relationship Lending: Characteristics and Real Effects
Miguel Acosta-Henao, Sangeeta Pratap, Manuel Taboada

DTBC – 998
International Sourcing during COVID-19: How did Chilean firms fare?
Jennifer Peña, Elvira Prades

DTBC – 997
A Preliminary Assessment of the Economic Effects of Climate Change in Chile
Felipe Beltrán, Luigi Durand, Mario González-Frugone, Javier Moreno

DTBC – 996
Monetary Policy Tightening and Bank Lending Standards: Evidence from the Chilean Bank Loan Survey
Helmut Franken, Alejandro Jara

DTBC – 995
Financial Constraints and Firm Adjustments During a Sales Disruption
Juan-Andrés Castro, Enzo Cerletti

DTBC – 994
Forward Guidance: Estimating a Behavioral DSGE Model with System Priors
Agustín Arias, Benjamín García, Ignacio Rojas

DTBC – 993
The origins of monetary policy disagreement: the role of supply and demand shocks
Carlos Madeira, João Madeira, Paulo Santos Monteiro

DTBC – 992
The Heterogeneous Effect of Monetary Policy Shocks: Evidence for US Households
Tomás Opazo

DTBC – 991
The impact of the Covid Pension Fund Withdrawals in Chile on the future retirement income of the Social Security affiliates and their households
Alejandra Inzunza, Carlos Madeira

DTBC – 990
Financial and real effects of pandemic credit policies: an application to Chile
Felipe Garcés, Juan F. Martínez, M. Udara Peiris, Dimitrios P. Tsomocos

DTBC – 989
Hard Commodities Hit Harder: Global Financial Risk and Commodity Exporters
Gabriela Contreras

DTBC – 988
Precios y Holgura en el Mercado de Arriendo: Análisis de Avisos Listados
Felipe Córdova, Alejandra Cruces, Sergio Díaz

DTBC – 987
Measurement of Efficiency and its Drivers in the Chilean Banking Industry
Adriana Cobas, Alexandros Maziotis, Andrés Villegas

DOCUMENTOS DE TRABAJO Noviembre 2023