THE JOURNAL OF FINANCE • VOL. LXI, NO. 4 • AUGUST 2006

Do Banks Affect the Level and Composition of Industrial Volatility?

BORJA LARRAIN*

ABSTRACT

In theory, better access to bank credit can reduce or increase output volatility depending on whether firms are more financially constrained during contractions or expansions. This paper finds that the volatility of industrial output is lower in countries with more bank credit. Most of the reduction in volatility is idiosyncratic, which follows from the ability of banks to pool and diversify shocks. Systematic volatility is reduced less strongly. Volatility dampening is achieved via countercyclical borrowing: At the firm level, short-term borrowing is less (or more negatively) correlated with sales and inventories in countries with high levels of bank credit.

THERE IS A DEBATE ABOUT THE EFFECT OF FINANCIAL INTERMEDIARIES—or financial development more generally—on the volatility of output. In theory, the effect on volatility of having more financial intermediation is ambiguous, depending on the stage of the country's development (Aghion, Bacchetta, and Banerjee (2004)) or the type of shocks that affect the economy (e.g., real vs. monetary shocks as in Bacchetta and Caminal (2000), or credit demand versus credit supply shocks as in Morgan, Rime, and Strahan (2004)). The existing empirical evidence is also inconclusive. For instance, while Acemoglu et al. (2003) show that macroeconomic aggregates are less volatile in more developed countries, Beck, Lundberg, and Majnoni (2004) find no robust relation between financial intermediation and output volatility when considering different types of macro shocks. Understanding output volatility is important because volatility has a negative effect on growth (Ramey and Ramey (1995), Aghion et al. (2005)), in other words, because stability breeds growth.

This paper revisits the debate on finance and volatility using industry-level and firm-level data. From the perspective of a financially constrained firm,

*Borja Larrain is at the Federal Reserve Bank of Boston. This paper is based on the second chapter of my dissertation at Harvard University. An earlier working paper version circulated under the title "Financial Development, Financial Constraints and the Volatility of Industrial Output (2004)" I thank my thesis advisors John Campbell, Andrei Shleifer, and Jeremy Stein for their support and guidance throughout this project. I also thank Matías Braun, Miklós Koren, Krishna Kumar, John Matsusaka, Robert Stambaugh (the editor), Gustavo Suárez, Adam Szeidl, Francesco Trebbi, Motohiro Yogo, an associate editor, an anonymous referee, and seminar participants at the Federal Reserve Bank of Boston, Harvard University, IESE, Ohio State University, the University of Michigan, and the University of Southern California for helpful comments. All errors are my own. The views expressed here are not necessarily those of the Federal Reserve Bank of Boston or the Federal Reserve System.

having better access to credit has an ambiguous effect on output volatility. If a firm is more financially constrained during output contractions, then more credit reduces volatility. In contrast, if a firm is more financially constrained during output expansions, then more credit increases volatility. Despite this theoretical ambiguity, I find that on average financial intermediaries have a dampening effect on volatility, which suggests that financial constraints are mostly countercyclical, that is, tighter during contractions.

This paper studies two further issues in relation to finance and volatility—the composition of volatility and the cyclical behavior of firm borrowing. These two issues, which refer more specifically to the provision of liquidity, make the connection between banks and volatility more explicit.

First, this paper documents the effect of banks on the different components of output volatility. I decompose volatility into systematic and idiosyncratic components, where idiosyncratic volatility is defined as the volatility of an industry that is uncorrelated with the GDP of the country. The dampening effect of banks on volatility is stronger in the idiosyncratic component. This is explained by the advantage of banks in smoothing idiosyncratic shocks: Intermediaries operate by pooling resources of firms and households and diversifying shocks across them. In this sense, idiosyncratic shocks are the primary shocks for banks to tackle. However, there is less space for diversification in the case of a large-scale shock or highly correlated shocks. Moreover, in the case of aggregate shocks, intermediaries face capital constraints that reduce the liquidity services they can provide (Holmstrom and Tirole (1997, 1998), Caballero and Krishnamurthy (2001)). It follows, not surprisingly, that idiosyncratic volatility is affected more strongly than systematic volatility as banks develop. Another way of interpreting this finding is that many risk-sharing opportunities are wasted in countries with underdeveloped banking systems.

A second contribution of this paper is to examine the mechanism through which volatility is reduced. In particular, if banks are the reason for the dampening of volatility, then lower volatility has to be accompanied by increased *countercyclical* borrowing. Conversely, a hypothetical increase in volatility would be accompanied by increased *procyclical* borrowing. At the firm level, I find that short-term debt is less correlated with sales and inventories as bank credit increases, which suggests that short-term debt is used in a more countercyclical way. This firm-level evidence shows that shocks do not disappear—rather, they are buffered by financial intermediaries—and thus challenges those who are skeptical about the finance-volatility connection, or those who argue that more developed countries are less volatile for other reasons. In this sense, no debate about banks and volatility can be effectively resolved unless we look at the mechanism through which shocks are dampened or amplified.

This paper is related to several strands of the literature. First, I borrow from the extensive literature on financial development and growth (see Levine (2004) for a survey). Here I focus on short-run fluctuations instead of long-run growth, but the tools are similar. For instance, the identification strategy in the empirical section of this paper is taken from Rajan and Zingales (1998, hereafter RZ), who study the connection between growth and financial development using a combination of cross-country and cross-industry comparisons. RZ identify from an a priori base those industries that depend more on external financiers and that consequently should benefit more from financial development. I borrow their index of financial dependence to analyze cross-industry comparisons in the patterns of volatility. In this respect, this paper is also related to the work of Raddatz (2003), who studies volatility using a strategy that follows RZ. Raddatz develops a measure of liquidity needs and shows that financial development reduces volatility, particularly in the liquidity-dependent sectors. However, Raddatz does not look at idiosyncratic and systematic volatilities separately nor does he examine firms' borrowing.

There is also a large literature on the business cycle effects of financial frictions. These models study aggregate fluctuations and explore how frictions can amplify and propagate real and monetary shocks (Bernanke and Blinder (1988), Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Stein (1998)). The empirical work is centered on the cross-sectional implications of these theories, namely that more financially constrained firms or banks are hit harder during episodes of contractionary shocks (i.e., NBER recessions).[1] The paper by Braun and Larrain (2005) is a recent addition to this literature. The main finding in Braun and Larrain is that financially dependent industries (also using the RZ index) do relatively poorly during recessions, particularly so in countries with underdeveloped financial systems. The present paper complements the findings in Braun and Larrain by studying fluctuations that are unrelated to the business cycle (i.e., idiosyncratic volatility). At the same time, it allows us to evaluate the capacity of banks to provide liquidity under different circumstances. As expected, we find that banks are more successful in smoothing idiosyncratic fluctuations than recessions or booms. Also, this paper provides a test of the mechanism through which fluctuations are smoothed. In particular, the evidence on inventories is important given their role in aggregate fluctuations.

Finally, the mechanism studied in this paper entails financial constraints that arise from agency problems and asymmetric information. A large literature studies the impact of financial constraints on real activity (see the surveys by Hubbard (1998) and Stein (2003)). This literature shows that the financial position of a firm affects capital expenditures, inventory accumulation, employment, pricing strategies, and other real variables. The current paper adds fresh evidence to this literature in terms of both the volatility (systematic and idiosyncratic) and borrowing behavior of financially constrained firms.

The organization of this paper is as follows. Section I provides a preliminary discussion of the main hypotheses. Section II describes the empirical strategy and the data. Section III shows the reduction in volatility and its decomposition using industrial data. Section IV explores the mechanism behind the reduction in volatility using firm-level data. Section V concludes.

[1] In terms of firm-level evidence some important papers are Bernanke, Gertler, and Gilchrist (1996), Gertler and Gilchrist (1994) and Kashyap, Lamont, and Stein (1994). For bank-level evidence see Kashyap and Stein (2000) and Kashyap, Stein, and Wilcox (1993).

I. Bank Credit, Financial Constraints, and Volatility: Preliminary Discussion

The effect of banks on output volatility is not obvious. In fact, it depends on whether firms need to borrow more during output contractions or expansions. If financial constraints are tighter during contractions, then more credit reduces volatility by helping firms avoid a decrease in output.[2] In contrast, if constraints are tighter during expansions, then more credit increases volatility by allowing firms to take on new projects quickly. Because the real world provides a broad mix of contractions and expansions with different characteristics, the net effect of banks on output volatility is an empirical issue. Thus the empirical findings speak about the average cyclicality of financial constraints. If banks reduce volatility, it is because financial constraints are countercyclical (tighter during contractions) on average, and if banks increase volatility, it is because financial constraints are procyclical (tighter during expansions) on average.

The first derivative is worth studying empirically in the case of output volatility (σ) with respect to bank credit (B), since the sign of $\partial\sigma/\partial B$ is theoretically ambiguous. It is also common in the literature on financial constraints to examine cross-sectional derivatives, that is, how firms in different financial positions change their volatility in response to a given change in bank credit. This corresponds to a second derivative such as $\partial^2\sigma/\partial B\partial W$, where W is an indicator of the financial position of the firm, for example, the availability of internal funds. Not surprisingly, the sign of the second derivative is also theoretically ambiguous. In fact, it can be very misleading when considered in isolation from the main effect of banks on volatility. A similar point is noted by Kaplan and Zingales (1997) in the context of investment-cash flow sensitivities.

In the case of countercyclical financial constraints, we expect $\partial^2\sigma/\partial B\partial W > 0$, since better access to banks and internal funds are substitutes in terms of avoiding a larger decrease in output during a contraction. In a world with tighter constraints during contractions, firms with abundant internal funds initially have low volatility, and thus banks are relatively less useful for them. In this case, the first derivative $\partial\sigma/\partial B$ is less negative for these firms and therefore $\partial^2\sigma/\partial B\partial W > 0$. If, on the other hand, constraints are tighter during expansions, we obtain a negative sign on the second derivative if diminishing returns in production are strong, meaning that the increase in volatility is smaller for firms with high W. However, a positive sign is also possible if diminishing returns are not too strong. In this case, banks increase volatility because firms want to expand their production after a good shock, but their willingness to expand depends on diminishing returns. In terms of empirical implementation, the above suggests that we can never consider the cross-sectional derivatives apart from the main effect. In particular, a positive second derivative does not ensure a positive first derivative.

[2] The term financial constraint is applied to the gap between funds that are internal to the firm and investment needs. A tighter financial constraint is when the *gap* is wider, not necessarily when the *level* of internal funds is low or the *level* of investment needs is high.

Liquidity provision is foremost about mitigating the risks involved in *individual* projects. Banks pool resources and lend to those firms in need: At a particular point in time, banks coordinate the flow of cash from firms that are net lenders to firms that are net borrowers (Kashyap, Rajan, and Stein (2002)). This works well when shocks are idiosyncratic or not highly correlated across firms. In the case of large or highly correlated shocks, however, the liquidity that banks can provide is heavily reduced since net lenders are in scarce supply. Also, intermediaries face capital constraints that aggravate during aggregate shocks, further reducing liquidity (Holmstrom and Tirole (1997, 1998), Caballero and Krishnamurthy (2001)). The extreme case, noted by Diamond and Dybvig (1983), is the failure of the banking system: a bank run occurs when everyone demands liquidity simultaneously. It follows that banks have a stronger effect on the volatility associated with individual projects that are not correlated with the rest of the economy, that is, the idiosyncratic volatility. Simply put, banks have a comparative advantage in handling idiosyncratic shocks as compared to aggregate shocks. Note that idiosyncratic shocks can lead to a contraction or an expansion of firm output, and therefore the sign of the effect is still ambiguous. Of course, this is a relative statement—whatever the sign is, the effect of banks is stronger in idiosyncratic than in aggregate volatility.[3]

This paper also studies the behavior of credit. The tightness of financial constraints during contractions and expansions already indicates the role of banks. If financial constraints are countercyclical, then borrowing has to become more countercyclical in order to reduce the volatility imposed by these constraints. In other words, credit has to be negatively correlated with activity if bank credit reduces output volatility: A decrease in output is dampened by increasing borrowing during a contraction. The converse applies for procyclical financial constraints. Credit has to be positively correlated with activity if bank credit increases output volatility: An expansion in output is amplified by increasing borrowing. In a related paper, Galindo, Micco, and Suárez (2004) show that credit is less procyclical in U.S. states in which creditor rights are more protected (a proxy for the degree of financial development). This result supports the idea that credit is needed mostly to sustain higher output during periods of scarce liquidity. I reach a similar conclusion here.

The restrictions that output volatility imposes on the behavior of credit—if there is such a financial mechanism—are usually ignored by the literature. A proper test of the theory has to look at both in order to establish the existence of a financial channel in output fluctuations. This paper fills a gap in that respect.

[3] Models of production and financial constraints do not make the distinction between aggregate and idiosyncratic shocks very often. For instance, Bernanke and Gertler (1989) assume that there are always sufficient savings to finance the entire investment plan of the productive sector, so there is no aggregate shortage of funds and the interest rate is constant. A notable exception is Holmstrom and Tirole (1998). Allen and Gale (1997) note that banks can smooth aggregate shocks to some extent by intertemporal risk-sharing, diversifying across generations. Gatev and Strahan (2004) also examine the ability of banks to respond to aggregate liquidity shocks.

Finally, our analysis of short-term debt examines one of the instruments that banks use to provide liquidity. Evidence for the United States suggests that most of the increase in the business sector's net borrowing that follows a contractionary shock is in the form of short-term debt (Christiano, Eichenbaum, and Evans (1996)). This paper provides further evidence about the importance of short-term debt in a large cross-section of firms and countries.

II. Empirical Strategy

A. Data Sources

The industry data are taken from UNIDO's *Industrial Statistics Database* data set (2001), which provides annual observations (1963–1999) on production indexes for 28 three-digit ISIC (International Standard Industrial Classification) manufacturing segments in a large number of countries. The sample consists of 57,078 observations that correspond to 1,574 country-industry units across 59 different countries. The actual number of industries varies by country. On average each country has 26 industries, and 32 countries have data on all 28 industries. The sample period also varies by country and by industry, although each country-industry unit has at least 26 years of continuous data. While the UNIDO database reports information for more than 100 countries, for a large number of them there are observations on only a few industries or a few years. This last issue is particularly important since the time series is necessary for computing reliable estimates of volatility. This consideration, plus the restriction that we have data on banks, reduces the final sample to 59 countries. The trend in the different data series is removed using either the Baxter and King (1999) filter or log differences.[4] I describe the firm-level data in Section IV.

B. Basic Regression

The regression in (1) tests the direct effect of bank credit on industrial volatility, controlling for other country characteristics and industry fixed effects

$$\begin{aligned} \mathit{Standard\,Deviation}_{i,c} = {} & \alpha_1 \mathit{Bank\,Credit}_c + \alpha_2 \mathit{Country\,Controls}_c \\ & + \alpha_3 \mathit{Industry\,Dummies}_i + \varepsilon_{i,c}. \end{aligned} \tag{1}$$

The dependent variable is the standard deviation of the detrended output of industry i in country c. *Bank Credit* is the average private credit by deposit money banks over GDP, following Beck, Demirgüç-Kunt, and Levine (2000). The *Country Controls* include the averages of per capita GDP, government

[4] The weights for the BK filter can be found in table 4 of Baxter and King (1999). The fact that we detrend the data implies that we abstract from the long-run prospects of an industry (e.g., the tobacco industry probably faces a downward trend in production). We examine fluctuations around that trend.

expenditures as a percentage of GDP, and the country's trade openness (the Frankel and Romer (1999) index).[5] The same regression is run for systematic and idiosyncratic volatilities. The regression for firm-level data is an extension of this basic regression.

This is a purely cross-sectional regression, and thus ignores changes in volatility and bank credit over time. I take this approach because computing volatilities for shorter periods increases measurement error significantly. Ignoring the changes in bank credit over time should not be a major concern, however, since the country ranking of bank credit does not change dramatically throughout the sample period.[6]

In order to control for the endogeneity of bank credit, I also report instrumental variables (IV) regressions, where bank credit is instrumented using legal and institutional variables. The instruments consist of dummy variables from La Porta et al. (1998) that represent the legal origin of the country and a corruption index from the International Country Risk Guide.[7] The corruption index captures the transparency and efficiency of the legal environment. In the cross-country regression that includes the country controls (per capita GDP, government expenditures, and openness), the test of joint insignificance of the instruments is rejected with a p-value below 1% (F-statistic = 9.04).

C. Exploiting Cross-Industry Differences

I need a measure of the typical financial position of an industry in order to test the cross-industry impact of bank credit on volatility. For this purpose I use the index of external finance dependence developed by RZ.[8] This index measures the gap between investment and cash flows. The index is defined as capital expenditures minus cash flows from operations divided by capital expenditures, aggregating U.S.-based, publicly listed firms into industries for the 1980s and 1970s (I use the average of these two indexes). Since RZ average capital expenditures and cash flows both over time and across firms (mature and young), their index is a good approximation of the typical dependence of an industry, not just the dependence at the initial stage of a firm. This last point is important since the relation I want to measure is the relative dependence that arises when an industry is hit by a transitory shock, not when it is planning a long-term expansion. Note that the relevant measure is the need for funds *net* of internal funds available; a pure measure of needs is not necessarily informative of the dependence on external financiers.

[5] The data on country GDP (in constant local currency units), per capita GDP, and government expenditures are taken from the World Bank.

[6] As noted by Rajan and Zingales (2003), striking reversals in financial development occur when extending the sample period to the early 20th century.

[7] I take the corruption index reported by La Porta et al. (1998). For those countries with missing values in La Porta et al. (1998), I use the ICRG issue of April 2002 (Table 3B).

[8] Levine (2004) reviews the assumptions and advantages of the RZ methodology.

One way to study differences across industries is to run the basic regression by subsamples created according to the ranking of industries in the RZ index. Another possibility is to run the regression

$$\begin{aligned} \mathit{Standard\,Deviation}_{i,c} = {} & \beta_1(\mathit{Bank\,Credit}_c \times \mathit{High\,Financial\,Dependence}_i) \\ & + \beta_2 \mathit{Country\,Dummies}_c + \beta_3 \mathit{Industry\,Dummies}_i \\ & + \xi_{i,c}. \end{aligned} \tag{2}$$

The specification in (2) includes country and industry dummies to control for any unobservable characteristic at the country and industry levels. The country fixed effects now absorb the direct effect of bank credit. The coefficient of interest is the interaction of bank credit and high financial dependence, which is akin to the cross-derivative $\partial^2\sigma/\partial B \partial W$ (though financial dependence is the inverse of net worth, W). High financial dependence is a dummy that takes the value of one if industry i is above the median of the RZ index, and zero otherwise. I use a dummy instead of the RZ index itself to allow for nonlinearities in the effect of financial dependence.

A negative β_1 is expected if bank credit reduces volatility on average, showing that financially needy industries reduce volatility *more* as banks develop. These industries have particular trouble getting through periods of relatively low output and cash flows, and therefore, credit enables them to recover more output lost as compared to less financially dependent industries. The sign of β_1 is ambiguous if volatility increases, as explained in the preliminary discussion.

III. Empirical Evidence on Bank Credit and Industrial Volatility

A. Bank Credit Reduces Total Volatility

Table I presents the results for regressions (1) and (2). For regression (1), I split the industries into two groups, namely, high and low financial dependence. I then run the regression in each subsample separately.

Bank credit significantly reduces volatility in both groups of industries. The levels of economic development (per capita GDP) and government size also reduce volatility. Trade openness, in contrast, increases industrial volatility.[9] The coefficient on bank credit in the high dependence group is approximately 50% larger than the coefficient in the low dependence group (ordinary lest squares (OLS) regression). This difference is significant at the 7% level. The cross-sample differences between coefficients of the other country controls are never significant at conventional levels (below 10%).

In order to appreciate the magnitudes involved, we consider the effect of an increase in bank credit of 50% of GDP (approximately two standard deviations

[9] Beck (2002) studies the link between trade openness and financial development. The Frankel–Romer measure considers the fraction of real openness exogenously explained by geography and population.

Table I

The Effect of Bank Credit on the Volatility of Industrial Output

This table presents results from two regressions

$$\begin{aligned} \textit{Standard Deviation}_{i,c} &= \alpha_1 \textit{Bank Credit}_c + \alpha_2 \textit{Country Controls}_c \\ &\quad + \alpha_3 \textit{Industry Dummies}_i + \varepsilon_{i,c} \end{aligned} \tag{1}$$

$$\begin{aligned} \textit{Standard Deviation}_{i,c} &= \beta_1 (\textit{Bank Credit}_c \times \textit{High Financial Dependence}_i) \\ &\quad + \beta_2 \textit{Country Dummies}_c + \beta_3 \textit{Industry Dummies}_i + \varepsilon_{i,c}. \end{aligned} \tag{2}$$

Standard deviations of industrial output are computed using Baxter–King filtered data in the sample period 1963–1999. In the panel with the results of regression (1), the sample of industries is split into two according to whether the industry scores above or below the median of the index of financial dependence. The set of instruments for the IV regressions includes dummies for the legal origin of the country and a corruption index. The row called Effect of banks shows the reduction in volatility when bank credit over GDP increases by 50% of GDP (two standard deviations of bank credit). The row called Differential effect considers the differential impact of increasing bank credit by 50% of GDP over industries with high versus low financial dependence. These effects are shown as a percentage of the median standard deviation in the sample. Industry and country dummies are not reported. Robust standard errors clustered by country are reported below the coefficients in parentheses. Significance (two-sided): * 10%, ** 5%, *** 1%.

Regression (1)	OLS		IV	
	Industry Subsample		Industry Subsample	
	High Financial Dependence	Low Financial Dependence	High Financial Dependence	Low Financial Dependence
Bank credit	−0.0457***	−0.0325**	−0.0657**	−0.0599**
	(0.0172)	(0.0159)	(0.0263)	(0.0241)
Log per capita GDP	−0.0143	−0.0119**	−0.0106	−0.0068
	(0.0056)	(0.0047)	(0.0066)	(0.0054)
Openness	0.0173***	0.0167***	0.0187***	0.0187***
	(0.0057)	(0.0039)	(0.0060)	(0.0038)
Government expenditure	−0.0009***	−0.0007***	−0.0009***	−0.0007***
	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Adjusted R^2	0.326	0.220	0.337	0.229
Number of observations	683	686	683	686
Effect of banks	35%	25%	50%	45%
Regression (2)	**OLS**		**IV**	
Bank credit × High financial dependence	−0.0172***		−0.0238***	
	(0.0048)		(0.0109)	
Adjusted R^2	0.5263		0.5519	
Number of observations	1,574		1,574	
Differential effect	13%		18%	

of bank credit).[10] The line labeled "Effect of banks" reports the reduction in volatility (as a percentage of the median volatility in the sample) that occurs if we consider this change. This exercise is repeated throughout the paper. Table I shows that highly dependent industries reduce volatility by 35%

[10] A 50% increase in bank credit over GDP is comparable, for example, to the difference in credit between two countries such as Ecuador (14%) and Singapore (64%).

of the median volatility, while the other industries reduce volatility by only 25%.

The IV regressions confirm the significance of bank credit in reducing volatility. Interestingly, per capita GDP is not significant once we instrument for bank development.

The specification in equation (2) focuses only on the differential effect of bank credit on industries of high financial dependence. Confirming the cross-sample results above, I obtain a negative coefficient on the interaction between bank credit and financial dependence. The IV results are again supportive of the OLS results.[11]

In order to get a sense of the cross-industry differences, consider the last row in Table I. Here I report the effect of a 50% increase in bank credit over GDP on the highly dependent versus the less dependent industries. We see that the highly dependent industries reduce volatility approximately 13–18% *more* than the less dependent industries.

The results from regression (2) are powerful since the country fixed effects control for any country-specific characteristic. Regression (2) also represents a test at the level of second derivatives, as it examines the differential effect of bank credit on industries sorted by financial dependence. The possibility still exists, however, that the interaction of bank credit and financial dependence reflects a pattern that is produced by other combinations of country and industry characteristics. For instance, the reduction in volatility may be achieved by nonfinancial arrangements or shocks may change in a way that generates lower volatility. In the interest of brevity, these robustness checks are not presented for the case of total volatility. However, I return to them when I examine the composition of volatility in Table V. For now, it suffices to say that in the case of total volatility, the interaction of bank credit and financial dependence survives the addition of all the alternative interactions presented in that table.[12]

B. Systematic and Idiosyncratic Volatility

Total volatility is divided into two components, namely, systematic volatility and idiosyncratic volatility. Systematic volatility corresponds to fluctuations that are correlated with the GDP of the country (or the business cycle), whereas idiosyncratic volatility is uncorrelated with GDP, and therefore is specific to a particular industry in a given country.[13] In order to perform this decomposition, consider the following regression:[14]

$$\Delta y_{i,c,t} = \beta_{i,c} \Delta gdp_{c,t} + \varepsilon_{i,c,t}, \tag{3}$$

[11] In the IV estimation of regression (2) the interaction of bank credit and high financial dependence is instrumented by the interactions of the legal variables and high financial dependence.

[12] Raddatz (2003) includes different interactions than those presented here, which shows that the reduction in total volatility is a very robust finding.

[13] Total GDP is more than the sum of the 28 industries in the UNIDO data set since these industries are only in manufacturing.

[14] Since I work with detrended data, the intercept of this regression is negligible.

Table II

Variance Decomposition of the Volatility of Industrial Output

This table shows the variance decomposition of industrial volatility according to

$$\sigma_{ic}^2 = \beta_{ic}^2 \sigma_{gdp,c}^2 + \sigma_{\varepsilon,ic}^2.$$

In Panel A, the first column shows the average variance of industrial output. The second and third columns show the percentage of total variance (left-hand side of the equation above) that corresponds to systematic and idiosyncratic variance (first and second terms in the right-hand side of the equation above), respectively. Results for the subsample of countries that score below (above) the median of bank credit to GDP are shown in the row Low (High) Credit Countries. Panel B computes the difference in variance between countries with low credit and countries with high credit. The last row shows this difference as a percentage of the variance in countries with low credit in each category. Results are presented using Baxter–King filtered data in the sample period 1963–1999.

	Total Variance	Systematic	Idiosyncratic
Panel A: Variance Decomposition			
Entire sample	0.0091	13%	87%
Low credit countries	0.0133	11%	89%
High credit countries	0.0049	19%	81%
Panel B: Changes in Variance within Category			
Low–High	0.0084	0.0005	0.0079
Difference as % of variances in low credit countries	63	36	67

where $\Delta y_{i,c,t}$ is the cyclical output of industry i in country c at time t, $\Delta gdp_{c,t}$ is the cyclical fluctuation of aggregate GDP, and $\varepsilon_{i,c,t}$ is an idiosyncratic shock that is orthogonal to aggregate GDP fluctuations. The coefficient $\beta_{i,c}$ represents the sensitivity of the industry to aggregate fluctuations, and is a function of industry and country characteristics. For example, industries that produce durable goods usually have a higher $\beta_{i,c}$ than industries that produce nondurables.

Let $\Delta gdp_{c,t}$ and $\varepsilon_{i,c,t}$ have standard deviations of $\sigma_{gdp,c}$ and $\sigma_{\varepsilon,ic}$, respectively. The total variance of output is then

$$\sigma_{ic}^2 = \beta_{ic}^2 \sigma_{gdp,c}^2 + \sigma_{\varepsilon,ic}^2. \tag{4}$$

The first term on the right-hand side of (4) is the systematic variance and the second term is the idiosyncratic variance. Both components can be estimated by running the regression in (3) and computing the volatility of fitted values and residuals. Table II shows the summary of the variance decomposition.

Systematic variance represents between 10% and 20% of industrial volatility. There is an increase in the fraction attributed to systematic volatility in countries with more bank credit despite the overall drop in volatility. The source of this change is a more pronounced reduction in idiosyncratic volatility (67%) compared to the reduction in systematic volatility (36%). Figure 1 illustrates this change by showing both systematic and idiosyncratic volatilities as

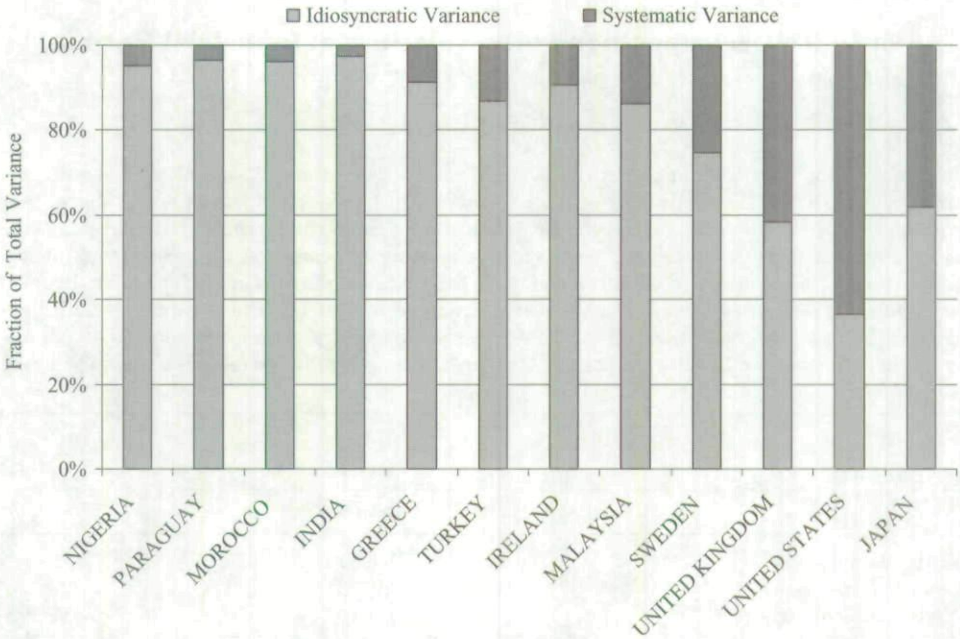

Figure 1. Systematic and idiosyncratic variance. The figure shows the fraction of the average variance of industrial output that is systematic and idiosyncratic in each country. Countries are shown from left to right in ascending order according to the level of bank credit over GDP.

fractions of total volatility for several countries. Systematic volatility accounts for 50% or more of industrial volatility in the United States, while it is less than 10% in countries such as Nigeria and Paraguay that are characterized by lower levels of bank credit.

The correlation coefficient between industrial output and GDP measures the fraction of total volatility that corresponds to systematic volatility. One can also think of the squared correlation as the R^2 of the regression in (3).

$$\operatorname{Corr}(\Delta y_{i,c,t}, \Delta gdp_{c,t})^2 = \beta_{ic}^2 \sigma_{gdp,c}^2 / \sigma_{ic}^2. \tag{5}$$

Table II suggests that correlations increase with bank credit, which is equivalent to saying that systematic volatility accounts for a larger fraction of total volatility. This implies that industries move more closely together when banks are more developed. This is not the result of larger measurement error—and potentially more idiosyncratic noise—in less developed countries, since the cross-industry pattern is again present. The regressions for idiosyncratic volatility in Table III are very similar to the regressions with total volatility. The coefficients for bank credit are again larger in the group of industries with high financial dependence. The regression with the interaction term confirms this finding: Idiosyncratic volatility is particularly lower in financially more dependent industries. The differential effect is stronger than the one identified in Table I for total volatility (16% vs. 13%), which is a reflection of the steeper reduction in

Table III

The Effect of Bank Credit on Idiosyncratic and Systematic Volatilities

This table shows OLS results for regressions

$$Idiosyncratic\,Std.\,Dev_{i,c} = \alpha_1 Bank\,Credit_c + \alpha_2 Country\,Controls_c + \alpha_3 Industry\,Dummies_i + \varepsilon_{i,c} \quad (1)$$

$$Idiosyncratic\,Std.\,Dev_{i,c} = \beta_1 (Bank\,Credit_c \times High\,Financial\,Dependence_i) + \beta_2 Country\,Dummies_c + \beta_3\,Industry\,Dummies_i + \varepsilon_{i,c}. \quad (2)$$

The same regressions are run for the systematic standard deviation. The variance decomposition follows equation (4) in the text. Standard deviations are computed using Baxter–King filtered data in the sample period 1963–1999. In the panel with the results of regression (1), the sample of industries is split into two according to whether the industry scores above or below the median of the index of financial dependence. The row called Effect of Banks shows the reduction in volatility when bank credit over GDP increases by 50% of GDP (two standard deviations of bank credit). The row called Differential effect considers the differential impact of increasing bank credit by 50% of GDP over industries with high versus low financial dependence. These effects are shown as a percentage of the corresponding median standard deviation in the sample. Industry and country dummies are not reported. Robust standard errors clustered by country are reported below the coefficients in parentheses. Significance (two-sided): * 10%, ** 5%, *** 1%.

	Idiosyncratic St. Deviation		Systematic St. Deviation	
	High Financial Dependence	Low Financial Dependence	High Financial Dependence	Low Financial Dependence
	Regression (1)			
Bank credit	−0.0434**	−0.0314**	−0.0074	−0.0076
	(0.0175)	(0.0157)	(0.0109)	(0.0064)
Log per capita GDP	−0.0168***	−0.0129***	0.0027	0.0004
	(0.0054)	(0.0048)	(0.0036)	(0.0021)
Openness	0.0203***	0.0168***	−0.0028	0.0019
	(0.0055)	(0.0038)	(0.0034)	(0.0019)
Government expenditure	−0.0008***	−0.0006***	−0.0003	−0.0002
	(0.0003)	(0.0002)	(0.0002)	(0.0001)
Adjusted R^2	0.361	0.227	0.050	0.124
Number of observations	683	686	683	686
Effect of banks (%)	40	29	12	12
	Regression (2)			
Bank credit ×	−0.0172***		−0.0001	
High financial dependence	(0.0046)		(0.0038)	
Adjusted R^2	0.5356		0.4193	
Number of observations	1,574		1,574	
Differential effect	16%		0.1%	

idiosyncratic volatility. The IV coefficients (not reported) are again larger than the OLS coefficients and highly significant.

The regressions for systematic volatility in Table III indicate a negative coefficient on bank credit and on the interaction of bank credit and financial dependence, but these estimates are not significant at conventional levels. The coefficients on the other country variables such as per capita GDP are not significant either. In any case, systematic volatility is not increasing with bank credit; if anything, it is only moderately decreasing.

This last result can be somewhat of a puzzle when compared to the strong smoothing effect of financial development on recessions (Braun and Larrain (2005)). However, the fact that systematic volatility decreases only moderately is not necessarily inconsistent with Braun and Larrain's finding about recessions, because systematic volatility takes into account aggregate ups and downs. The fact that banks amplify booms nearly as much as they dampen recessions helps reconcile the two results. Table V in Braun and Larrain provides evidence in this respect: Booms are stronger in well-developed financial systems and especially in financially dependent industries, though the effect is smaller in magnitude than during recessions. This can explain the moderately decreasing systematic volatility that we find here. The lack of power in the tests with systematic volatility is also consistent with the inconclusive evidence presented by Beck et al. (2004) about the effect of financial intermediaries in the response of GDP to macro shocks.

The results highlight the fact that liquidity provision is mostly concerned with idiosyncratic fluctuations. The effect of banks on aggregate fluctuations is dwarfed in comparison. For example, the hypothetical reduction in the volatility of a firm that moves to a country with more developed banks consists of 95% idiosyncratic volatility and only 5% systematic volatility (see Table II). I study how this volatility reduction is achieved in Section IV.

C. Regressions with the Correlation of Industrial Output and GDP as the Dependent Variable

These regressions explore the effect of bank credit on the ratio of systematic to total volatility, that is, the correlation. In some sense, this is just another way of presenting the information contained in Table III.

Table IV shows that correlations increase with bank credit in industries with high and low financial dependence, though the effect is stronger in the first group (33% vs. 12%). The differential effect between industries is quite large at around 18% of the median correlation in the sample, which is to say that the correlations of highly dependent industries increase by 18% *more* than those of the less dependent industries when bank credit increases by 50% of GDP (in the cross-section of countries). The right panel in Table IV shows the regressions using correlations of log-differences to emphasize that the detrending method is of no material importance for obtaining these results.[15]

Table V presents several robustness checks applied to the interaction approach. One hypothesis is that, since bank credit allows a higher degree of specialization in financially dependent industries, the higher correlations can

[15] Since correlations are bounded between –1 and 1, I apply a logistic transformation before running the regressions and obtain basically the same results as those reported here. Moreover, none of the fitted values in the reported regressions lie outside the [−1, 1] interval.

Table IV

The Effect of Bank Credit on Industrial Correlations with GDP

This table shows OLS results for regressions

$$Correlation_{i,c} = \alpha_1 Bank\,Credit_c + \alpha_2 Country\,Controls_c + \alpha_3 Industry\,Dummies_i + \varepsilon_{i,c} \quad (1)$$

$$Correlation_{i,c} = \beta_1 (Bank\,Credit_c \times High\,Financial\,Dependence_i) + \beta_2 Country\,Dummies_c + \beta_3 Industry\,Dummies_i + \varepsilon_{i,c} \quad (2)$$

The correlations of industrial output with GDP use Baxter–King filtered data (left panel) and log differences (right panel) in the sample period 1963–1999. In the panel with the results of regression (1), the sample of industries is split into two according to whether the industry scores above or below the median of the index of financial dependence. The row called Effect of banks shows the rise in correlations when bank credit over GDP increases by 50% of GDP (two standard deviations of bank credit). The row called Differential effect considers the differential impact of increasing bank credit by 50% of GDP over industries with high versus low financial dependence. These effects are shown as a percentage of the corresponding median correlation in the sample. Industry and country dummies are not reported. Robust standard errors clustered by country are reported below the coefficients in parentheses. Significance (two-sided): * 10%, ** 5%, *** 1%.

	Correlation (BK Filter)		Correlation (Log Differences)	
	High Financial Dependence	Low Financial Dependence	High Financial Dependence	Low Financial Dependence
	Regression (1)			
Bank Credit	0.2221*	0.0826	0.2095*	0.1971
	(0.1161)	(0.1046)	(0.1233)	(0.1270)
Log per capita GDP	0.1068**	0.0829**	0.0908*	0.0565
	(0.0442)	(0.0394)	(0.0481)	(0.0465)
Openness	−0.1363***	−0.0827***	−0.1258***	−0.1067***
	(0.0365)	(0.0285)	(0.0417)	(0.0330)
Government expenditure	0.0014	0.0016	0.0009	0.0026
	(0.0023)	(0.0020)	(0.0023)	(0.0024)
Adjusted R^2	0.291	0.228	0.258	0.234
Number of observations	683	686	683	686
Effect of banks (%)	33	12	29	27
	Regression (2)			
Bank credit × High financial dependence	0.1202**		0.0508*	
	(0.0473)		(0.0279)	
Adjusted R^2	0.5358		0.5817	
Number of observations.	1,574		1,574	
Differential effect (%)	18		7	

be mechanically driven by size instead of by reductions in volatility. Basically, an industry is more correlated with GDP when it is a larger fraction of it. One immediate problem with this hypothesis is that, on average in the sample, an industry represents less than 2% of manufacturing value added, and manufacturing itself is about 20% of GDP in industrialized countries. Therefore, the

Table V

The Differential Effect of Bank Credit on Industrial Correlations with GDP: Alternative Interactions and Controls

This table adds different interaction effects to regression (2) in Table IV. The estimation method is OLS. Correlations are computed using Baxter–King filtered data in the sample period 1963–1999. See the text for the description of the variables. The row called Differential effect considers the differential impact of increasing bank credit by 50% of GDP over industries with high versus low financial dependence. This effect is measured as a percentage of the median correlation in the sample. Industry and country dummies are not reported. Robust standard errors clustered by country are reported below the coefficients in parentheses. Significance (two-sided): * 10%, ** 5%, *** 1%.

	Dependent Variable: Correlation with GDP				
Bank credit × high financial dependence	0.0914* (0.0497)	0.0584 (0.0478)	0.1697*** (0.0472)	0.1623*** (0.0339)	0.1238*** (0.0466)
Average industry size in each country	0.4927*** (0.1767)	–	–	–	–
Log per capita GDP × high financial dependence	–	0.0326** (0.0142)	–	–	–
Government expenditure × high financial dependence	–	–	−0.0007 (0.0009)	–	–
Country openness × high financial dependence	–	–	–	−0.0640*** (0.0202)	–
Country openness × tradable goods producer	–	–	–	–	−0.0536 (0.0523)
Adjusted R^2	0.5357	0.5372	0.5438	0.5395	0.5362
Number of observations	1,548	1,574	1,369	1,574	1,574
Differential effect (%)	14	9	26	25	19
Bank credit × high financial dependence	0.0849* (0.0439)	0.0964** (0.0483)	0.0844* (0.0443)	0.1226*** (0.0471)	–
Bank credit × orthogonal financial dependence	–	–	–	–	0.1186** (0.0603)
Log per capita GDP × durable goods producer	0.0409** (0.0182)	–	–	–	–
Log per capita GDP × investment goods producer	–	0.0369 (0.0297)	–	–	–
Log per capita GDP × oil intensive technology	–	–	1.0045 (1.6061)	–	–
Log per capita GDP × capital intensive technology	–	–	–	−0.2532 (0.2548)	–
Adjusted R^2	0.5384	0.5363	0.5589	0.5363	0.5336
Number of observations	1,574	1,574	1,477	1,574	1,574
Differential effect (%)	13	15	13	19	8

increment in size for the average industry is negligible in terms of its effect on GDP. Thus, while size does come in significantly if we include it in the regression, it is hard to infer causality because of the simultaneity of effects.[16] The coefficient of the interaction is still significant, albeit smaller than the coefficients in other specifications.

If industries depend on government subsidies, it may be the case that in countries with large governments, correlations are higher as a product of cyclical variation in tax receipts. I find no evidence supporting this hypothesis.

Openness to trade, as seen in Tables IV and V, is a source of reduced comovement between financially dependent industries and a country's GDP. Nevertheless, the main interaction is still significant at the 1% level when I add interactions of openness with financial dependence or industry tradability.[17]

Other potential explanations for the increase in correlations propose that economic development increases the exposure of a group of industries to particular sources of *aggregate* shocks. As seen in the second column of Table V, the interaction of per capita GDP with financial dependence makes the interaction with bank credit insignificant. Given the high correlation of per capita GDP and bank credit, this observation is hard to interpret as conclusive evidence against a financial mechanism.

I test more direct mechanisms of how economic development affects correlations by including interactions with other industry characteristics. For example, economic development can change the productive structure of the country in a way that increases its exposure to oil shocks—a frequently mentioned source of aggregate fluctuations. If this is the case, then oil-dependent industries should observe a higher increase in their correlations with GDP.[18] The second panel in Table V shows that there is no evidence in support of this channel.

Economic development can also affect industries that produce durable or investment goods. Empirical results show that this channel may be operating. However, it is hard to rule out the influence of finance, since durable goods and investment goods are usually purchased with credit. Moreover, for those industries that use a capital-intensive technology (Braun (2002)), the effect—if present—is to decrease the exposure to systematic risk.

Overall, the interaction of bank credit and financial dependence survives the interactions of other industry characteristics with economic development, though the magnitude of the coefficient is reduced in some cases. As a last robustness test, note that the results are almost intact when I include the interaction of bank credit with a measure of financial dependence that is orthogonal

[16] Size is computed as the average ratio of the industry's value added to total manufacturing value added of the country.

[17] The industry characteristics used in Table V are taken from Braun and Larrain (2005) except where noted.

[18] Oil dependency is computed for each industry as the ratio of input from industries 353 and 354 (oil-related industries) to total input. Industries 353 and 354 are excluded from this variable. The data come from the BEA's *use* tables (www.bea.gov/bea/dn2.htm), and therefore correspond to U.S. firms.

to the rest of the industry variables studied.[19] This last piece of evidence makes the case for the presence of a distinctive financial mechanism beyond the correlation of financial dependence with other industrial characteristics.

IV. Exploring the Mechanism with Firm-Level Data

Countercyclical borrowing is central to the mechanism that explains the reduction in output volatility: If banks reduce the volatility of output, it is by disassociating borrowing and output, in other words, by breaking the pattern of low output and low borrowing. Given the previous results on volatility, I expect to find more countercyclical borrowing when banks are more developed. I turn to firm-level data, which provides data on borrowing, to explore this issue.

A. Data and Preliminary Evidence

The firm-level data are from the *Compustat Global Industrial/Commercial* database. This data set provides annual balance sheet information on firms from multiple countries for the years 1991 to 2002. I restrict the sample to those firms in the manufacturing sectors that match the previous industry data, within the same 59 countries. I consider only those firms with five or more years of data since the tests require time-series variation. After performing these adjustments, the data consist of almost 47,000 observations that correspond to approximately 5,700 firms in 42 countries. The average number of years per firm is eight.[20]

Because there is no production index at the firm level, I measure output with sales and inventory investment, which are linked by the identity: Production = sales + inventory investment, or, $Q = S + \Delta I$. Using this identity I can approximate the previous section's results on the volatility of industrial output.[21] Also, my interest in inventories derives from the link between inventory investment and credit conditions in the United States (Gertler and Gilchrist (1994), Kashyap et al. (1994)).

In terms of borrowing, I concentrate on short-term debt. My definition of short-term debt includes notes payable and accounts payable (trade credit and others), but it excludes long-term debt due in 1 year, accrued expenses, taxes payable, and proposed dividends.[22] In order to examine fluctuations I take

[19] The orthogonal finance dependence is the residual of the regression of finance dependence on durable goods, investment goods, tradable goods, and capital intensity. Oil intensity is not included so that I keep all 28 industries. The R^2 of this regression ($N = 28$) is 22%.

[20] I also drop observations with missing values for assets, with missing debt plus equity, with assets not equal to debt plus equity, or with negative equity. These represent only minor adjustments.

[21] The identity implies that $\mathrm{Var}(Q) = \mathrm{Var}(S) + \mathrm{Var}(\Delta I) + 2\mathrm{Cov}(S, \Delta I)$. The covariance is estimated to be positive in empirical studies (Ramey and West (1999)), showing that inventories are procyclical.

[22] Demirgüç-Kunt and Maksimovic (1999) use an earlier version of this same database. The definition of short-term debt in their paper includes long-term debt due in 1 year, accrued expenses, taxes payable, and proposed dividends.

Table VI

The Effect of Banks on Volatility and Borrowing Using Firm-Level Data: Preliminary Evidence

The table presents the average firm-level standard deviation (or correlation) of the log-changes in sales (S), sales over assets (S/A), inventory (I), inventory over sales (I/S), and short-term debt (D). The sample period is 1991–2002. The table presents four groups: two groups of industries and two groups of countries within each industry classification. Industries are divided into high and low financial dependence (FD) categories according to the median of the financial dependence index. Countries are divided into high and low bank credit according to the median bank credit in the sample. The number of firms in each bin varies between 1,000 and 2,000 firms. Not all bins have the same number of observations because not all countries and industries have the same number of firms. The column labeled Δ is the difference between countries of high and low bank credit. All firm variables are winsorized at the 1% and 99% levels.

	High FD Industries			Low FD Industries		
	Bank Credit over GDP			Bank Credit over GDP		
	High	Low	Δ	High	Low	Δ
$SD(\Delta\log(S))$	0.22	0.43	−0.21	0.25	0.42	−0.17
$SD(\Delta\log(S/A))$	0.19	0.23	−0.04	0.20	0.21	−0.01
$SD(\Delta\log(I))$	0.29	0.51	−0.22	0.29	0.48	−0.19
$SD(\Delta\log(I/S))$	0.25	0.30	−0.05	0.21	0.26	−0.05
$Corr(\Delta\log(S), \Delta\log(D))$	0.40	0.45	−0.05	0.33	0.37	−0.04
$Corr(\Delta\log(I), \Delta\log(D))$	0.45	0.55	−0.10	0.39	0.49	−0.10

the log change in sales ($\Delta\log(S)$), inventories ($\Delta\log(I)$), and short-term debt ($\Delta\log(D)$). [23]

Table VI shows preliminary results on the volatility and correlation of these variables. The table compares a firm's average volatility in countries with high and low bank credit, while differentiating among firms in more and less financially dependent industries. It is clear that volatility is lower in countries with more developed banks, both in terms of sales and inventories. Moreover, the reduction in volatility is stronger in the financially dependent firms. This result holds even if we examine the volatility of the ratios of these variables to assets (A) or sales (e.g., $\Delta\log(S/A)$ or $\Delta\log(I/S)$). Because ratios can smooth the effects of mergers and acquisitions, in a sense they provide cleaner results. For instance, a firm that acquires another firm can mechanically have high inventory growth even in the absence of any shock.

The correlations of sales or inventories with debt are also lower in countries with higher bank credit. Low correlations, although positive, signal that borrowing is more countercyclical. As a pure measure of comovement—one that is independent of the volatilities of sales, inventories, or debt—a lower correlation indicates that debt and production move more frequently in opposite directions when banks are more developed. In other words, in more developed banking

[23] The lines from Compustat Global are: inventories (data66), sales (data1), short-term debt (data96 + data97 + data101), and total assets (data89).

systems, firms tend to borrow more as sales fall and to pay more debt as sales increase. As noted before, this countercyclical behavior of borrowing is expected when financial constraints are relatively tighter during contractions of activity (low sales or low inventories).

B. The Volatility of Sales, Inventories, and Production

A more careful analysis of the data can be performed using the basic regression augmented to control for firm characteristics, that is,

$$\begin{aligned} \mathit{Standard\,Deviation}_{i,c,f} = {} & \alpha_1 \mathit{Bank\,Credit}_c + \alpha_2 \mathit{Country\,Controls}_c \\ & + \alpha_3 \mathit{Industry\,Dummies}_i + \alpha_4 \mathit{Firm\,Controls}_{i,c,f} \\ & + \varepsilon_{i,c,f}. \end{aligned} \tag{6}$$

I run this regression with the standard deviation of sales, inventories, and production as dependent variables. I use ratios, which are cleaner measures as argued above, though the results do not rely on using ratios or levels. The subscript f refers to a firm, which is now the unit of observation. In addition to the country controls and industry fixed effects (at the three-digit ISIC level), I include three firm controls that are usually associated with leverage (Rajan and Zingales (1995)), specifically, the log of sales as proxy for size, profitability defined as earnings before interest, taxes, depreciation, and amortization (EBITDA) over assets, and tangibility defined as tangible assets over total assets. I use the time average of each variable for each firm.

The results displayed in Table VII confirm the dampening effect of bank credit on the volatility of sales, inventories (as a ratio of assets or sales), and total production. The other country variables in the regressions have a weak effect, suggesting that bank credit is the main channel through which output is smoothed. The firm variables are all statistically significant and take the expected signs: Large, profitable firms, and firms with more tangible assets have lower volatility. The difference between the more and less financially dependent industries is not significant at conventional levels, though the point estimates show a stronger effect for more dependent firms in the case of inventories. These results are robust to considering the subsample of non-U.S. firms and to instrumenting bank credit with the legal variables used in the previous sections (results not reported). Finally, the decomposition of volatility, which is examined in the previous section with industrial data, is not performed here because the time series is too short.

Following our previous illustration of the magnitude of the effects, an increase in bank credit equal to 50% of GDP reduces the volatility of the median firm by approximately 50% across the different measures in Table VII. The coefficients on bank credit reported for production volatility in the last two columns should be comparable to the previous industry estimates; however, it turns out that they are between two to four times larger than those coefficients. Besides the obvious sample differences that can account for the variation, another possible explanation is that many firm-level fluctuations wash out within an industry

Table VII

The Effect of Bank Credit on the Volatilities of Sales and Inventories Using Firm-Level Data

The regression estimated by OLS is

$$Standard\,Deviation_{i,c,f} = \alpha_1 Bank\,Credit_c + \alpha_2 Country\,Controls_c + \alpha_3 Industry\,Dummies_i + \alpha_4 Firm\,Controls_{i,c,f} + \varepsilon_{i,c,f}.$$

The sample period is 1991–2002. The dependent variables are: standard deviation of Δlog(sales/assets), standard deviation of Δlog(inventories/assets), standard deviation of Δlog(inventories/sales), and standard deviation of Δlog(production/assets). Production is defined as sales plus inventory investment. Country controls include the log of per capita GDP, openness, and government expenditure. Firm controls include firm size (log of sales), profitability, and tangibility, averaged for each firm during the sample period. Results are reported for two subsamples of firms that correspond to industries with high and low financial dependence (FD) according to the median of the financial dependence index. The row called Effect of banks shows the reduction in volatility when bank credit over GDP increases by 50% of GDP (two standard deviations of bank credit). This effect is reported as a percentage of the corresponding median volatility in the sample. The last row reports the p-value of the test that the effect of banks is stronger in the group of highly dependent firms. All firm variables are winsorized at the 1% and 99% levels. Industry dummies are not reported. Robust standard errors clustered by country-industry units are reported below the coefficients in parentheses. Significance (two-sided): * 10%, ** 5%, *** 1%.

	SD(Δlog(S/A)) Industry Subsample		SD(Δlog(I/A)) Industry Subsample		SD(Δlog(I/S)) Industry Subsample		SD(Δlog(Q/A)) Industry Subsample	
Independent Variables	High FD	Low FD	High FD	Low FD	High FD	Low FD	High FD	Low FD
Bank credit	−0.163***	−0.193***	−0.197***	−0.139***	−0.173***	−0.135***	−0.103***	−0.131***
	(0.029)	(0.036)	(0.038)	(0.034)	(0.036)	(0.032)	(0.033)	(0.032)
Log per capita GDP	−0.020*	−0.008	−0.017	−0.023***	−0.035**	−0.028***	−0.009	−0.014*
	(0.011)	(0.009)	(0.016)	(0.008)	(0.015)	(0.009)	(0.011)	(0.008)
Openness	−0.002	−0.018*	0.031***	0.014	0.038***	0.019**	0.007	−0.004
	(0.008)	(0.010)	(0.012)	(0.009)	(0.010)	(0.009)	(0.009)	(0.011)
Government expenditure	−0.001	0.001	−0.004***	−0.002***	−0.003***	−0.001	0.001	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm size	−0.018***	−0.017***	−0.018***	−0.016***	−0.019***	−0.019***	−0.014***	−0.011***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Profitability	0.784***	−1.132***	−0.615***	−0.803***	−0.682***	−0.814***	−0.544***	−0.650***
	(0.065)	(0.142)	(0.058)	(0.113)	(0.056)	(0.099)	(0.063)	(0.176)
Tangibility	−0.108***	−0.086***	−0.201***	−0.085***	−0.187***	−0.085***	−0.111***	−0.100***
	(0.039)	(0.030)	(0.059)	(0.029)	(0.048)	(0.030)	(0.040)	(0.029)
Adjusted R^2	0.371	0.475	0.270	0.286	0.267	0.267	0.160	0.175
Number of observations	2,821	2,830	2,805	2,750	2,804	2,750	2,710	2,655
Effect of banks (%)	59	70	60	42	46	36	38	49
p-value high < low		26%		13%		21%		27%

and they do not show up in industry aggregates. For instance, higher sales in one firm can be compensated by lower sales in another firm, leaving total industry sales (and output) unchanged. In fact, firm-level volatility is more than twice as large as industrial volatility on average (see Table AI). Thus the effect of banks on firm fluctuations overstates the effect of banks on industry fluctuations, as we observe here. Alternatively, we can interpret this as yet another illustration of the power of banks with respect to idiosyncratic versus (more) aggregate fluctuations.

C. The Countercyclical Behavior of Borrowing

The comovement of debt and output is a central part of the story that links banks and volatility. In order to explore this comovement, we run firm-level regressions that use the correlation of sales or inventories with short-term debt as dependent variables.

As seen in columns one and two of Table VIII, bank credit reduces the correlation of sales and debt, which confirms that borrowing is less procyclical as credit grows. The correlation reduction happens mostly among firms in financially dependent industries. In fact, the difference with respect to the less dependent industries is statistically significant at the 1% level. A 50% increase in bank credit reduces the correlation of sales and debt in the median firm from 0.10 to 0.01 (using the estimate in the first column). A similar pattern is observed in inventories. A 50% increase in bank credit reduces the correlation of inventories and debt in the median firm from 0.24 to 0.12 (using the estimate in column three of Table VIII).

One striking result in Table VIII is that economic development (proxied by per capita GDP) significantly increases the correlation of output and debt. The fact that the coefficients on GDP and bank credit have opposite signs confirms that the mechanisms working behind economic and financial development are different. In terms of firm controls, the only variable that has a significantly negative effect is profitability, although it is not surprising that profitable firms can borrow more as sales or inventories fall.

The last two columns in Table VIII study the behavior of the inventory to sales ratio. We see that the countercyclical behavior of this ratio is enhanced with more credit, that is, firms in more developed financial systems do not need to liquidate as much inventory as sales fall. Again, the coefficient is larger and more significant for the group of financially dependent industries. This result coincides with the evidence in Bernanke et al. (1996) and Gertler and Gilchrist (1994), which relates to the cyclical behavior of small firms—the proxy for more financially constrained in that series of papers. They show that the inventory to sales ratio in small firms falls even after negative monetary shocks, implying that these firms shed inventory faster than their sales decline. Less constrained firms, on the other hand, can afford to carry more inventory by borrowing more easily.

It is well known that inventory moves procyclically—firms build up inventory in expansions and cut back inventory in recessions—and, moreover, that

Table VIII

The Effect of Bank Credit on the Correlations of Sales, Inventory, and Short-Term Debt Using Firm-Level Data

The regression estimated by OLS is

$$Correlation_{i,c,f} = \alpha_1 Bank\ Credit_c + \alpha_2 Country\ Controls_c + \alpha_3 Industry\ Dummies_i + \alpha_4 Firm\ Controls_{i,c,f} + \varepsilon_{i,c,f}.$$

The sample period is 1991–2002. The dependent variables are: correlation of Δlog(sales/assets) and Δlog(short-term debt/assets), correlation of Δlog(inventories/assets) and Δlog(short-term debt/assets), and correlation of Δlog(inventories/sales) and Δlog(sales). Country controls include the log of per capita GDP, openness, and government expenditure. Firm controls include firm size (log of sales), profitability, and tangibility, averaged for each firm during the sample period. Results are reported for two subsamples of firms that correspond to industries with high and low financial dependence (FD) according to the median of the financial dependence index. The row called Effect of banks shows the reduction in correlation when bank credit over GDP increases by 50% of GDP (two standard deviations of bank credit). This effect is reported as a percentage of the corresponding median correlation in the sample. The last row reports the p-value of the test that the effect of banks is stronger in the group of highly dependent firms. All firm variables are winsorized at the 1% and 99% levels. Industry dummies are not reported. Robust standard errors clustered by country-industry units are reported below the coefficients. Significance (two-sided): * 10%, ** 5%, *** 1%.

	Corr(Δlog(S/A), Δlog(D/A)) Industry Subsample		Corr(Δlog(I/A), Δlog(D/A)) Industry Subsample		Corr(Δlog(I/S), Δlog(S)) Industry Subsample	
Independent Variables	High FD	Low FD	High FD	Low FD	High FD	Low FD
Bank credit	−0.184**	0.106	−0.246***	−0.052	−0.207**	−0.121*
	(0.076)	(0.070)	(0.070)	(0.063)	(0.083)	(0.072)
Log per capita GDP	0.103***	0.055***	0.060*	0.061***	0.105***	0.056***
	(0.029)	(0.021)	(0.032)	(0.021)	(0.027)	(0.020)
Openness	−0.006	0.019	0.021	0.051**	0.026	−0.015
	(0.023)	(0.020)	(0.018)	(0.020)	(0.026)	(0.020)
Government expenditure	−0.005***	−0.005***	−0.005***	−0.004**	0.000	0.002
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Firm size	0.000	−0.007*	−0.001	−0.007*	0.022***	0.013***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Profitability	−0.384***	−0.453***	−0.253***	−0.232*	0.757***	0.426***
	(0.097)	(0.095)	(0.095)	(0.122)	(0.116)	(0.136)
Tangibility	−0.199**	−0.025	−0.039	−0.091	−0.079	0.016
	(0.099)	(0.074)	(0.103)	(0.074)	(0.072)	(0.069)
Adjusted R^2	0.030	0.040	0.019	0.016	0.051	0.032
Number of observations	2,821	2,830	2,805	2,750	2,804	2,750
Effect of banks (%)	92	−53	51	11	38	23
p-value high < low		0%		2%		22%

inventory can account for a large fraction of GDP fluctuations. Ramey and West (1999) report that in G7 countries during the 1990s inventory decline accounts for 30% of the decrease in GDP in recessions. In this respect, our results on banks and inventory add flesh to Braun and Larrain's (2005) findings with regard to the smoothing effect of financial development on recessions.[24] The results in this paper suggest that one important factor for the dampening of recessions is that well-developed banking systems allow firms to have more stable inventories.

The last issue I take up here concerns the role of other financial institutions in volatility. In particular, so far I restrict the analysis to banks, without paying attention to the development of the stock market. However, stock markets can also reduce volatility by allowing, for example, for better risk management in each firm.

The literature on growth and financial structure concludes that, at least empirically, whether a firm is located in a market-based or a bank-based system makes little difference (Levine (2004)). In the case of volatility, both systems have advantages, and they are probably good complements. The results in Table IX indicate that both banks and the stock market have a dampening effect on volatility, however, the effect of banks is larger (−0.15 vs. −0.02) and more significant.

The variable that captures the *relative* development of the stock market compared to banks does not significantly reduce volatility when bank credit is absent from the regression. This shows that financial structure per se does not explain the results so far. One rationale for the inclusion of financial structure in the regression is that a more developed stock market relative to banks—independent of the *level* of bank credit—can allow banks to specialize in short-term lending and therefore help to reduce volatility. The idea is that when the stock market grows, banks can delegate long-term financing to other agents, concentrating on the provision of liquidity. While it is true that banks tend to focus more on short-term lending than other financial institutions, this hypothesis implies that the structure of the financial system affects the cyclical behavior of debt (previously discussed). In other words, according to this story, when we compare two countries with the same level of bank credit over GDP, we should find that short-term lending is more countercyclical in the country that has a more developed stock market. Despite the appeal of this hypothesis, the regressions that include the correlations of inventory and debt (similarly for sales and debt) do not show signs of such additional specialization of banks in short-term lending. Thus, neither stock market capitalization nor financial structure is significant in making short-term debt more countercyclical.

Overall, the firm-level evidence supports the idea that deeper financial intermediation not only allows faster growth as shown in previous papers, but also provides liquidity to smooth fluctuations of sales and inventory. The results are consistent with the previous industry evidence, though they have to be taken with caution because of data limitations. First, a longer time series is required to compute volatilities and correlations that are less noisy and not affected by a particular sample period (the 1990s in this case). Second, knowing more about

[24] I thank the referee for suggesting this point.

Table IX

The Effect of Banks and Stock Markets on Volatility and Borrowing Using Firm-Level Data

The basic regression estimated by OLS is the same as in Table VIII. The two additional variables included are the stock market capitalization as a fraction of the country's GDP and the log of bank credit over stock market capitalization. The sample period is 1991–2002. The dependent variables are: standard deviation of Δlog(inventories/assets), and correlation of Δlog(inventories/assets) and Δlog(short-term debt/assets). Country controls include the log of per capita GDP, openness, and government expenditure. Firm controls include firm size (log of sales), profitability, and tangibility, averaged for each firm during the sample period. The row called Effect of banks shows the reduction in volatility or correlation when bank credit over GDP increases by 50% of GDP (two standard deviations of bank credit). This effect is reported as a percentage of the corresponding median volatility or correlation in the sample. All firm variables are winsorized at the 1% and 99% levels. Country controls, industry dummies, and firm controls are not reported. Robust standard errors clustered by country-industry units are reported below the coefficients in parentheses. Significance (two-sided): * 10%, ** 5%, *** 1%.

	SD($\Delta\log(I/A)$)					Corr($\Delta\log(I/A)$, $\Delta\log(D/A)$)				
Bank credit	−0.169***		−0.158***		−0.187***	−0.133		−0.151***		−0.121**
	(0.024)		(0.024)		(0.025)	(0.049)		(0.053)		(0.049)
Stock market capitalization		−0.065***	−0.027*				0.006	0.042		
		(0.016)	(0.015)				(0.037)	(0.040)		
Log (market/banks)				−0.009	−0.025***				0.027	0.017
				(0.006)	(0.006)				(0.018)	(0.017)
Adjusted R^2	0.277	0.265	0.277	0.262	0.280	0.020	0.018	0.020	0.019	0.020
Number of observations	5,555	5,555	5,555	5,555	5,555	5,555	5,555	5,555	5,555	5,555
Effect of banks (%)	51		48		57	27		31		25

the composition of short-term debt is necessary to derive definite conclusions. For instance, it would be interesting to know what fraction of the shocks is smoothed through different channels such as credit lines or commercial paper, and also to what extent hedging instruments contribute to the reduction of volatility.

V. Conclusions

I document three main findings in this paper. First, bank credit reduces industrial output volatility. Second, the reduction in volatility comes mainly from a reduction in idiosyncratic volatility. As a corollary of this point, correlations between industries and GDP increase with bank credit. Third, at the firm level, short-term debt is more negatively correlated with firm activity as bank credit increases, suggesting that debt serves to smooth output.

This paper contributes primarily to the ongoing debate about the impact of financial intermediation (and particularly banks) on volatility. The results show that banks smooth real shocks, particularly idiosyncratic shocks, and that one way in which this is achieved is through the use of short-term debt.

A final interesting issue concerns the implications of these findings for the behavior of stock markets. Morck, Yeung, and Yu (2000) show that stocks in less developed countries tend to have more synchronized movements, that is, the correlation of a particular stock with the market is higher in a less developed country. I show that exactly the opposite pattern is true in terms of output correlations with GDP, which may appear as a contradiction to the finding of Morck et al.

Reconciling and understanding both the above results is an important area for future research. The sample selection is a relevant issue: The industrial data in this paper include more firms than those listed in the local stock market, and the characteristics of the listed firms can explain why the correlations using output and stock prices are different. Also, my findings relate to short-run fluctuations, while the stock market reflects firms' long-run prospects. For example, in the case that stock markets understand the idiosyncratic nature of most fluctuations in underdeveloped countries, it is possible to observe higher correlations among stocks if long-run fundamentals are more correlated (because of macro risk for instance).

Morck et al. argue that their results show the poor efficiency of stock markets in developing countries. At this stage the results in this paper do not necessarily support or contradict that hypothesis. In any case, the interplay between the real economy (cash flows, output) and stock markets in an environment of financial underdevelopment certainly deserves more study.

Table AI
Selected Summary Statistics

	Total Numbers of Observations	Mean	Median	St. Dev.	Min	Max
Bank credit over GDP (country-level)	59	0.345	0.269	0.262	0.051	1.423
Industry-level dependent variables						
Correlation with GDP (BK filter)	1,574	0.331	0.332	0.283	−0.650	0.926
Correlation with GDP (log differences)	1,574	0.353	0.360	0.263	−0.661	0.898
Total standard deviation (BK filter)	1,574	0.080	0.066	0.052	0.009	0.564
Total variance (BK filter)	1,574	0.009	0.004	0.017	0.000	0.319
Systematic variance (BK filter)	1,574	0.001	0.001	0.002	0.000	0.038
Idiosyncratic variance (BK filter)	1,574	0.008	0.003	0.017	0.000	0.308
Firm data (winsorized at 1%–99%)						
Firm-level dependent variables						
SD($\Delta\log(S)$)	5,774	0.310	0.155	0.475	0.025	2.835
SD($\Delta\log(S/A)$)	5,773	0.202	0.138	0.209	0.029	1.340
SD($\Delta\log(I)$)	5,673	0.371	0.225	0.473	0.047	2.874
SD($\Delta\log(I/A)$)	5,673	0.225	0.165	0.195	0.037	1.193
SD($\Delta\log(I/S)$)	5,672	0.250	0.187	0.207	0.041	1.274
SD($\Delta\log(Q/A)$)	5,480	0.196	0.135	0.198	0.019	1.238
Corr($\Delta\log(S)$, $\Delta\log(D)$)	5,773	0.381	0.463	0.463	−0.862	0.998
Corr($\Delta\log(S/A)$, $\Delta\log(D/A)$)	5,773	0.074	0.100	0.509	−0.950	0.961
Corr($\Delta\log(I)$, $\Delta\log(D)$)	5,673	0.461	0.562	0.439	−0.816	0.998
Corr($\Delta\log(I/A)$, $\Delta\log(D/A)$)	5,673	0.196	0.243	0.474	−0.907	0.973
Corr($\Delta\log(I/S)$, $\Delta\log(S)$)	5,672	−0.219	−0.269	0.486	−0.979	0.896
Firm-level controls						
Firm size (log sales)	5,773	14.385	14.064	2.994	8.000	21.796
Profitability	5,748	0.098	0.105	0.104	−0.432	0.317
Tangibility	5,773	0.322	0.305	0.163	0.040	0.759

REFERENCES

Acemoglu, Daron, Simon Johnson, James A. Robinson, and Yunyong Thaicharoen, 2003, Institutional causes, macroeconomic symptoms: Volatility, crises and growth, *Journal of Monetary Economics* 50, 49–123.

Aghion, Philippe, George-Marios Angeletos, Abhijit Banerjee, and Kalina Manova, 2005, Volatility and growth: Financial development and the cyclical composition of investment, NBER Working paper no. 11349.

Aghion, Philippe, Philippe Bacchetta, and Abhijit Banerjee, 2004, Financial development and the instability of open economies, *Journal of Monetary Economics* 51, 1077–1106.

Allen, Franklin, and Douglas Gale, 1997, Financial markets, intermediaries, and intertemporal smoothing, *Journal of Political Economy* 105, 523–546.

Bacchetta, Philippe, and Ramón Caminal, 2000, Do capital market imperfections exacerbate output fluctuations? *European Economic Review* 44, 449–468.

Baxter, Marianne, and Robert G. King, 1999, Measuring business cycles: Approximate band-pass filters for economic time series, *Review of Economics and Statistics* 81, 575–593.

Beck, Thorsten, 2002, Financial development and international trade. Is there a link? *Journal of International Economics* 57, 107–131.

Beck, Thorsten, Asli Demirgüç-Kunt, and Ross Levine, 2000, A new database on financial development and structure, *World Bank Economic Review* 14, 597–605.

Beck, Thorsten, Mattias Lundberg, and Giovanni Majnoni, 2004, Financial intermediary development and growth volatility: Do intermediaries dampen or magnify shocks? *Journal of International Money and Finance* (forthcoming).

Bernanke, Ben, and Alan Blinder, 1988, Credit, money, and aggregate demand, *American Economic Review* 78, 435–439.

Bernanke, Ben, and Mark Gertler, 1989, Agency costs, net worth, and business fluctuations, *American Economic Review* 79, 14–31.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist, 1996, The financial accelerator and the flight to quality, *Review of Economics and Statistics* 78, 1–15.

Braun, Matías, 2002, Financial contractibility and assets' hardness: Industrial composition and growth, Working paper, UCLA.

Braun, Matías, and Borja Larrain, 2005, Finance and the business cycle: International, inter-industry evidence, *Journal of Finance* 60, 1097–1128.

Caballero, Ricardo, and Arvind Krishnamurthy, 2001, International and domestic collateral constraints in a model of emerging market crises, *Journal of Monetary Economics* 48, 513–548.

Christiano, Lawrence, Martin Eichenbaum, and Charles Evans, 1996, The effects of monetary policy shocks: Evidence from the flow of funds, *Review of Economics and Statistics* 78, 16–34.

Demirgüç-Kunt, Asli, and Vojislav Maksimovic, 1999, Institutions, financial markets, and firm debt maturity, *Journal of Financial Economics* 54, 295–336.

Diamond, Douglas, and Philip H. Dybvig, 1983, Bank runs, deposit insurance, and liquidity, *Journal of Political Economy* 91, 401–419.

Frankel, Jeffrey, and David Romer, 1999, Does trade cause growth? *American Economic Review* 89, 379–399.

Galindo, Arturo, Alejandro Micco, and Gustavo Suárez, 2004, Creditor protection and the cyclical properties of credit, Working paper, Harvard University.

Gatev, Evan, and Philip Strahan, 2004, Banks' advantages in hedging liquidity risk: Theory and evidence from the commercial paper market, *Journal of Finance* 61, 867–892.

Gertler, Mark, and Simon Gilchrist, 1994, Monetary policy, business cycles, and the behavior of small manufacturing firms, *Quarterly Journal of Economics* 109, 309–340.

Holmstrom, Bengt, and Jean Tirole, 1997, Financial intermediation, loanable funds, and the real sector, *Quarterly Journal of Economics* 112, 663–691.

Holmstrom, Bengt, and Jean Tirole, 1998, Private and public supply of liquidity, *Journal of Political Economy* 106, 1–40.

Hubbard, R. Glenn, 1998, Capital-market imperfections and investment, *Journal of Economic Literature* 36, 193–225.

Kaplan, Steven, and Luigi Zingales, 1997, Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quarterly Journal of Economics* 112, 169–215.

Kashyap, Anil K., Owen Lamont, and Jeremy Stein, 1994, Credit conditions and the cyclical behavior of inventories, *Quarterly Journal of Economics* 109, 565–592.

Kashyap, Anil K., Raghuram G. Rajan, and Jeremy Stein, 2002, Banks as providers of liquidity: An explanation for the co-existence of lending and deposit-taking, *Journal of Finance* 57, 33–73.

Kashyap, Anil K., and Jeremy Stein, 2000, What do a million observations on banks say about the transmission of monetary policy? *American Economic Review* 90, 407–428.

Kashyap, Anil K., Jeremy Stein, and David W. Wilcox, 1993, Monetary policy and credit conditions: Evidence from the composition of external finance, *American Economic Review* 83, 78–98.

Kiyotaki, Nobuhiro, and John Moore, 1997, Credit cycles, *Journal of Political Economy* 105, 211–248.

La Porta, Rafael, Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert Vishny, 1998, Law and finance, *Journal of Political Economy* 106, 1113–55.

Larrain, Borja, 2004, Financial development, financial constraints, and the volatility of industrial output, *Public Policy Discussion Paper* no. 04-6, Federal Reserve Bank of Boston.

Levine, Ross, 2004, Finance and growth: Theory and evidence, NBER Working Paper no. 10776.

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics* 58, 215–260.

Morgan, Donald, Bertrand Rime, and Philip Strahan, 2004, Bank integration and state business cycles, *Quarterly Journal of Economics* 119, 1555–1584.

Raddatz, Claudio, 2003, Liquidity needs and the vulnerability to financial underdevelopment, Working Paper no. 3161, World Bank.

Rajan, Raghuram G., and Luigi Zingales, 1995, What do we know about capital structure? Some evidence from international data, *Journal of Finance* 50, 1421–1460.

Rajan, Raghuram G., and Luigi Zingales, 1998, Financial dependence and growth, *American Economic Review* 88, 559–586.

Rajan, Raghuram G., and Luigi Zingales, 2003, The great reversals: The politics of financial development in the twentieth century, *Journal of Financial Economics* 69, 5–50.

Ramey, Garey, and Valerie Ramey, 1995, Cross-country evidence on the link between volatility and growth, *American Economic Review* 85, 1138–1151.

Ramey, Valerie, and Kenneth D. West, 1999, Inventories, in John B. Taylor and Michael Woodford, eds.: *Handbook of Macroeconomics* (North Holland, Amsterdam).

Stein, Jeremy, 1998, An adverse selection model of bank asset and liability management with implications for the transmission of monetary policy, *Rand Journal of Economics* 29, 466–486.

Stein, Jeremy, 2003, Agency, information and corporate investment, in George M. Constantinides, Milton Harris, and Rene Stulz, eds.: *Handbook of the Economics of Finance* (Elsevier North Holland, Amsterdam).

UNIDO Industrial Statistics Database (3-digit ISIC: CD-ROM, New York), 2001.

World Bank, 2001, World Development Indicators (CD-ROM).