Financial Innovations, Idiosyncratic Risk, and the Joint Evolution of Real and Financial Volatilities

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Abstract:

This paper presents a model in which financial innovations explain three widely discussed stylized facts regarding trends in economic volatility over the past two decades. Aggregate volatility of real variables such as output has fallen. In particular, the covariance between firm and industry activities has declined, and so has employment volatility for the majority of firms. In contrast, the volatility of quantities of financial variables has increased at both the firm and aggregate level. The model links these outcomes to a single hypothesized cause: advances in financial technology brought about by a declining cost of information processing. As a result, the marginal cost of external funds has likely declined, reducing the need for firms to smooth cash flows. Firms, trading off cash-flow vs. production smoothing, therefore have more incentive to smooth production. This explains why financial volatility may go up as real volatility goes down. Moreover, financial innovations have likely also altered the composition of volatility toward a greater share of idiosyncratic risk, by facilitating diversification and thus lowering the premium demanded on idiosyncratic risk. At the margin, the cost advantage to projects with idiosyncratic returns reduces the covariance of financial as well as real activities across firms. Since variance and covariance of real quantities trend in the same direction, real aggregate volatility declines. But the net effect on financial variables is ambiguous and so can yield greater aggregate volatility. The paper then presents evidence that the share of idiosyncratic risk has risen in bank portfolios, indicating that the same has occurred for individual borrowers as well.

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Introduction

It is by now a well-known fact that U.S. economic activity in the aggregate has become less volatile since the mid-1980s. The behavior of financial variables, on the other hand, roughly tracks the output variance of publicly-traded firms, which appears to have risen over the past four decades. However, striking new evidence based on employment data shows that private firms have become less volatile during the same period over which public firms have become more volatile. Aggregate employment volatility, dominated by the behavior of the private firms, therefore has declined. Finally, several studies have shown that there has been a reduction in the *covariance* of output growth among industries and firms; this also helps fill the apparent inconsistency between rising output volatility in large firms and declining volatility in the aggregate.

This paper develops a model that can *simultaneously* explain this collage of findings, in particular 1) why the volatility of real variables (such as output and employment) may *decrease* even while the volatility of financial variables (such as dividends and net borrowing) *increases*, and 2) why idiosyncratic risk has grown in importance and led to falling cross-section covariance in both real and financial variables.

The paper shows that these seemingly disparate trends can plausibly be the joint outcomes of a common cause – technological progress in the financial sector. The paper posits that advances in information and communication technology (ICT) have greatly lowered the marginal cost of collecting, processing and transmitting information in general, and credit information in particular (for example, by using computer-based credit scoring models). As a result, banks today make loans to more borrowers, and also to smaller borrowers.

If banks face a convex cost of external funds, due to asymmetric information problems or a convex cost of supplying deposit services, then it is optimal for them to smooth the total volatility of their cash flows. When banks' loan portfolios were far from well diversified for various reasons,[1] what

[1] Apart from geographic concentration of loans due to regulatory constraints, other reasons include the desire to utilize increasing returns to scale associated with accumulated special knowledge of a particular industry or region.

affected a portfolio's total return variability at the margin was each additional loan's total volatility, not just its systematic volatility. Thus, the expected yield required by lenders traditionally rose not only with a loan's systematic risk but also with its idiosyncratic risk.[2]

Since cheaper and better ICT lowers the cost of making each extra loan, standard intuition says that a smaller number of banks will hold larger numbers of loans in each of their portfolios. Each loan's idiosyncratic risk would thus account for a falling share of its marginal contribution to the portfolio's total volatility, which would eventually come to be dominated by the loans' covariances with the systematic factors. As a result, the *required* rate of return on each loan would come to depend increasingly on the loan's systematic risk. In the limit, any increase in return variability due to loan-specific volatility would not raise the interest rate a borrower *expects* to pay ex ante.

The diversification-enhancing effect from an increasing number of loans in each portfolio, however, can be more than offset by shifts in equilibrium credit supply toward borrowers whose returns are less correlated with the systematic factors. So the degree of diversification in bank loan portfolios may in fact even *fall* over time. This seemingly counterintuitive outcome can arise because the same force – a relatively lower risk premium on idiosyncratic risk – acts on banks as well as their borrowers.

First, for the borrowing firms, a falling premium on idiosyncratic risk relative to that on systematic risk – a "relative price" change – will confer a cost advantage to firms with returns less correlated with the systematic factors. Furthermore, facing the lower relative price on idiosyncratic risk, borrowers may find it optimal to adopt operation plans that lead to less exposure to systematic risk. Consequently, such projects will account for a bigger share of the potential demand for credit at each bank.

Such a demand shift, however, may or may not offset the positive effect on portfolio diversification from having a larger number of loans. Net change in the diversification of a loan pool as a whole will ultimately be determined by the bank's choice, both as a lender to nonfinancial firms and as a

[2] By comparison, the promised yield – interest rate charged in a loan contract *ex ante* – should rise in a borrower's total risk, including her idiosyncratic risk, even in a perfectly diversified portfolio because higher idiosyncratic volatility too raises the probability of default.

borrower in financial markets. Diversification at the portfolio level will on net *decline* unambiguously if banks also face a lower relative cost of idiosyncratic risk when borrowing in the markets, since each bank should react like its borrowers and raise the overall exposure to bank-specific risk. The risk premium on bank-specific volatility falls because the financial markets have also become more efficient at processing credit information owing to ICT and the ensuing innovations.

This paper's empirical section then investigates whether, as would be predicted by the above reasoning, the degree of diversification has in fact decreased over time for loan portfolios of a given size. And, using stock return data of publicly traded bank holding companies, it does indeed find evidence that diversification has not increased in these intermediaries. This suggests that these bank holding companies have altered the composition of their loan pools so much that the increase in idiosyncratic risk exposure at the loan level on average more than offsets the increase in loan numbers.

The paper then turns to modeling the effects of this change in equilibrium lending behavior on real activity. Naturally, more funding for projects with idiosyncratic returns implies that the correlation between projects will likely decline over time, consistent with the empirical finding of falling covariance across firms and industries over the past few decades.

More subtly, greater idiosyncratic volatility on the financial side may in fact coincide with lower volatility – largely idiosyncratic volatility – of real variables at the firm level. The falling risk premium on the idiosyncratic risk of borrowing firms' cash flows has the implication that firms will find it optimal to place more weight on smoothing output and less on smoothing cash flows. Firms have a standard production-smoothing motive in the face of demand shocks because of convex production costs. Firms also have an incentive to smooth cash flows because, like banks, they too face a convex cost of external funds due to asymmetric information problems. To the extent that inventories rise when future sales and thus revenue are expected to exceed the current level, and so inventory accumulation needs to be funded by borrowing, firms have to optimally trade off these two smoothing needs. With a lower marginal cost of external financing, especially diminishing "penalty" for firm-specific cash flow fluctuations, firms will find it optimal to allow more production smoothing and accept more volatile cash flows as a consequence.

As a result, we are likely to observe that real variables such as output, employment and investment become *less* volatile, even while financial variables such as cash flow and the demand for external funds – net debt or equity issues – become *more* volatile. This prediction is consistent with the macro evidence that the volatility of aggregate output and its components has declined, whereas the volatility of aggregate financial variables such as the amount of debt outstanding has mostly increased. It can also explain why firm-level employment volatility has declined for the overall population of firms, which comprises mostly private firms that rely on financial intermediaries for credit. The observed volatility increase in public firms, on the other hand, is likely to be the result of changes in the selection mechanism – which firms can and do choose to go public.

In summary, this study shows that a single mechanism – technological advances and innovations in the financial sector consisted of both intermediaries and those institutions that make the markets – can link the mosaic of stylized facts of trends in aggregate vs. firm-level volatility, volatility of real vs. financial variables, and the changing importance of systematic relative to idiosyncratic risk. Its proposed explanation is especially applicable to private firms, which constitute the majority of the firm population. The ideal data for empirically testing the model's predictions would be matched bank-borrower data on both production and financial variables. Data on private firms would be especially informative. Such data not being available, this paper provides a variety of evidence from the financial markets in support of its hypothesis.

The paper is organized as follows. Section I briefly reviews the set of relevant empirical findings and how they relate to one another according to the model presented here. Section II spells out how intermediaries' lending behavior should change in response to ICT advances and the implied trend of their portfolio diversification, and then reports the actual trend. Section III shows the implications for nonfinancial firms' real and financial activities and how they are consistent with the existing empirical evidence. Section IV concludes and discusses extensions.

I. Solving A Jigsaw Puzzle

One of the most striking features of economic fluctuations in the U.S. in the past thirty years has been the noticeable decline in volatility around mid 1980s. In particular, the standard deviation of GDP growth is about one third lower since 1984 than it was during 1960 to 1983.[3] Kim and Nelson (1999) and McConnell and Perez-Quiros (2000) first identify the break date to be 1984. This decline in volatility is widespread across sectors as well as the U.S. states (e.g., Owyang, Piger and Wall, 2006). Similar declines in aggregate volatility are also found in the other developed countries, although the timing and exact features differ across countries. (See Stock and Watson 2003 for a summary).

The initial evidence at the firm level, however, seems to indicate a contrary trend. For example, using accounting and stock market data of firms publicly trade in the U.S., Comin and Philippon (2005) find that firm-specific volatility in terms of sales, earnings, employment, and capital expenditure has been trending up since 1960. At the same time, finance studies have also find an upward trend in the firm-specific volatility of stock returns (e.g., Campbell *et al*. 2001). Increased share of idiosyncratic volatility implies decreased correlation across firms. Furthermore, Campbell and Taksler (2003) document a concurrent rise in the corporate-Treasury bond yield spreads. They show that the yield spread of a corporate bond rises in the idiosyncratic risk of the firm's stock, which in fact has nearly as much explanatory power as credit rating.

For firm-level volatility to rise and yet aggregate volatility to fall, the covariance between firms obviously must decline. That is exactly what Irvine and Schuh (2005) find using industry data. They discover that average covariance of output growth across finely classified industries has declined, and surmise that it is the result of the increasing role of inventories as buffer stock. Comin and Philippon (2005) also note that, between 1959 and 1996, there has been a decline in the covariance of growth across sectors for value added per worker and TFP.

A new twist to the story, however, has just surfaced. Using employment data of not only the

[3] Blanchard and Simon (2001), on the other hand, argue that a downward trend in economic volatility started as early as the 1950s and was interrupted in the 1970s and 80s.

publicly traded firms but virtually all the private firms, Davis *et al*. (2006) find that firm-level employment volatility has in fact *declined* in the private firms, as has the aggregate volatility. This suggests an explanation for the decline in aggregate output volatility without resorting to lower covariances. But Davis *et al*. (2006) also confirm an increase of volatility in the public firms, as found by Comin and Philippon (2005). They speculate that the diverging trends in employment volatility between public and private firms may be due to changes in the selection criteria of public firms.

These pieces of empirical facts – seemingly contradictory at times – add up to a sort of jigsaw puzzle and have, not surprisingly, attracted much research interest. Early attempts to explain the "great moderation" in aggregate volatility focused primarily on the role of milder economic shocks and better monetary policy, as well as changes in propagation mechanisms such as improvements in inventory management technology (see Stock and Watson 2003 for a review). Over time, more attention has been paid to another potential explanation: increasing efficiency of financial markets and institutions may have reduced shocks emanating from the financial sector as well as moderated the propagation of real shocks. For instance, Dynan *et al*. (2005) explore possible links between financial innovations and the observed moderation in economic activity, and suggest that financial innovations should be added to the list of likely contributors to the increasing stability since mid-1980s.

Financial development is also suggested as an explanation of the increase in idiosyncratic volatility, and possibly a simultaneous decrease in aggregate volatility.[4] Thesmar and Thoenig (2006) posit that easier or cheaper access to financial markets facilitates risk sharing for the individual entrepreneur so that idiosyncratic volatility becomes less costly in utility terms, and this spurs entrepreneurs to adopt more risky technologies and thus leads to greater firm-specific volatility. Recently Jermann and Quadrini (2006) suggest that greater financial flexibility, defined as firms' ability to substitute between external debt and equity issues, can in fact lead to *higher* volatility of financial

[4] Additional candidates proposed to explain the volatility trends include endogenous technology growth and increased competition. Comin and Mulani (2005) presents a model in which firms choose the relative resource allocation between two types of R&D activities that jointly determine idiosyncratic and aggregate volatility of technology growth. Philippon (2003) and Gaspar and Massa (2004) explain the increase in idiosyncratic volatility as a result of rising competition in product markets.

variables while effecting lower volatility of real variables.

Both of these arguments, however, are relevant only for publicly traded firms, not the majority of firms, which are private and relatively small. Morgan, Rime and Strahan (2004), on the other hand, provide some evidence that better diversification on banks' part, through interstate banking, leads to lower volatility of employment at the state level. But they do not distinguish between volatility of real and financial variables, nor between idiosyncratic and aggregate volatility.

Like these previous studies, this paper also proposes developments in the financial sector as an explanation, but for *both* the joint evolution of firm-specific vs. aggregate volatility and the possible divergence between the volatility trends of real and financial variables. Its value added to the literature lies primarily in its ability to consistently explain the variety of volatility trends using a unified, technology-based mechanism that is relevant for the majority of firms. This is achieved by highlighting the technological evolution in financial intermediaries, on whom most firms rely for credit.

Table 1 summarizes the stylized facts this study seeks to explain. It organizes the relevant price and quantity variables into two categories: real (such as output, investment and employment) vs. financial (such as dividends, net borrowing and equity issuance).[5] All trends concern the growth rate. The model developed here mainly tries to explain two trend patterns. First, the volatility of financial quantities seems to have trended up even while the volatility of real quantities has trended down. For example, Figure 1 depicts the 5-year trailing standard deviation of the 4-quarter growth of net borrowing by nonfarm corporate business. It displays an upward trend since early 1970s and especially in the 90s. Moreover, volatility trends for real and financial quantities seem to diverge at both the firm and aggregate level. Second, correlation and even covariance across firms have declined for most variables, indicating the growing importance of idiosyncratic volatility.

[5] Note that the financial variables in the table concern risky instruments issued by the private sector, not credit-risk-free Treasurys. This distinction is important, because the volatility of Treasury yields has in fact declined, in large part because inflation has become much less volatile (Stock and Watson, 2003). In contrast, the volatility of stock index returns has not trended down (Campbell *et al*. 2001). The reason likely lies in the volatility of risk premium. At monthly or even annual frequency, risk premium is an order of magnitude more volatile than the credit-risk-free rates and thus dominates the return volatility.

The model traces the root cause for both observations to cheaper and better computing and communications technology (popularly referred to as ICT), which enables financial institutions to process all types of information more efficiently, be it credit information or simple fund transfers. Financial firms top the list of beneficiaries of ICT improvements because information processing is at the core of their operation, as evidenced by their heavy investment in ICT. As Inklaar *et al*. (2005) show (in their Table 3), the contribution of ICT deepening to productivity growth is nearly five times higher in the financial sector than in the ICT industry itself and more than two times higher than in business services.

Advances in ICT has substantially lowered (both marginal and average) cost of external financing, especially for small firms and households. The cost reduction is partly effected through greater competition among financial institutions, as ICT has enabled the processing of many types of financial information to be standardized. The lower marginal funding cost allows small borrowers to tolerate more volatile cash flows and achieve greater production smoothing. This is because the small borrowers likely face convex cost for external funds, in addition to the usual convex cost for production. They thus must trade off the need to smooth the amount of borrowing vs. production.[6] This is the mechanism underlying the divergent trends between real and financial quantities.[7] It should be noted that the predicted increase in cash flow volatility should be interpreted as *relative* to the volatility of demand. This means that, if each firm's sales become sufficiently less volatile over time, then the volatility of its cash flows can in fact decline as well, but by less.

Furthermore, lending to a larger number of smaller borrowers boosts a portfolio's diversification, reducing the premium on idiosyncratic risk. In addition, ICT has both enabled and stimulated financial innovations, such as new financial contracts (i.e., securities, such as derivatives) along with new markets for their trading. These innovations enhance risk sharing and thus further lower the premium on

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[6] An incentive to smooth borrowing likely translates into an incentive to smooth cash flows, as long as funding needs, for capital and inventory investment, are not perfectly correlated with cash flows.

[7] This model does not explicitly consider financial frictions in the form of quantity constraints. The combination of greater volatility of financial quantities with little trend in market return volatility in Table 1 can plausibly be interpreted as the effect of less quantity restrictions owing to financial development. Since the supply of loanable funds is likely to be quite elastic, it determines the volatility of the rate of returns, while demand variations determine the volatility of quantity.

idiosyncratic risk. This change in the relative price of components of risk underlies the growing importance of idiosyncratic volatility.

Combining the above two predictions implies that the predicted increase in cash flow volatility should be accounted for mostly by idiosyncratic risk. By the same token, the quantity of a narrowly defined type of financial instrument is likely to become more volatile *relative* to the sum across multiple types, as financial markets become better integrated and credit restrictions less binding. That is, buyers of funds can more freely "diversify" across different instruments to minimize the cost of external funds.

Note that, in terms of the impact of ICT on operating efficiency, intermediaries and markets are modeled qualitatively the same in this study. It is reasonable to hypothesize that ICT advancement has also boosted the productivity of the financial institutions that organize the markets. On the other hand, intermediaries and markets have difference comparative advantages that lead them to specialize in processing different kinds of information and serving different kinds of borrowers and investors. This paper shows how the combination of intermediaries and markets enables households and most firms to still benefit from innovations in the markets, even though direct access to financial markets is prohibitively expensive for these agents.

This paper proposes that intermediaries such as banks serve as a conduit between markets and those small borrowers. Banks specialize in processing the credit information of a large number of small scale projects, and then pool loans of similar attributes to minimize idiosyncratic risk. They then access financial markets, which in turn diversify away intermediary-specific risk. The cost savings enjoyed by intermediaries owing to more efficient markets will most likely be passed on to the private borrowers, who thus benefit indirectly. In fact, households and private firms nowadays can even "directly" share in such cost savings because the rapid growth of secondary markets for loans means that many loan pools are securitized and directly held by market investors, while banks continue to specialize in servicing small accounts. Small firms' better intermediated access to markets is evidenced by the fact that the external debt balance of nonfarm noncorporate business has become almost perfectly correlated with that of nonfarm nonfinancial corporate business (Figure 2).

Direct testing of the predictions of this model requires matched bank-borrower data. It not being available, the empirical section of this paper resorts to a variety of indirect evidence, in particular the increasing share of idiosyncratic risk in banks' asset portfolios. The validity of such a test rests upon a "symmetry" argument between banks and their borrowers. If banks raise the idiosyncratic volatility of their financial return in response to more efficient diversification of idiosyncratic risk in the markets, then optimizing firms should behave likewise in response to better diversification in banks' portfolios.

The next section develops the financial side of the model, showing how the composition of risk changes in response to better technology and how firm's and bank's volatility evolve jointly.

II. Financial Intermediation Technology and the Optimal Loan Interest Rate

This section details how the optimal debt or loan interest rate charged, the average size of loans made, and the risk composition of loan portfolios evolve in response to advances in ICT. Here I adopt the costly-state-verification framework a la Townsend (1979), in which case intermediaries' *raisons d'être* is to resolve borrowers' private information.[8] For clarity of exposition, I assume that intermediaries possess a monitoring technology that enables them to resolve the information asymmetry fully.[9] This can be viewed as the limiting case for the capability of lending technology.

It must be emphasized up front that, although the analysis is specified in the context of nonfinancial firms borrowing from banks, the logic is virtually the same for the case of banks (as well as nonfinancial firms) borrowing in the public markets. In public debt markets, the counterpart to banks – intermediary that resolves information problems – is the credit rating agencies. Most importantly, the key conclusion that better lending technology and the ensuing greater diversification leads to lower price of idiosyncratic risk also applies to the public debt issued by banks. This in turn has important implications for banks' borrowers as well: it helps further lower the price of credit to them.

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[8] Adding screening by banks will not change any of the properties of the lending technology considered here. For details, see Wang, Basu and Fernald (2004).

[9] I also do not analyze the optimal contract issue and only consider deterministic monitoring, which can be the optimal contract if commitment is limited, see Krasa and Villamil (2000).

Assume that borrower *i* has one continuously scalable project in period *t*, and denote the project's size as K_t^i. The borrower may put up her own wealth (denoted W_t^i) to finance part of the project and borrow the rest (i.e., $K_t^i - W_t^i$). Assume the project's gross return, denoted R_{t+1}^i, is non-negative.[10] A loan is deemed in default if, at the end of period *t*, the borrower's return falls short of the required interest payment, i.e., $R_{t+1}^i K_t^i < \hat{Z}_{t+1}^i (K_t^i - W_t^i)$, where $\hat{Z}_{t+1}^i$ is loan *i*'s promised yield (i.e., interest rate specified in the contract that the borrower would pay if solvent),[11] and R_{t+1}^i is a realized value of return. So, for given W_t^i, there is a one-to-one mapping between $\hat{Z}_{t+1}^i$ and a threshold value of R_{t+1}^i (denoted $\hat{R}_{t+1}^i$, and again note that it is known at time *t*, despite its time subscript), below which loan *i* is considered in default:

$$\hat{R}_{t+1}^i = [\hat{Z}_{t+1}^i (K_t^i - W_t^i)] / K_t^i = \hat{Z}_{t+1}^i k_t^i, \qquad (1)$$

where $k_t^i = (K_t^i - W_t^i)/K_t^i$ is borrower *i*'s debt-to-asset ratio (i.e., leverage). (1) shows intuitively that, for any given $\hat{Z}_{t+1}^i$, higher leverage raises a borrower's odds of default (i.e., a higher k_t^i leads to a higher $\hat{R}_{t+1}^i$).

To make further derivations more tractable, we now assume that the value of the project/firm follows a standard geometric random walk, and so

$$r_{t+1}^i = \ln(R_{t+1}^i) = \ln(K_{t+1}^i) - \ln(K_t^i) = \alpha^i + \xi_{t+1}^i, \qquad (2)$$

where α^i is the positive drift of the process, and ξ_{t+1}^i is the innovation.

Define the default indicator d_{t+1}^i=1 if the firm defaults (i.e., $r_{t+1}^i < \hat{r}_{t+1}^i = \ln(\hat{R}_{t+1}^i)$), and 0 otherwise. When default occurs, the lender monitors (or, more precisely, audits) the borrower to find out the project's true residual value. This activity is qualitatively similar to producing other information services such as consulting and accounting. It incurs resource cost, such as to hire labor and purchase capital and

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[10] The subscript of R_{t+1}^i signifies that it is not known until the end of period *t* (= the beginning of *t*+1). In general, time subscripts in this paper denote the period when the variable's value becomes known, unless noted otherwise.
[11] Even though $\hat{Z}_{t+1}^i$ is contracted and thus known at the beginning of *t*, we keep the (*t*+1) subscript to signify its connection with R_{t+1}^i, when it becomes known whether $\hat{Z}_{t+1}^i$ can be met.

materials. Denote the (marginal) cost of monitoring a loan as $\upsilon_t(\mathbf{\Lambda})$, where $\mathbf{\Lambda}$ is the vector of relative loan characteristics (e.g., size, borrower's industry and repayment history, etc.). This marginal cost is most likely concave in loan size, since, intuitively, a \$2 million loan unlikely requires twice as much processing as a \$1 million loan. (See Wang, Basu and Fernald 2004 and Wang 2003a, for more in-depth discussion of the properties of banks' technology for processing information.) For simplicity, consider the case where $\upsilon_t(\bullet)$ is only a function of loan size (i.e., $\mathbf{\Lambda}$ is a scalar), and assume $\upsilon_t' \geq 0$ while $\upsilon_t'' \leq 0$. A simple example would be $\upsilon_t(K_t^i - W_t^i) = a_t + b_t(K_t^i - W_t^i)$.

Then the lender's rate of return on loan *i* can be expressed as[12]

$$z_{t+1}^i = \ln(Z_{t+1}^i) \approx \min\{r_{t+1}^i - \frac{\upsilon_{t+1}^i}{K_t^i R_{t+1}^i}, \hat{r}_{t+1}^i\} - \ln k_t^i = \left(r_{t+1}^i - \frac{\upsilon_{t+1}^i}{K_t^i R_{t+1}^i}\right) d_{t+1}^i + \hat{r}_{t+1}^i (1 - d_{t+1}^i) - \ln k_t^i . \qquad (3)$$

Clearly, both z_{t+1}^i and d_{t+1}^i are random variables, and the expected default probability is

$$\text{prob}(d_{t+1}^i = 1) = \text{E}_t(d_{t+1}^i) \equiv \bar{d}_{t+1}^i = \text{prob}(r_{t+1}^i < \hat{r}_{t+1}^i) = \Phi\left(\frac{\hat{r}_{t+1}^i - \mu_r^i}{\sigma_r^i}\right), \qquad (4)$$

if assuming the project's return follows a normal distribution. $\Phi(.)$ is the c.d.f. of the standard normal, and $\text{E}_t(.)$ denotes the expectation conditional on the information set at *t*. μ_r^i and σ_r^i are the mean and standard deviation of the project's return, respectively.

Then the rate of return the lender expects to receive on loan *i* is

$$\text{E}_t(z_{t+1}^i) = \text{E}_t\left[\left(r_{t+1}^i - \frac{\upsilon_{t+1}^i}{K_t^i R_{t+1}^i}\right) d_{t+1}^i + \hat{r}_{t+1}^i (1 - d_{t+1}^i)\right] - \ln k_t^i . \qquad (5)$$

Intuitively, that the overall expected return on a loan depends on not only the default probability but also the recovery rate in case of default.

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[12] In levels, the lender's return equals $K_t^i\left[R_{t+1}^i\left(1 - \frac{\upsilon_{t+1}^i}{K_t^i R_{t+1}^i}\right) d_{t+1}^i + \hat{R}_{t+1}^i (1 - d_{t+1}^i)\right]$. Taking log and simplifying with the relationship $\ln\left(1 - \frac{\upsilon_{t+1}^i}{K_t^i R_{t+1}^i}\right) \approx -\frac{\upsilon_{t+1}^i}{K_t^i R_{t+1}^i}$ assuming the monitoring cost is small relative to the project's total payoff under default.

Denote the expected rate of return *required* by a lender on loan *i* as μ_{t+1}^{i} (known in period *t*). For a perfectly diversified lender, μ_{t+1}^{i} depends only on loan *i*'s systematic risk, which stems from the correlation between the systematic factors and *i*'s default event (i.e., d_{t+1}^{i}) as well as its recovery rate.[13] However, for less than fully diversified portfolios, risk-averse lenders also demand compensation for unexpected losses, which can be substantial. (See Amato and Remolona 2003 for a detailed discussion of how the difficulty of diversifying debt portfolios, due to the extreme skewness of debt return distribution, may explain the corporate-Treasury bond spreads, which seem unreasonably wide in general.)

The equilibrium condition that determines the interest rate on a debt is

$$\mu_{t+1}^{i} = \mathrm{E_t}(\,z_{t+1}^{i}\,) = \mathrm{E_t}\left[\left(r_{t+1}^{i} - \frac{\upsilon_{t+1}^{i}}{K_t^i R_{t+1}^{i}}\right)d_{t+1}^{i} + \hat{r}_{t+1}^{i}(1-d_{t+1}^{i})\right] - \ln k_t^i \,. \qquad (6)$$

Obviously, the promised yield $\hat{z}_{t+1}^{i}$ rises in the required return μ_{t+1}^{i}, since

$$\frac{\partial \hat{z}_{t+1}^{i}}{\partial \mu_{t+1}^{i}} = \frac{1}{\partial \mathrm{E_t}(z_{t+1}^{i})/\partial \hat{z}_{t+1}^{i}} = \frac{1}{\partial \mathrm{E_t}(z_{t+1}^{i})/\partial \hat{r}_{t+1}^{i}} = \frac{1}{1-\overline{d}_{t+1}^{i}} > 0\,. \qquad (7)$$

This is the condition that underlies the evolution toward greater exposure to idiosyncratic risk in borrowers' cash flows and in turn banks' loan portfolios: a relatively lower premium on idiosyncratic risk confers a cost advantage to borrowers with greater specific risk and in turn reduces the cost of funds in general.

Given μ_{t+1}^{i}, the monitoring cost leads to a higher promised yield:

$$\frac{\partial \hat{z}_{t+1}^{i}}{\partial \upsilon_{t+1}^{i}} = \mathrm{E_t}\left(\frac{d_{t+1}^{i}}{K_t^i R_{t+1}^{i}}\right)\Big/(1-\overline{d}_{t+1}^{i}) > 0\,. \qquad (8)$$

The monitoring cost is the element that truly drives a wedge *ex ante* between the cost of external and internal funds. As better technology lowers lenders' marginal cost of processing an extra borrower's credit information, the wedge should shrink.

[13] According to the pioneering analysis of corporate debt pricing by Merton (1974), the rate of return on a company's bond should be perfectly correlated with that on its equity. In the CAPM context, this requires that a corporate bond's market beta normalized by its idiosyncratic volatility equals the corresponding stock's market beta normalized by its idiosyncratic volatility.

The promised yield also rises with a borrower's leverage:[14]

$$\frac{\partial \hat{z}_{t+1}^i}{\partial k_t^i} = \frac{1/k_t^i + \mathrm{E}_t\left(d_{t+1}^i \upsilon_{t+1}^{i}{}' / R_{t+1}^i\right)}{\partial \mathrm{E}_t(z_{t+1}^i)/\partial \hat{z}_{t+1}^i} > \frac{1/k_t^i}{1-\bar{d}_{t+1}^i} > 0\,. \qquad (9)$$

The second term in the numerator stems from the fact that, for a project of given size, higher leverage means a larger loan balance and thus monitoring cost in expectation since $\upsilon_{t+1}^{i}{}' > 0$. Hence, the more a project borrows, the higher the interest rate it has to promise. This establishes the case of a convex borrowing cost, which is by now a common assumption made in models of financial frictions, such as Froot, Scharfstein and Stein (1997) and Bernanke, Gertler and Gilchrist (1998).

For a borrower with a given scale of operation, $\partial \hat{z}_{t+1}^i / \partial k_t^i$ is equivalent to the marginal cost of extra borrowing. Clearly, this marginal cost rises in $\upsilon_{t+1}^{i}{}'$ – the extra cost for the lender to process a marginally larger loan – since

$$\partial \hat{z}_{t+1}^i / \partial k_t^i \, \partial \upsilon_{t+1}^{i}{}' > 0\,. \qquad (10)$$

We will see that it is condition (10) that leads to falling marginal cost of funds, giving each borrower incentive to allow more fluctuations in cash flows and in turn the amount of borrowing, and consequently achieve greater smoothing of real output. Note the different effect of a falling $\upsilon_{t+1}^{i}{}'$ vs. that of a falling premium on idiosyncratic risk on the cost of funds. The former lowers a borrower's marginal cost of funds regardless of the nature of her cash flow volatility whereas the latter is only for idiosyncratic volatility.

On the other hand, given the leverage ratio k_t^i, the promised yield falls with a loan's balance if $\upsilon_{t+1}(\bullet)$ is strictly concave:

$$\frac{\partial \hat{z}_{t+1}^i}{\partial (K_t^i - W_t^i)} = \mathrm{E}_t\left(\frac{\upsilon_{t+1}^{i}{}'}{K_t^i R_{t+1}^i} - \frac{\upsilon_{t+1}^i}{(K_t^i)^2 R_{t+1}^i}\right) = \mathrm{E}_t\left[\frac{\upsilon_{t+1}^i}{K_t^i R_{t+1}^i}\left(\frac{\upsilon_{t+1}^{i}{}'}{\upsilon_{t+1}^i} - \frac{1}{K_t^i}\right)\right] < 0\,. \qquad (11)$$

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[14] The monitoring cost likely also rises in a borrower's leverage, and that will make the promised yield increase even faster with leverage.

This is because, given the concavity assumption, the extra cost of monitoring a marginally bigger loan will not exceed the average cost, and so $\upsilon_{t+1}^{i}{}' - \upsilon_{t+1}^{i} / K_t^i < 0$. If monitoring even a small loan involves a fixed cost that is greater than the extra cost of monitoring a marginally bigger loan, i.e., $\upsilon_{t+1}^{i}{}'(\varepsilon) - \upsilon_{t+1}^{i}(\varepsilon) < 0$ for a small positive ε, then the marginal cost will asymptote to the average from below.

More importantly, as the cost of monitoring an extra loan falls regardless of loan size (e.g., a in $\upsilon_{t+1}(K_t^i - W_t^i) = a_{t+1} + b_{t+1}(K_t^i - W_t^i)$), small loans benefit more in the sense that their promised interest rates fall more than large loans' rates:

$$\frac{\partial \hat{z}_{t+1}^{i}}{\partial (K_t^i - W_t^i)\partial \upsilon_{t+1}^{i}} = \mathrm{E}_t\left(-\frac{1}{(K_t^i)^2 R_{t+1}^i}\right) < 0 . \qquad (12)$$

This implies that, if advances in lending technology manifest more in lowering the per-loan marginal cost regardless of loan size, then it has the *direct* effect that every bank makes more loans of smaller size on average, since more projects now qualify, assuming the same distribution of project returns. In fact, banks will seek to merge in order to take advantage of the greater increasing returns to scale. This is consistent with the merger wave observed between the mid 1980s and late 1990s. More importantly, most of the additions to the loan pool are small loans.[15]

Now consider the ensuing indirect effect of technological advances on the risk composition of bank loan portfolios. All of the above analysis assumes a constant expected rate of return required by a lender. But the determination of the required rate of return on a marginal loan changes as a loan portfolio becomes better diversified. Greater diversification means that each additional loan's idiosyncratic risk matters less to the resulting new portfolio's volatility, which in the limit will be entirely determined by the systematic risk of the constituent loans.

This indirect effect can be illustrated by giving more structure to the shocks to a project's return

[15] A likely general equilibrium effect is that, as capital intensity rises owing to more net investment, marginal product of capital falls and thus the new projects funded will eventually have lower average rate of return as well.

(ξ_{t+1}^i). Assume ξ_{t+1}^i has the following multi-factor structure:

$$\xi_{t+1}^i = \boldsymbol{\beta}^{i\prime}\mathbf{m}_{t+1} + \sigma^i \varepsilon_{t+1}^i \text{, with } \varepsilon_{t+1}^i \text{~i.i.d.(0, 1).} \quad (13)$$

$\mathbf{m}_{t+1}$ is an $m \times 1$ vector of systematic factors (such as GDP growth, risk-free interest rate, etc.), while $\boldsymbol{\beta}^{\mathrm{i}}$ is the vector of i's factor loadings. ε_{t+1}^i is the i.i.d. firm-specific shock, with standard deviation σ^i.

Assume $\mathbf{m}_{t+1} \sim \mathrm{N}(\boldsymbol{\mu}_{t+1}^m, \boldsymbol{\Sigma}_{t+1}^m)$, then r_{t+1}^i has mean $\mu_r^i = \alpha^i + \boldsymbol{\beta}^{i\prime}\boldsymbol{\mu}_{t+1}^m$ and variance $\sigma_r^{i2} = \boldsymbol{\beta}^{i\prime}\boldsymbol{\Sigma}_{t+1}^m\boldsymbol{\beta}^i + \sigma^{i2}$.

$\boldsymbol{\beta}^{i\prime}\boldsymbol{\Sigma}_{t+1}^m\boldsymbol{\beta}^i$ and σ^{i2} measure the size of the systematic and the idiosyncratic risk, respectively.

In this setup, the required rate of return rises in σ^i, i.e., $\partial\mu_{t+1}^i / \partial\sigma^i > 0$, but the increase *decelerates* in a portfolio's degree of diversification. This can be shown by recognizing that, in general, total risk of each loan's return can be decomposed as

$$\mathrm{var}(z_{t+1}^i) = \mathrm{E}_{\mathbf{m}}[\mathrm{var}(z_{t+1}^i \mid \mathbf{m}_{t+1})] + \mathrm{var}_{\mathbf{m}}[\mathrm{E}(z_{t+1}^i \mid \mathbf{m}_{t+1})].$$

And the variance of loan i's return conditional on the systematic factors is bounded:

$$\begin{aligned}\mathrm{var}_{\mathbf{m}}(z_{t+1}^i \mid \mathbf{m}_{t+1}) &= (\hat{r}_{t+1}^i)^2 \,\mathrm{var}\left[\left(1 - \frac{r_{t+1}^i - \upsilon_{t+1}^i / K_t^i R_{t+1}^i}{\hat{r}_{t+1}^i}\right) d_{t+1}^i \mid \mathbf{m}_{t+1}\right] \\ &= (\hat{r}_{t+1}^i)^2 \left\{\mathrm{E}_{\mathbf{m}}[(\varphi_{t+1}^i d_{t+1}^i)^2 \mid \mathbf{m}_{t+1}] - [\mathrm{E}_{\mathbf{m}}(\varphi_{t+1}^i d_{t+1}^i \mid \mathbf{m}_{t+1})]^2\right\} \\ &\le (\hat{r}_{t+1}^i)^2 \left\{\mathrm{E}_{\mathbf{m}}(\varphi_{t+1}^i d_{t+1}^i \mid \mathbf{m}_{t+1}) - [\mathrm{E}_{\mathbf{m}}(\varphi_{t+1}^i d_{t+1}^i \mid \mathbf{m}_{t+1})]^2\right\} \le (\hat{r}_{t+1}^i)^2 / 4.\end{aligned}$$

$\varphi_{t+1}^i \equiv 1 - \dfrac{r_{t+1}^i - \upsilon_{t+1}^i / K_t^i R_{t+1}^i}{\hat{r}_{t+1}^i}$ $\varphi_{t+1}^i \in (0,1)$ is the fraction of loss for the lender given a loan's default, and so $\varphi_{t+1}^i \in (0,1)$ and $(\varphi_{t+1}^i d_{t+1}^i)^2 \le \varphi_{t+1}^i d_{t+1}^i$. Therefore, as N → ∞,

$$\mathrm{E}_{\mathbf{m}}[\mathrm{var}(Z_{N,t+1} \mid \mathbf{m}_{t+1})] = \mathrm{E}_{\mathbf{m}}\left[\sum_{i=1}^N (w_t^i)^2 \,\mathrm{var}_{\mathbf{m}}(z_{t+1}^i \mid \mathbf{m}_{t+1})\right] \le \frac{1}{4}\sum_{i=1}^N (w_t^i \hat{r}_{t+1}^i)^2 \to 0,$$

since, conditional on the systematic factors, the idiosyncratic returns are independent.[16] w_t^i is the portfolio weight of loan i, and N the number of loans in the portfolio.

[16] When a portfolio is less well diversified, its return variance rises in $\sum_{j=1}^N (w_t^i)^2$. $\lim_{N\to\infty}\sum_{j=1}^N (w_t^i)^2 = 0$ under the granularity condition $\sum_{j=1}^N (w_t^i)^2 = O(N^{-1})$, so in the limit weight distribution of individual loans no longer matters

Therefore, as a portfolio becomes more diversified, its return variance becomes dominated by variations of the systematic factors:

$$\lim_{N\to\infty} \mathrm{var}(Z_{N,t+1}) = \lim_{N\to\infty} \left\{ \mathrm{E}_{\mathbf{m}}[\mathrm{var}(Z_{N,t+1} \mid \mathbf{m}_{t+1})] + \mathrm{var}_{\mathbf{m}}[\mathrm{E}(Z_{N,t+1} \mid \mathbf{m}_{t+1})] \right\} = \lim_{N\to\infty} \left\{ \mathrm{var}_{\mathbf{m}}[\mathrm{E}(Z_{N,t+1} \mid \mathbf{m}_{t+1})] \right\}.$$

That is, a portfolio's total risk asymptotes to its systematic risk, which stems entirely from individual loans' return correlation with the systematic factors. Hence, in the limit N→ ∞, $\partial\mu_{t+1}^{i} / \partial\sigma^{i}$ =0. Jarrow, Lando and Yu (2005) also show that, under certain conditions that permit the construction of diversified portfolios, the default of any particular firm will not command a risk premium.

The implication is that, as a portfolio becomes sufficiently diversified, loans with low systematic risk would face relatively lower μ_{t+1}^{i} and thus pay lower interest rates (see equation (7)), regardless of their idiosyncratic risk. This means, as more and smaller loans are added to a portfolio, projects whose return variations are accounted for more by idiosyncratic risk will face a lower borrowing cost. Thus, even *given* the distribution of loan-level systematic vs. idiosyncratic risk composition, the share of loans that have greater idiosyncratic volatility will rise in loan portfolios in the new equilibrium.

As mentioned in the beginning of this section, the exact same logic applies to banks' borrowing in the public debt markets as well. As investors in the debt markets become better diversified, they demand lower premium on the bank-specific risk of each debt issue. As a result, all else equal, the cost of external funds will fall for banks whose return variance is more accounted for by idiosyncratic risk. The forces underlying market investors' ability to better diversify are essentially the same as those that enable banks to diversify, namely ICT and financial innovations, which make it possible for financial institutions serving the markets to provide funds more cheaply.

The relationship between bank-specific and loan-specific risk can be illustrated using the simple

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for portfolio risk. For example, under the Vasicek (1991) model, for a portfolio consisted of loans with identical return distribution, the variance of its loss equals $\bar{d}_t(1-\bar{d}_t)\left\{\rho^* + (1-\rho^*)\sum_{j=1}^{N}(w_t^i)^2\right\}$, where ρ^* is the correlation between any two loans' defaulting, all conditional on period t's information, including the outcome of the systematic factors. If two projects' returns follow a joint normal distribution, then their default correlation $\rho^*(\bar{d}_t,\rho) = \dfrac{\Phi_2[\Phi^{-1}(\bar{d}_t),\Phi^{-1}(\bar{d}_t),\rho] - \bar{d}_t^2}{\bar{d}_t(1-\bar{d}_t)}$, where ρ is correlation between the two projects' returns.

CAPM model. First, a bank's asset return can be decomposed as

$$r_t^b = \beta_{bm} r_t^m + \varepsilon_t^b , \tag{14}$$

where r_t^b and r_t^m are the excess returns on bank *b* and the market portfolio, respectively. ε_t^b is the bank-specific return, orthogonal to r_t^m by construction. The above analysis indicates that, as market investors become better diversified, the premium on the volatility of ε_t^b will decline and asymptote to zero, i.e., $\partial \mu_t^b / \partial \sigma_\varepsilon^b \to 0$.

Within each bank, the return of loan *i* can be written as

$$r_t^{ib} = \beta_{ib} r_t^b + \varepsilon_t^{ib} = \beta_{ib}\beta_{bm} r_t^m + \beta_{ib}\varepsilon_t^b + \varepsilon_t^{ib} = \beta_{im} r_t^m + \beta_{ib}\varepsilon_t^b + \varepsilon_t^{ib} , \tag{15}$$

and $r_t^b = \sum_{i \in b} w_t^i r_t^{ib}$, with $\sum_{i \in b} w_t^i = 1$ and $\sum_{i \in b} w_t^i \beta_{ib} = 1$. So, better diversification for a bank's loan portfolio is defined with regard to *loan*-specific volatility ε_t^{ib}. There can still be non-degenerate *bank*-specific volatility ε_t^b even when a bank becomes well diversified and thus $\partial \mu_t^{ib} / \partial \sigma_\varepsilon^{ib} \to 0$. And since the covariance between loans *i* and *j* within the bank $\text{cov}(r_t^{ib}, r_t^{jb}) = \beta_{im}\beta_{jm}(\sigma^m)^2 + \beta_{ib}\beta_{jb}(\sigma^b)^2$, the loans' covariance with the bank-wide shocks will still command a risk premium (i.e., β_{ib} does not asymptote to zero).[17] It is only with *market* investors' better diversification will $\partial \mu_t^b / \partial \sigma_\varepsilon^b \to 0$.

This will induce banks to choose a higher $(\sigma_\varepsilon^b)^2 / [\beta_{bm}^2 (\sigma^m)^2 + (\sigma_\varepsilon^b)^2]$, and possibly even a higher σ_ε^b in level. If at the same time σ_ε^{ib} rises sufficiently *relative* to σ_ε^b (that is, enough to offset the decline in the cross-loan average $(\sigma_\varepsilon^{ib})^2 / [\beta_{ib}^2 (\sigma^b)^2 + (\sigma_\varepsilon^{ib})^2]$ as the number of loans in a portfolio grows), then the diversification across loans *within* the bank can fall as well.[18] By comparison, a lower correlation with the market return at the portfolio level automatically means that individual loans are now less correlated

[17] Note that the derivation here is more statistical than causal, in that it does not address the causality of ε_t^b – whether it is the non-market comovement among the bank's loans or shocks initiated by the bank.
[18] It is also possible that a lower correlation with the market return at the portfolio level coincides with a higher diversification across loans within the bank if $\beta_{ib}\beta_{jb}(\sigma^b)^2$ exceeds $(\sigma_\varepsilon^{ib})^2$, which can arise if a bank chooses to originate loans with similar attributes. But this outcome is much less likely given the observed evolution of bank portfolios.

with the market as well, that is, a lower $(\sigma_{\varepsilon}^{b})^2 / [\beta_{bm}^2 (\sigma^m)^2 + (\sigma_{\varepsilon}^{b})^2]$ implies a lower $(\sigma_{\varepsilon}^{ib})^2 / [\beta_{im}^2 (\sigma^m)^2 + (\sigma_{\varepsilon}^{ib})^2]$.

The saving on *banks'* cost of funds as $\partial \mu_t^b / \partial \sigma_{\varepsilon}^b \to 0$ will be passed on to their borrowers, at least partly, since it seems unlikely that individual banks' market power in the loan market has increased enough to fully offset it. So, the key conclusion to draw from (14) plus (15) is that lower financing costs, in large part owing to lower premium on idiosyncratic risk, that stem from financial market developments can benefit even firms that do not or cannot access the markets. The savings are passed on to such private firms through financial intermediaries such as commercial banks, which have better access to the markets.

Next we discuss an important indirect effect of a falling premium on idiosyncratic risk relative to that on systematic risk on the risk composition of borrowers' cash flows. This change in the relative premium is essentially a change in relative prices investors are willing to pay for debt securities of different risk attributes: less price discount on a debt if its volatility is more idiosyncratic. Thus, sellers of debt securities (viz. borrowers) naturally react by offering more debt characterized by idiosyncratic risk. The implication for borrowers' operation is that they should adopt strategies that lead to fluctuations less correlated with aggregate conditions.

Only a weak condition on borrowers' behavior is sufficient for the above argument to hold: the tradeoff between return and total risk has not changed as much for each individual borrower. So the operation plan chosen by borrowers under the old lending technology must generate positive surplus for them under the new technology. In response, they may even increase total project risk in order to attain maximum utility. In fact, firms may prefer to assume greater idiosyncratic risk, in such forms as a narrower product line, since more concentration may well allow more specialized and thus efficient production technology, as well as a better fit to the taste of the target market and hence higher markups. This is basically the idea of a "core competency." In summary, borrowers optimal reaction to the relative premium change will further the compositional change of loan portfolios in the new equilibrium, a bigger share of which will be accounted for by projects whose volatility consists more of idiosyncratic risk.

Note that the above reasoning of borrowers' optimal reaction applies to any firm that seeks external funds, which includes banks themselves. This means that, even as a bank's portfolio becomes better diversified so that *average* loan-specific volatility (i.e., $\sum_{i \in b} (w_t^i \sigma_\varepsilon^{ib})^2$) declines, bank-specific risk σ_ε^b may account for a bigger share of total bank return volatility. Nonetheless, if σ_ε^{ib} rises relative to σ_ε^b, the correlation across loans within a bank will still decline.

Furthermore, if the new technology allows not only investors but also borrowers to attain better risk sharing, then it will likely give borrowers additional incentive to raise just the project-specific risk. The reason is straightforward: if borrowers can diversify away more of the project-specific return volatility through insurance and other contracts, and if a project's mean return rises with its total risk – including the idiosyncratic risk – then the borrowers will want to increase the project-specific risk because the marginal benefit (i.e., incremental mean return) exceeds the marginal cost (i.e., utility loss).[19] This is essentially the mechanism studied in Thesmar and Thoenig (2006).

The model's implication for the degree of diversification in financial intermediaries' loan portfolios is detailed in Appendix 1. The goal is to formulate indirect empirical tests of the model by checking whether changes in financial intermediaries' diversification over time are consistent with the model's predictions. This is a second best solution given the data limitations. A direct test of the model is not feasible, since it would call for observations of matched bank and borrower-loan data.

II.2 Empirical Analysis

A. Time Series of Bank Risk Decomposition and Testing of Model Predictions

As explained above, one of the model's predictions is that, for a financial intermediary of a given size, its degree of diversification is likely to have fallen as the efficient scale of operation has risen over the past two decades or so. To test these predictions, we estimate equations of the following structure:

$$\ln(\sigma_{i,t}) = \alpha_i + \beta_0 t + \beta_1 \ln(A_{i,t-1}) + \beta_2 t \bullet \ln(A_{i,t-1}) + \boldsymbol{\gamma}' \mathbf{Z}_{i,t} + \varepsilon_{i,t} \,. \tag{16}$$

[19] Since the borrowers (especially those small firms, which are often operated by owners) are likely to be less diversified than the lenders, total risk but not just systematic risk matters for their welfare.

The dependent variable $\sigma_{i,t}$ is a measure of the degree of diversification for intermediary *i* in period *t*. For comparison, I also regress the systematic, idiosyncratic and total risk. α_i is the fixed-effects term, to capture all the unobserved intermediary-specific characteristics that may affect its risk properties. *t* is a time trend, and $A_{i,t-1}$ is the real size of *i*'s portfolio at the beginning of the period. $\mathbf{Z}_{i,t}$ is a vector of control variables that in theory can also affect an intermediary's risk characteristics, and they will be discussed later in greater detail.

The null hypothesis according to the model then is $\beta_2 < 0$, with or without separate log assets and time trend terms, when the dependent variable $\sigma_{i,t}$ measures the degree of diversification. (β_2 is expected to be more negative with the other two terms.) If the interaction term is omitted, the sign of β_0 is ambiguous, since BHC size has grown substantially and so the average level of diversification could have risen over the sample period. Without the interaction term, $\beta_1 > 0$ is expected, since theory would suggest, and previous research has provided indirect evidence, that the share of systematic risk is generally higher for larger firms.[20]

When $\sigma_{i,t}$ measures idiosyncratic risk, β_2 is again expected to be negative. The hypothesis is that, owing to cheaper and better ICT, it is now profitable for banks to make smaller loans. Thus a given dollar volume now corresponds to a larger number of loans, most likely leading to smaller idiosyncratic risk, and so $\beta_2 < 0$. Without the interaction term, β_0 is expected to be negative as well while β_1 positive. The signs of these coefficients are less clear when $\sigma_{i,t}$ measures total and systematic risk.

It is worth noting that, if the effect from decreasing average size of loans is strong enough, it can in fact dominate the effect from new assets' greater idiosyncratic risk and result in *increasing* degrees of diversification over time. Therefore, the coefficients from regressions of the risk components together with that from the regression of diversification can offer clues to the likely mechanisms that have brought about the changes in BHCs' risk composition. If we see decreasing idiosyncratic risk along with non-increasing (i.e., negative or insignificant β_2) diversification, then it is most likely that the new assets

[20] For example, Demsetz and Strahan (1997) found that idiosyncratic risk is lower for larger BHCs.

added to bank portfolios over time are subject to greater proportions of idiosyncratic risk. The systematic risk must be declining as well in this case, and so thus so does total risk.

The financial intermediaries considered in this model mostly correspond to banks and bank holding companies in the real world. They lend to private and mostly small firms, which do not or cannot obtain funding from the markets.[21] Since high frequency return data necessary for estimating the change in risk is only available for public firms, our sample is all the publicly traded bank holding companies. The risk measures used in the estimation of (16) are based on monthly stock returns.

To obtain the dependent variables in (16), we decompose return variance according to asset pricing models. That is, we first estimate an asset pricing equation such as the CAPM, and take the fitted values as a measure of the security's systematic returns, and the residuals a measure of its idiosyncratic returns. Standard deviations of total rate of return on the stock and its two components then measure the total, systematic and idiosyncratic risk, respectively. The degree of diversification is measured as the unadjusted R^2 from the asset pricing regressions, which quantifies the fraction of a stock's return variation that can be explained by the systematic factors. For financial intermediaries, which can be viewed as (actively managed) portfolios of financial contracts, the R^2 statistics can be interpreted as measuring how diversified the portfolios are.

Four asset pricing models are considered: the market model, the CAPM, and the CAPM augmented with the two Fama-French factors (referred to as the FF model from here on), and the FF model further augmented with one momentum factor (referred to as the momentum model from here on). Both the market model and the CAPM are familiar single-factor models. The Fama-French model augments the market factor in the CAPM with two additional factors called HML (i.e., high-minus-low) and SMB (i.e., small-minus-big). The momentum model further augments the FF model with a momentum factor, to proxy for the momentum effects on stock returns as documented in Jagadeesh and Titman (1993).

[21] Nowadays, there is a greater variety of financial institutions lending to private and small businesses, and a broader array of credit contracts. For example, credit card companies such as American Express is routinely used by small businesses for working capitals, and factoring has become widely available as well.

To measure how BHCs' risk has evolved over time, we construct a time series of annual estimates of each BHC's return risk composition by estimating the four asset pricing equations using monthly stock returns of each publicly traded BHC in each year *t*. To illustrate, consider the FF model, estimated as follows:

$$r_{i,t(j)} - r^f_{t(j)} = \alpha_{i,t} + \beta_{i,t}\left(r^m_{t(j)} - r^f_{t(j)}\right) + \gamma_{i,t} HML_{t(j)} + \lambda_{i,t} SMB_{t(j)} + \varepsilon_{i,t(j)}\,. \qquad (17)$$

$r_{i,t(j)}$ is the rate of return on BHC *i*'s stock in month *j* of year *t*. Likewise, $r^m_{t(j)}$ and $r^f_{t(j)}$ are the market return and risk-free rate, respectively, while $HML_{t(j)}$ and $SMB_{t(j)}$ are rates of returns on the two FF factors, all for the same month.[22] $r_{i,t(j)} - r^f_{t(j)}$ is the so-called excess return. The coefficients on these systematic factors are allowed to vary across BHCs and from year to year.

Standard errors of the fitted values and the residuals from (17) are used as the measure, respectively, of each BHC's systematic and idiosyncratic risk in each year. Standard deviation of monthly (excess) returns of *i*'s stock in a year is taken as the measure of total risk for that year. Unadjusted R^2 from each regression (*i*, *t*) is used to measure the degree of diversification for BHC *i* in year *t*.

There are obvious caveats of using stock return data to infer the evolution of the risk characteristics of individual loans in intermediary's loan portfolios. First and foremost, BHCs' capital structure may have changed so that the risk properties of their stocks are now different even without any changes in their loan portfolios. This possibility is especially relevant for total risk of BHCs' stock returns: if more stringent capital requirements and supervision since the implementation of Basel I have lowered banks' leverage, then total risk of stock returns should decline during the late 1980s and early 1990s, the first half of the sample period, and lead to $\beta_2 < 0$ or $\beta_0 < 0$ without the interaction term. However, this development has no definite implication for the evolution of either component of risk, and

[22] The CAPM model is specified the same but without the two FF factors. This differs from the standard CAPM specification in one regard: an intercept is allowed. Most tests of the CAPM cannot reject the null of a non-zero intercept, contrary to what the theory postulates. There is also a technical reason for including an intercept, and that is to allow us to directly use the R^2 statistic generated by the statistical software. R^2 is guaranteed to be within (0, 1) only if there is an intercept in the regression.

even less for the degree of diversification. Besides, if the change in capital structure manifests mostly in the capital-asset ratio, then including it in $\mathbf{Z}_{i,t}$ should mitigate if not eliminate the effect of changing leverage.[23]

Even without significant changes in capital structure, the risk characteristics of BHCs asset portfolios can change for reasons unrelated to the mechanisms recognized in the model. First of all, banks may have altered the composition of market securities vs. loans in their asset portfolios. One major contributor to the increase is securities in trading accounts, especially in large banks, which has grown from 7% of all securities holding in 1988 to 25% in 2005.[24] If such securities are chosen to be more risky, then their increased share may have raised the overall risk level of bank asset portfolios. But their impact on the composition of risk is not clear, since there is no definitive reason why these securities' greater risk exposure should mostly comes from idiosyncratic risk.[25] I control for possible influences of trading account assets using their share of total assets as a control variable.

In addition, banks' holding of mortgage-backed securities has also risen during the same period, contributing to the increase in the overall share of securities. This coincides with a growing share of residential mortgage loans in banks' loan portfolios. Data of both interest rates and default rates suggest that residential mortgage loans are on average less risky than C&I loans, and there is little evidence that idiosyncratic risk matters more for individual mortgage loans. Residential mortgages on average are also smaller than C&I loans. Moreover, ICT advances has made it feasible – optimal in fact – to manage portfolios consisted of much larger numbers of loans, and this effect seems particularly relevant for mortgage loans. Taken together, these features should imply that, as the share of mortgages and MBS rises, a BHC's idiosyncratic risk will tend to fall while its degree of diversification rise. This is exactly opposite to the model's prediction based on the evolution of business lending, and thus should bias

[23] It must be noted that many of the control variables are endogenous for the bank analyzed, and so the usual caveats of simultaneity apply.
[24] Based on data of assets and liabilities of domestically chartered commercial banks in the U.S., adjusted for mergers and seasonally adjusted, from the Federal Reserve statistical release H.8.
[25] One possible case is that idiosyncratic risk somehow yields excess return on an asset. Several empirical studies (e.g., Spiegel and Wang 2005, and Guo and Savickas, 2005) seem to find evidence that idiosyncratic risk matters for asset returns in the cross section.

against finding the result. I control for changes in the composition of loan portfolios using the share of different categories of loans.

On the other hand, positive bias is also possible, as changes in risk composition *within* the portfolio of mortgage loans and MBS may in fact mirror those within the portfolio of business loans, owing to the same forces recognized in the model above. That is, ICT and financial innovations also enable banks to lend to more cheaply and to more risky households. Moreover, the securitization of all conforming loans means that mortgage loans kept by banks on their balance sheet may be larger and more subject to idiosyncratic risk. This suggests that the degree of diversification within the mortgage loan portfolio may have fallen also. In fact, a similar argument in principle apply to all types of loans. In particular, for the other two major loan categories – C&I and consumer loans – the "diversification depressing" effect of lending to borrowers who are more subject to idiosyncratic risk is at least partly offset by the diversification enhancing effect of lending more and smaller borrowers. Changes in the risk of overall bank portfolio uncovered through regressions are the *net* effect. A finding of no increase in the degree of diversification over time can be interpreted to mean that the increase in loan numbers in the portfolio is not enough to offset the increased share of idiosyncratic risk of the new loans added.

In general, evolution of the risk structure of bank loan portfolios reflects changes in lending to both businesses and consumers, and one suspects that some changes are induced by the same underlying forces and thus positively correlated. As an attempt to distinguish among the contribution from different types of loans, we include the share of each category of loans (viz., C&I loans, real estate loans, consumer loans and agricultural loans) in the vector of control variables. In addition, a Herfindahl-Hirschman style index is constructed to measure the concentration across different loan categories within a BHC's portfolio and help capture possible nonlinear effects.

Besides changes in the composition of assets on the balance sheet, changing off-balance-sheet (OBS) activities also affect a BHC's risk. OBS activities, primarily the underwriting of various derivatives contracts such as interest rate swaps, forwards and options, have become a significant component of operations in the largest 20 or so BHCs. These OBS contracts all constitute either claims or liabilities of a BHC, and thus affect its risk-return profile. But it is not clear how they affect the risk decomposition. To help control the possible impact of OBS activities, we include the share of notional principal on interest rate swaps and foreign exchange futures to total assets. This is a rather imprecise measure, since notional value of derivatives often has little relation to the true economic value of the contracts. So it should be viewed more like dummy variables for the largest banks.[26]

Additional control variables include the ratio of noninterest income to net interest income, as a proxy for the BHC's operating efficiency.[27] Some deposit ratios, such as the size of total deposits relative to total assets, are included to control for diversification that may result from the deposit side. A variable measuring the turnover rate of market trading of the BHC's stock is introduced because previous research has found that market liquidity directly affects a stock's measured risk.

Last, to capture the impact of external environment on bank risk, we construct a variable that measures the volatility of economic activities in the BHC's market. Given the empirical evidence of declining volatility of real activities at both the aggregate level and the state level, and BHCs' substantial geographic expansion, it is possible that the lower risk of a BHC's stock stems from lower volatility of real activities in its market.[28] The control variable is the standard deviation of weighted monthly employment growth in each year (t) in the states where BHC i operates:

$$\Sigma_{i,t} = \frac{1}{12}\sum_{j=1}^{12}\left(\sum_{k=1}^{m} w_{i,t,k} N_{t(j),k} - \frac{1}{12}\sum_{j=1}^{12}\sum_{k=1}^{m} w_{i,t,k} N_{t(j),k}\right)^2 .$$

The weight for each relevant state's (indexed by k) employment growth rate in month j (i.e., $N_{t(j),k}$) is the share of i's deposits in state k for year t (i.e., $w_{i,t,k}$). Using deposit shares to weight growth by state is the best proxy possible given the available data. It would be more appropriate to use loan weights.

[26] For the same reason, the nature of activities at the non-bank subsidiaries of BHCs also affects the risk of BHC's stock returns. Such activities include bond and commercial paper underwriting and sales of insurance policies. Similarly, controls such as the ratio of non-bank subsidiaries' assets to total bank assets, can be applied. Short of the exact asset data, we use a dummy variable denoting whether a BHC has a Section-20 subsidiary.

[27] Many of the control variables are used in Demsetz and Strahan's (1997) study of BHC size and diversification. Their study, however, is only about the role of size in banks' diversification, and does not consider the variation in risk composition over time.

[28] The model above, however, would in fact point to a negative relationship between the volatility of real activities and diversification and possibly idiosyncratic risk at a bank.

B. Estimation Results

In the first stage, we estimate four asset pricing equations (in the general format of (17)) for each publicly traded BHC in each year, using monthly returns (inclusive of dividends) on its stocks in that year. The market model uses the actual monthly stock returns, whereas the other three asset pricing equations all use the excess return.[29] (See the data appendix for the summary statistics of the variables used in the first stage – asset-pricing – regressions.)

The sample period is chosen to be 1987 to 2004. It starts in 1987 because the BHC financial accounting data needed in the second stage is only available since 1986.[30] We further lose the first year because the beginning-of-year (i.e., end-of-last-year) values will be used. For each year, only those BHCs with no fewer than ten monthly return observations are included. The market return is measured using the monthly returns on the value-weighted broad-based market index, while the risk-free rate is measured using the constant maturity 90-day Treasury-bill rate. All the stock return data come from CRSP database; the Treasury-bill rates are published in the Federal Reserve Board's Statistical Release H.15.

Following Fama and French (1993, 1996), the factor HML is defined as the difference in stock returns between firms with high book-to-market ratios and those with low ratios, while SMB is the difference in returns between a group of small and a group of large firms (see the data appendix for details of how they are constructed). The momentum factor is essentially lagged returns, constructed as the cumulative return over the two months ending at the beginning of the prior month (following Choidia *et al*. 2001; also see appendix 2 for computation details).

[29] If the risk-free rate were constant, then the standard CAPM could be interpreted as statistically equivalent to imposing a restriction on the constant term in the market model. However, since the risk-free rate is also time varying, even allowing for a constant in the CAPM does not make it equivalent to the market model, although the difference between them is very minor, since the month to month return variations of T-bills are much smaller by comparison. Total risk is defined as the standard deviation of the dependent variable, which means the measure of total risk is identical for all but the market model.

[30] October 1987 is removed from the sample to minimize the influence of the market crash on the asset pricing estimations.

Since the market model and the CAPM have virtually the same single explanatory variable, they yield nearly identical return decompositions and estimates of diversification. So I will omit most of the detailed results from analysis based on the market model's estimates, and simply note that they are almost the same as results based on the CAPM.[31] Similarly, I also omit most detailed results based on the momentum model, since they are nearly the same as those from the FF model.[32] The FF model, in contrast, improves upon the CAPM noticeably (see data appendix 3 for the increase in the goodness of fit), and leads to rather different outcome in the second stage regressions.

Log standard deviations of total, systematic and idiosyncratic return volatilities become the dependent variables in (16). The degree of diversification, however, needs to be transformed differently. Since R^2 can only take on values between 0 and 1, linear regressions are in principle problematic, as in the case of binary dependent variables. The estimation methods developed for fraction variables, which too can only have values between 0 and 1, can be applied since R^2 can be interpreted as a fraction – of an asset's return variations. Here we adopt the so-called "log odds" transformation:[33]

$$\pi_{i,t} = \ln\left(R^2 \big/ 1 - R^2 \right).$$

This monotonic transformation yields a dependent variable that can take on any real values. This method has the virtue of allowing simple linear estimation, but also one drawback in this case.[34] The coefficient estimates are difficult to interpret: it is impossible to estimate a fitted value E (y | **x**) without further assumptions, and still difficult to do so even with further assumptions (see Wooldridge, 2002, p. 616-8).[35] Nonetheless, it does provide correct estimates of the direction of change.[36]

[31] Detailed results of all these other regressions can be requested from the author.
[32] Adding the momentum factor improves upon the FF model only marginally. Part of the reason may be that there are only between 10 to 12 monthly returns in each asset regression, and the degree of freedom becomes strained with three factors plus a constant.
[33] The need for this transformation is one reason why we use the unadjusted R^2, because adjusted R^2 can become negative. But more importantly, the ranking of R^2 and adjusted R^2 are perfectly correlated within each asset pricing regression. So, to the extent that we mostly care about signs, using either reaches the same conclusion.
[34] The other drawback is irrelevant here, since none of observations take on the boundary values 0 or 1.
[35] In later drafts, I plan to consider an alternative that avoids this problem. It models E (y | **x**) as a logistic function and estimate using quasi maximum likelihood. (See Papke and Wooldridge, 1996). One drawback of this method is that it is incompatible with the fixed effects model, which would lead to the incidental parameters problem in this case. Even the random effect model may not be consistent in some cases.

The second stage regressions, i.e., (16), are estimated using the fixed effects model, and every regression includes a full set of year dummies, whose coefficients are omitted here. The size of a BHC is measured as the real book value of its assets, that is, book value deflated with the GDP deflator. We also experiment with measuring BHC size using the balance of net loans.[37] The control variables are as discussed above.

Both the data on BHC asset size and the data needed to construct the control variables are from the Y-9C regulatory filings by all the BHCs to the Federal Reserve. For annual observation, data are taken from the 4th quarter reports. All the values are computed for the beginning of the period (that is, based on data from the prior year's 4th quarter). A key dataset that maps between a BHC's RSSD identification code in the Y-9C reports and its PERMNO code in CRSP before 2000 is kindly provided by Kevin Stiroh of the New York Fed. ID codes of an additional 130 BHCs are manually matched for 2001-4. The branch level deposit data used to calculate the weighted average employment volatility ($\Sigma_{i,t}$) are from the Federal Reserve Board (before 1994) and the FDIC (since 1994).[38] (See the data appendix for more details.)

C. Trends in Risk and Diversification

Now let us examine the estimates of trends in the volatility of the return components and the degree of diversification. (We do not report detailed results of the asset pricing regressions from the first stage. See Appendix 3 for summary statistics of the parameter estimates.)

First, when total return variance is decomposed according to models where the single factor is the broad stock market return (i.e., the market model and the CAPM), the degree of diversification indeed

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[36] For robustness check, we have also simply used R^2 as the dependent variable, and the coefficient estimates are qualitatively the same, and over 98% of the fitted values are within (0, 1).
[37] In an earlier version, I have also experimented using the stock market capitalization to measure BHC size, and obtained qualitatively the same results. We abandoned the equity-value-based measure of size because we feel it does not well represent the overall asset portfolio of the bank. One natural alternative then is to construct a market value of assets by summing up the market value of equity with the book value of liabilities. The latter is a reasonable proxy, to the extent that bank liabilities are mostly short-term instruments.
[38] Ronnie McWilliams at the Board and Peggy Gilligan at the Boston Fed kindly assisted in retrieving the deposit data.

declines over time for BHCs of a given size. That is, the coefficient (i.e., β_2) is indeed significantly negative (Table 2), with or without the control variables. Moreover, as conjectured, when the interaction term is omitted, the coefficient on the time trend is significantly negative. The parameter estimates (reported in Table A.2 in Appendix 3), are very similar based on the diversification measure from the market model. Including the control variables makes little difference to the coefficient on the interaction term or the time trend, and especially not to the significance levels. In fact, most of the control variables are insignificant.

Measures of the risk components based on the same single-factor models also exhibit a downward trend over time. Tables 3, 4 and 6 report the parameter estimates for the idiosyncratic, systematic and total risk, respectively.[39] Given the downward trend for both the systematic and idiosyncratic risk, it is not surprising that β_2 is negative for total risk as well. One thing to note is that several of the control variables now become significant. In particular, higher shares of deposits, especially foreign deposits, coincides with decreasing idiosyncratic risk. Lower leverage (i.e., higher capital ratio) has a similar effect, although the magnitude is much smaller. Greater turnover, on the other hand, correlates with greater idiosyncratic risk. These last two variables have similar effects on the systematic risk as well, and in turn similar effects on total risk too.

The shift over time in the slope coefficient can be seen intuitively in Figures 3 through 5. Figure 3 is a scatterplot of BHCs' diversification against the (log) size of their assets. 1988 (the first normal year, in red) and 2004 (the last year, in green) are picked to maximize the contrast. A separate line is fitted for the observations in each year.[40] The difference between their slopes is visually distinct. A similar pattern can be seen for the systematic risk (Figure 4) and idiosyncratic risk (Figure 5).

Table 5 reports the parameter estimates from regressing beta (i.e., loading on the market factor) on the same set of right-hand-side variables. Given that these are single-factor models, and given

[39] The corresponding regressions based on return estimates from the market model are extremely similar and thus omitted to save space. The details can be obtained from the author upon request.
[40] Note that the slope coefficients of these lines are not the same as those estimated in Table 3, because R^2 is plotted directly without the "log odds" transformation.

evidence from previous research that there is no significant trend in volatility of the market return, it is not surprising that very similar patterns of coefficient estimates emerge for the systematic risk and the factor loading.

As a robustness check, we also estimate the same equations with the real balance of net loans substituting for total assets as the measure of BHC size. The parameter estimates are reported in Tables A.4 and A.5 in Appendix 2. Comparing them with Tables 2 to 5 reveals that using net loan balance yields similar estimates when all the variables are included.

Now we move on to trends in risk compositions based on multi-factor models for asset pricing. Tables 7 through 10 report all the results of estimating (16) with the dependent variables derived from the FF model.[41] Compared with parameter estimates associated with the single-factor models above, the most striking difference here is that the coefficient on the interaction term is no longer significant for diversification, but remains significantly negative for volatilities of the two return components.[42] So is the coefficient on the time trend, when the interaction term is left out. Including the control variables only makes a difference for the market beta – the interaction term now becomes significantly negative. The signs, magnitude and significance of coefficients on the control variables are similar to their counterparts in the regressions based on the market model and the CAPM, especially when the components of risk are the dependent variables.

These regression results can again be inspected graphically. Figures 6-8 are the FF-model-based counterpart to Figures 3-5, respectively. The most striking contrast is between Figure 3 and 6. While the CAPM-based estimates of diversification mostly flock around zero, they are much higher and more

[41] For estimates based on the momentum model, only the regressions for diversification are reported in Table A.3 in Appendix 3. Comparing Tables 9 and A.3 clearly shows that the results are very similar for the two models, and the same holds for all the other dependent variables. There is, however, a significant difference between the two models when the year 1987 is entirely excluded from the asset pricing regressions in the first stage. The second-stage coefficient on the interaction term is significant based on the diversification measure from the momentum model (see Tablel A.6 in appendix 2 but not the FF model.

[42] Note that since these multi-factor models, the loading on one factor does not necessarily behave similarly to the systematic risk as a whole. Regressions for the volatility of total return are omitted because they are identical (up to any sampling errors stemming from any difference – nonn in this case – in the exact sample used in the estimations) to those based on the CAPM, because the two models share the same definition of total return.

dispersed when estimated with the two FF factors added. Patterns of the difference between 1988 and 2004 are similar for volatility of the return components regardless of the asset pricing model used.

Combining these results, one observation seems prominent, and that is the degree of diversification has *not* risen in BHCs despite their much increased size over the past two decades or so. On the other hand, the explanatory power of market returns as a factor does appear to have diminished significantly over time. This accords with findings in previous studies, such as Campbell *et al*. (2001) and Comin and Philippon (2005). Both studies note the deterioration in the explanatory power of the CAPM over time. It is in fact more extraordinary to see similar declines in connection with BHCs' stock returns, in that the number of financial service firms have grown to be the largest among all public firms, and financial firms are the second largest in terms of market capitalization (see Campbell *et al*. 2001). Given that most large industries have a beta near unity (the beta for the financial industry is 0.97, see Campbell *et al*. 2001), the market return should in fact have become a more important factor for the financial firms, *ceteris paribus*. And yet the explanatory power of the market return has waned for the financial firms too.

By comparison, the explanatory power of the two Fama-French factors seems to have held up well and in fact made up for the loss in the power of the market return. The FF factors are constructed to capture two major asset pricing anomalies – the size and the book-to-market effects. So one conclusion is that over time financial firms' returns have become less correlated, both within and without the industry. At the same time, the non-beta risk factors have become increasingly important in accounting for the cross-section variations in return.

Regardless of how the regime of asset pricing may have changed, the salient feature of trends in the risk decomposition for BHCs remains, and that is the degree of diversification in BHCs has declined over time, while during the same period the size of BHCs has increased considerably. This study presents one plausible explanation for this development. More importantly, the mechanism proposed can explain not only trends in BHCs' risk, but also trends in the volatility of nonfinancial firms' activities that have been documented by a growing body of research.

III. Joint Evolution of the Volatility of Real and Financial Quantities

III.A. Background assumptions for A Firm's Optimization Problem

The production technology is assumed to be Cobb-Douglas with constant returns to scale: $y_i = z_i l_i^{\alpha} k_i^{1-\alpha}$, where y_i is firm i's output, and l_i and k_i its inputs of labor of capital, respectively. In the first version, we assume there are no productivity shocks. So each firm's productivity, z_i, once drawn in period 0, remains fixed throughout.

So the short-run cost function, given capital stock k_i, is:

$$C(y_i, k_i, z_i, w) = w\left(\frac{k_i^{\alpha-1}}{z_i} y_i\right)^{\frac{1}{\alpha}}, \tag{18}$$

where w is the (constant) wage rate. Since $\alpha < 1$, it is obvious the short-run cost function is convex. Specifically, marginal cost, denoted as c, equals

$$c(y_i, k_i, z_i, w) = \frac{w}{\alpha}\left(\frac{k_i^{\alpha-1}}{z_i}\right)^{\frac{1}{\alpha}} y_i^{\frac{1-\alpha}{\alpha}} \equiv A_i y_i^{\beta} > 0, \tag{19}$$

where the constant coefficient $A_i \equiv \frac{w}{\alpha}\left(\frac{k_i^{\alpha-1}}{z_i}\right)^{\frac{1}{\alpha}}$ depends on the firm's' productivity draw and its predetermined optimal capital stock, while the exponent $\beta \equiv (1-\alpha)/\alpha$ equals the ratio between capital's and labor's share in income. Since $\alpha < 1$, it is obvious that $c_y > 0$ (subscripts standing for partial derivatives) as well, i.e., convex production cost. This is the standard assumption for short-run production cost, giving rise to the production-smoothing motive.

In terms of demand, each firm is assumed to engage in monopolistic competition, and the representative consumer's overall consumption is given by the familiar Dixit-Stiglitz aggregation formula:

$$Q = \left(\sum_{i=1}^{n} (1+\tilde{\varepsilon}_i)^{\frac{1}{\sigma}} q_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{20}$$

and $\sigma > 1$. (20) differs from the standard formulation only in that it contains idiosyncratic demand shocks $\tilde{\varepsilon}_i$ which are i.i.d. across goods. For simplicity, these shocks are assumed to be normally distributed.[43]

Then the demand for firm i's output is:

$$q_i = (1+\tilde{\varepsilon}_i)\frac{E}{P}\left(\frac{p_i}{P}\right)^{-\sigma}, \tag{21}$$

where E is aggregate expenditure, and P is the aggregate price index, given by $P = \left(\sum_{i=1}^{n}(1+\tilde{\varepsilon}_i)\,p_i^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$. Given the demand function (21), the optimal markup for firm i to charge is thus $\mu \equiv \dfrac{\sigma}{\sigma-1}$. And this markup remains constant throughout.

To simulate a short-run setting, the firm is assumed to optimize its production over three periods, t = 0, 1 and 2. Using backward induction, we solve the firm's problem starting from the last period.

Period 2:

The firm's optimization problem in Period 2 can be written as:

$$\max_{p_{i,2}} \quad \Pi_{i,2} = p_{i,2}q_{i,2} - C_{i,2}(y_{i,2}) - R_i(k_i) - \Gamma_{i,2}(B_{i,1}), \tag{22}$$

$$\text{subject to } B_{i,1} = \max(0, -\textstyle\sum_{t=0}^{1}\Pi_{i,t}) = -\iota\sum_{t=0}^{1}\Pi_{i,t}, \tag{23}$$

$$y_{i,2} = q_{i,2} - x_i, \tag{24}$$

$$y_{i,2} \geq 0 \text{ and } x_i \geq 0.$$

where $q_{i,2}$ and $y_{i,2}$ are, respectively, firm i's sales and output in period 2, while x_i is its finished-goods inventory at the beginning of the period. $C_{i,2}(.)$ is the production cost in period 2, with the time subscript signifying that it also depends on input prices, which can be time varying. $R(k)$ is the cost of external funds that finance the capital stock, determined in period 0 and thus a fixed cost in period 2. ι is an

[43] To be precise, $\tilde{\varepsilon}_i$ should follow truncated normal distribution, since demand cannot be negative. But we ignore this fine point in order to focus and simplify analysis, and just assume that the taste shocks are small enough to always ensure positive demand.

indicator variable defined as $\iota = 1$ if internal funds (i.e., cumulative cash flow by period 2, equal to $\Pi_{i,0}+\Pi_{i,1}$) are negative, and $\iota = 0$ otherwise;[44] so $B_{i,1}$ is the amount of external funds borrowed, if any, to finance inventories. $\Gamma_{i,2}(.)$ is the cost of borrowing, over and above the cost associated with internal funds, which is the risk-free interest rate, normalized to zero here. $\Gamma_{i,2}(.)$ is paid in period 2 but assumed to be set at the end of period 1 and thus predetermined as well. So the firm essentially maximizes period-2 producer surplus.

Since external funds are more costly, the firm will borrow only when internal funds are insufficient. Cash flows $\Pi_{i,0}$ and $\Pi_{i,1}$ will be derived below as outcomes of the firm's optimization in previous periods, while $\Gamma(.)$ while $\Gamma(.)$ satisfies $\Gamma(0) = 0$, $\Gamma'(0) = 0$, and $\Gamma'' > 0$.[45] That is, the cost of external funds is convex, as derived in the previous section.

The first order condition with respect to $p_{i,2}$ is:

$$p_{i,2} = \mu c_{i,2}(q_{i,2} - x_i) = \mu A_i \left[(1+\tilde{\varepsilon}_{i,2}) \frac{E_2}{P_2} \left(\frac{p_{i,2}}{P_2} \right)^{-\sigma} - x_i \right]^{\beta} . \tag{25}$$

It is easy to see that the optimal price ($p^*_{i,2}$) in period 2 depends on the amount of inventory (x_i). It is easily shown that $p^*_{i,2}$ rises with the demand shock but falls with inventory, i.e., $\partial p^*_{i,2} / \partial \tilde{\varepsilon}_{i,2} > 0$ and $\partial p^*_{i,2} / \partial x_i < 0$. The intuition for the latter is that, for given sales, inventories reduce the necessary amount of period-2 output one for one and thus result in a lower marginal cost. That in turn leads to a lower price, since the optimal markup is constant. Furthermore, lower $p^*_{i,2}$ along with lower marginal cost means that sales rises with inventory whereas output falls. In other words, for any realization of period-2 demand, the presence of inventory partly lowers optimal production and partly raises optimal sales.

[44] In this setup, cash flow and profit are equivalent, but in reality they differ due to non-cash expenses such as capital depreciation, as well as other discrepancies between cash-basis vs. accrual-basis accounting. I also omit tax-related differences, such as those due to investment tax credit and corporate income tax.
[45] I assume $\Gamma'(0) = 0$ merely for convenience – it makes the borrowing cost function differentiable at $B_i = 0$; all the conclusions will remain qualitatively the same if I instead assume $\Gamma'(0) > 0$.

<u>Period 1</u>:

In this period, given the capital stock, firm i's optimization problem is as follows:

$$\max_{p_{i,1},x_i} \quad \Pi_{i,1} + \mathrm{E}_1(\Pi_{i,2}) = p_{i,1}q_{i,1} - c(q_{i,1} + x_i) - R(k_i) + \mathrm{E}_1(\Pi_{i,2}) \,. \tag{26}$$

$$\text{subject to } x_i \geq 0. \tag{27}$$

$\mathrm{E}_1(.)$ denotes the expectation given period-1 information.

Then the FOC with regard to $p_{i,1}$ is:

$$q'_{i,1}\left\{\frac{p_{i,1}}{\mu} - c_{i,1}(q_{i,1} + x_i)\right\} + \iota\left(\Gamma'_{i,2}\,\frac{\partial \Pi_{i,1}}{\partial p_{i,1}}\right) = 0 \,. \tag{28}$$

ι is the indicator as defined in (23). When $\iota = 0$ (i.e., $\Pi_{i,0}+ \Pi_{i,1} \geq 0$), condition (28) becomes just like (25). Further investigation of (28) reveals that, supposing $p^{\#}_{i,1}$ satisfies

$$\frac{p^{\#}_{i,1}}{\mu} - c_{i,1}(q_{i,1} + x_i) = \frac{p^{\#}_{i,1}}{\mu} - A_i\left[(1+\tilde{\varepsilon}_{i,1})\frac{E_1}{P_1}\left(\frac{p^{\#}_{i,1}}{P_1}\right)^{-\sigma} + x_i\right]^{\beta} = 0 \,, \tag{29}$$

then $p^{\#}_{i,1}$ also satisfies (28), because $\partial \Pi_{i,1} / \partial p_{i,1} = 0$ at $p^{\#}_{i,1}$. Therefore, the optimal $p_{i,1}$ maximizes the within-period profit (or equivalently producer surplus), regardless of whether there is borrowing cost. The intuition is that the objective of maximizing today's profit coincides with that of minimizing borrowing and the resulting cost tomorrow (for any given x_i), and the choice of $p_{i,1}$ has direct effect only on current-period profit. Note, however, that the optimal value of $p_{i,1}$ does vary with the choice of inventories x_i, and $\partial p_{i,1} / \partial x_i > 0$. In fact, inventories' effect on output and sales is the opposite in period 1 vs. in period 2 – inventory investment partly lowers sales and partly raises production in period 1.

Likewise, the intertemporal FOC with respect to x_i is:

$$-c_{i,1}(q_{i,1} + x) + \frac{\partial \mathrm{E}_1(\Pi_{i,2})}{\partial x_i} = -c_{i,1}(q_{i,1} + x_i) + \mathrm{E}_1[c_{i,2}(q_{i,2} - x_i)] + \iota\left(\Gamma'_{i,2}\,\frac{\partial \Pi_{i,1}}{\partial x_i}\right) \leq 0 \,. \tag{30}$$

The inequality sign reflects the non-negativity constraint on x_i, that is, x_i is "asymmetric" – the firm cannot "take rainchecks" and shift production from period 1 to 2 even when period-2 demand is expected to be lower. Moreover, even at $x_i = 0$, it is possible that $\sum_{t=0}^{1} \Pi_{i,t} < 0$ if the realization of $\tilde{\varepsilon}_{i,0}$ and $\tilde{\varepsilon}_{i,1}$ are too low for the maximum within-period producer surplus to cover the fixed interest cost $R(k_i)$.[46] When $x_i^* > 0$, (30) holds with equality.

It is obvious that, without borrowing cost, (30) would become (with $x_i^* > 0$):

$$\mathrm{E}[c_{i,2}(q_{i,2} - x_i)] = c_{i,1}(q_{i,1} + x_i)\ . \tag{31}$$

That is, it is optimal for the firm to smooth production – equalize the expected marginal costs in the two periods. This is the familiar result given convex short-run cost function.

In addition, if $\beta < 1$, i.e., concave *marginal* cost function $c(.)$, (31) implies that, assuming constant factor prices in expectation, it is optimal to carry inventories only if demand is expected to be sufficiently higher in period 2, i.e., $\mathrm{E}(\tilde{\varepsilon}_{i,2}) > \tilde{\varepsilon}_{i,1}$ sufficiently. This can be seen by noting that when $\mathrm{E}(\tilde{\varepsilon}_{i,2}) = \tilde{\varepsilon}_{i,1}$ the firm should set $x_i^* = 0$, because

$$\mathrm{E}[c_{i,2}(q_{i,2})] = \mathrm{E}\{c_{i,1}[q_{i,2}^*(\tilde{\varepsilon}_{i,2})]\} < c_{i,2}\{q_{i,2}^*[\mathrm{E}(\tilde{\varepsilon}_{i,2})]\} = c_{i,1}[q_{i,1}^*(\tilde{\varepsilon}_{i,1})]\ .$$

This means if $\tilde{\varepsilon}_i$ shocks are assumed i.i.d., then the situation $\mathrm{E}(\tilde{\varepsilon}_{i,2}) > \tilde{\varepsilon}_{i,1}$ can arise if the realization of $\tilde{\varepsilon}_{i,1}$ is particularly low, that is, $\tilde{\varepsilon}_{i,1} << \mathrm{E}(\tilde{\varepsilon}_i)$.[47] In reality, the condition $\mathrm{E}(\tilde{\varepsilon}_{i,2}) > \tilde{\varepsilon}_{i,1}$ sufficiently to satisfy the FOC $\mathrm{E}\{c_{i,2}[q_{i,2}^*(\tilde{\varepsilon}_{i,2})]\} = c_{i,1}[q_{i,1}^*(\tilde{\varepsilon}_{i,1})]$ most likely occurs in recessions, when demand falls far short of its trend. The implication is that, all else equal, firms are more likely to accumulate inventories in recessions. In fact, this condition is augmented by the general equilibrium effect that factor prices tend to be high while demand is high – procyclical – as well.[48]

Comparing (30) and (31) shows that the existence of borrowing cost lowers the incentive to hold inventories, so that the expected marginal cost in period 2 now exceeds that in period 1 even when $x_i > 0$:

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[46] Note that the maximum producer surplus is always positive, since $MR(q=0) > MC(q=0)$ and $MR' < 0$ while $MC' > 0$.

[47] Note, however, that (31) can be satisfied even with i.i.d. $\tilde{\varepsilon}_i$'s if factor prices are expected to be sufficiently higher in the next period. If $\tilde{\varepsilon}_i$ follows randow walk, then firms should not hold inventories.

[48] Furthermore, as Bils and Kahn (2001) show, stock-out avoidance combined with counter-cyclical markup confers additional incentive for holding more inventories relative to sales in economic downturns. I will discuss further the implication of stock-out avoidance as a rationale for holding inventories.

$$\frac{\partial \Pi_{i,1}}{\partial x_i} = -c_{i,1}(q_{i,1} + x_i) < 0 \ .$$

That is, the FOC for the case of interest, where $x_i^* > 0$ and $\sum_{t=0}^{1} \Pi_{i,t}^* < 0$, is as follows:

$$\mathrm{E}[c_{i,2}(q_{i,2} - x_i)] = (1 + \Gamma'_{i,2})c_{i,1}(q_{i,1} + x_i) \ . \tag{32}$$

The intuition is clear: inventories now incur not only production cost but also financing cost. So the latter leads to lower inventory accumulation and thus less production smoothing than otherwise. This can be shown by fully differentiating (32) to yield

$$\frac{\partial x_i}{\partial \Gamma'_{i,2}} = -\frac{c_{i,1}(y_{i,1})}{\mathrm{E}\left[c'_{i,2}(y_{i,2})\left(1 - \partial q_{i.2} \big/ \partial x_i\right)\right] + (1 + \Gamma'_{i,2})c'_{i,1}(y_{i,1})\left(1 + \partial q_{i.1} \big/ \partial x_i\right)} > 0. \tag{33}$$

This is because $\partial q_{i.2} / \partial x_i < 1$ and $\partial q_{i.1} / \partial x_i > -1$:

$$\frac{\partial q_{i,2}}{\partial x_i} = \frac{\partial q_{i,2}}{\partial p_{i,2}} \frac{\partial p_{i,2}}{\partial x_i} = \frac{\partial q_{i,2}}{\partial p_{i,2}} \left[\frac{-\mu c'_{i,2}(y_{i,2})}{1 - \mu\left(\partial q_{i.2} / \partial p_{i,2}\right) c'_{i,2}(y_{i,2})} \right] < 1, \tag{34}$$

as the second equal sign follows from the period-2 FOC (25); likewise, the period-1 FOC with respect to $p_{i,1}$ implies that $\partial q_{i.1} / \partial x_i > -1$. Hence, with convex cost function, both the numerator and the denominator in (33) are positive, meaning $\partial x_i / \partial \Gamma'_{i,2} < 0$. The effect of borrowing costs on inventories is analogous to that of adjustment cost on capital investment. With adjustment cost, firms will invest only when the shadow price of capital (i.e., Tobin's q) exceeds the purchase price *plus* the adjustment cost. In the case of inventory investment, its shadow price equals the expected saving in next period's marginal cost, while its "purchase price" is the current marginal cost, and financing cost serves the role of adjustment cost.

One intuitive implication of the above result is that, when the firm needs to borrow to fund inventories, the optimal inventory rises with available internal funds. That is, fully differentiating (32) with respect to $\Pi_{i,0}$ and rearranging terms yields:[49]

$$\frac{\partial x_i}{\partial \Pi_{i,0}} = \frac{\partial x_i}{\partial \Gamma'_{i,2}} \Gamma''_{i,2} \left(\frac{\partial x_i}{\partial \Gamma'_{i,2}} c_{i,1} \Gamma''_{i,2} - 1 \right)^{-1} > 0, \tag{35}$$

since $\Gamma''_{i,2}(.) > 0$, $c_{i,1} > 0$, and $\partial x_i / \partial \Gamma'_{i,2} < 0$ according to (33). In contrast, if internal funds are sufficient or if there are no borrowing costs, then (31) is the relevant first order condition and the choice of x_i will not depend on $\Pi_{i,0}$.

The result in (33) also implies that the variance of output, conditional on period-1 information, is higher with borrowing costs. This is because, given the process of $\tilde{\varepsilon}_i$'s and factor prices, output variance rises with the *marginal* cost of external funds.[50] That is,

$$\text{var}_1(y_i) = \text{E}_1\left\{ \sum\nolimits_{t=1}^{2} \left[y_{i,t} - \text{E}_1(y_i) \right]^2 \right\} = \text{E}_1\left\{ \left[\frac{y_{i,1} - \text{E}_1(y_{i,2})}{2} \right]^2 \right\}, \text{ and so}$$

$$\frac{\partial \, \text{var}_1(y_i)}{\partial \Gamma'_{i,2}} = \frac{y_{i,1} - \text{E}_1(y_{i,2})}{2} \frac{\partial \left[y_{i,1} - \text{E}_1(y_{i,2}) \right]}{\partial x_i} \frac{\partial x_i}{\partial \Gamma'_{i,2}} = \left[y_{i,1} - \text{E}_1(y_{i,2}) \right] (2 - \frac{\partial q_{i,2}}{\partial x_i}) \frac{\partial x_i}{\partial \Gamma'_{i,2}} > 0, \tag{36}$$

since $y_{i,1} < \text{E}_1(y_{i,2})$ given (32), $\partial q_{i.2} / \partial x_i < 1$ as shown in (34) and $\partial x_i / \partial \Gamma'_{i,2} < 0$ as shown in (33). This result, combined with the assumption $\Gamma'(0) = 0$ and $\Gamma'' > 0$, implies that output variance is higher with borrowing costs. Note that, at the margin, it is the rate at which borrowing costs increase, but not the level of such costs, that matters for the variance of output.

More importantly, note that convex financing costs result in an incentive for the firm to smooth external borrowing and in turn cash flows while diminishing the incentive to smooth real output. This can be seen through the following comparative statics:

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[49] Fully differentiating (32) first gives

$$\frac{\partial x_i}{\partial \Pi_{i,0}} = \frac{\partial x_i}{\partial \Gamma'_{i,2}} \frac{\partial \Gamma'_{i,2}}{\partial \Pi_{i,0}} = -\frac{\partial x_i}{\partial \Gamma'_{i,2}} \Gamma''_{i,2} \left[1 + \left(\frac{\partial \Pi_{i,1}}{\partial p_{i,1}} \frac{\partial p_{i,1}}{\partial \Pi_{i,0}} + \frac{\partial \Pi_{i,1}}{\partial x_i} \frac{\partial x_i}{\partial \Pi_{i,0}} \right) \right] = -\frac{\partial x_i}{\partial \Gamma'_{i,2}} \Gamma''_{i,2} \left(1 - \frac{\partial x_i}{\partial \Pi_{i,0}} c_{i,1} \right), \text{ since } \partial \Pi_{i,1} / \partial p_{i,1} = 0,$$

and $\partial \Pi_{i,1} / \partial x_i = -c_{i,1}$.

[50] This is clearly a partial equilibrium result, since in general equilibrium, the process of factor prices would be affected as well. In fact, in addition to the GE effect on factor prices, the size of borrowing costs may affect firms' strategic interactions as well, which are not considered here.

$$\frac{d\left[\Pi_{i,1}+\mathrm{E}_1\left(\Pi_{i,2}\right)\right]}{d\Pi_{i,0}}=\frac{\partial\left[\Pi_{i,1}+\mathrm{E}_1\left(\Pi_{i,2}\right)\right]}{\partial\Pi_{i,0}}=\frac{\partial\left[-\Gamma_{i,2}\left(B_{i,1}\right)\right]}{\partial\Pi_{i,0}}=\iota\Gamma'_{i,2}\ \geq 0, \tag{37}$$

$$\frac{d^2\left[\Pi_{i,1}+\mathrm{E}_1\left(\Pi_{i,2}\right)\right]}{d\left(\Pi_{i,0}\right)^2}=\frac{d\left[\iota\Gamma'_{i,2}\left(B_{i,1}\right)\right]}{d\Pi_{i,0}}\ \leq 0, \tag{38}$$

Result (38) can be derived by applying the implicit function theorem to FOC (32), which implies

$$\frac{d\left[\iota\Gamma'_{i,2}\left(B_{i,1}\right)\right]}{d\Pi_{i,0}}=-\frac{\partial x_i}{\partial\Pi_{i,0}}\left\{\mathrm{E}\left[c'_{i,2}(y_{i,2})\left(1-\partial q_{i.2}/\partial x_i\right)\right]+(1+\Gamma'_{i,2})c'_{i,1}(y_{i,1})\left(1+\partial q_{i.1}/\partial x_i\right)\right\}.$$

This we know is negative because the sum in the curly bracket is positive according to (33) and $\partial x_i/\partial\Pi_{i,0} > 0$ according to (35). Taken together, (37) and (38) imply that, to the extent the firm has to borrow to fund inventories, its present value of expected profits is concave in its initial net worth, which in this model equals the cumulative cash flow up to the last period. Therefore, there is an incentive for the firm to smooth net worth and in turn cash flow. The firm should thus trade off the need of production smoothing with that of cash flow smoothing.

The implication, naturally, is that when the marginal cost of external financing declines, firms will optimally place more weight on smoothing production and less on smoothing cash flows. If that leads to greater volatility of the firm's rate of return, then the promised yield on the firm's borrowing will rise, even if the required rate does not in response to an increase in its idiosyncratic risk. This effect, i.e., Γ(.) dependent on the volatility of firm return, is not made explicit in the model for the sake of tractability, nor is the firm's default decision in period 2.

In this model, higher (but not cyclical) financing costs always lead to greater output volatility, regardless whether it is in a boom or a recession.[51] Part of the reason is the model's timing assumption: current period's production is carried out after current demand (i.e., sales) is known. So, assuming no exogenous changes in the financing cost function Γ(.), credit constraint always becomes more binding

[51] More precisely, it is if the financing cost schedule Γ(.) is more steep in the case of convex Γ(.), since it is the level of marginal financing cost that enters the FOC. The other possible case is for Γ(.) to shift in so that the marginal financing cost is higher at all levels of borrowing but no change in the convexity.

when future demand is expected to exceed the actual current demand and thus internal cash flows today are most likely to fall short of the financing need. In other words, the funding gap and hence the need for external funds rises with expected demand growth. Expectations of high demand growth can arise either because current demand is unusually low, or because future demand is anticipated to be even stronger. The former can be interpreted as economic downturns in the real world, while the latter can occur in booms, especially the early stages. Greater financing cost discourages inventory accumulation, all else equal. At the same time, less than optimal inventories always result in greater output fluctuations, since inventories in this model are purely for production smoothing. As a result, in models of production-smoothing for inventories, an invariably higher level of financing costs generally lead to greater output fluctuations at all times.

On the other hand, if the financing cost schedule $\Gamma(.)$ is counter-cyclical, that is, less steep in booms, then output will likely be less volatile in booms but more in slumps. Since the funding gap widens with expected demand growth, procyclicality of output volatility will be even more pronounced if the demand and in turn funding gap is greater in recessions than in booms. The other factor that affects a firm's profit and in turn cash flow is the markup on its products. In this model so far the markup is assumed to be constant. Some empirical studies (e.g., Chevalier and Scharfstein, 1996 and Bils and Kahn, 2001), however, have found evidence of counter-cyclical markups. This should partly offset the effect of counter-cyclical financing costs and dampen the cyclical variations in output volatility. Different timing of production relative to sales realization, and different models of inventories, on the other hand, can give rise to procyclical output volatility even with a constant financing cost schedule.

Note what the above analysis reveals is the change in idiosyncratic risk of cash flows *relative* to that of real sales. That is, *conditional* on the volatility of sales, which is taken to be exogenous, individual firms' net borrowing and likely cash flows as well become more volatile. This means that, if sales become sufficiently less volatile over time, then the idiosyncratic as well as total volatility of firms' cash flows can in fact decline as well, but by less.

Period 0: (incomplete)

At the beginning, the firm chooses how much to invest given its draw of productivity. All entrepreneurs are assumed to start with the same initial wealth, which is normalized to zero. This assumption is not restrictive, as it will become clear that the cost of capital will still differ across firms, driven by varying firm size, which is in turn determined by different draws of productivity. Consequently, the cost of funding inventories will differ as well.

The firm solves:

$$\max_{k_i} \quad E_0(\Pi_{i,1} + \Pi_{i,2}) = E_0\left[\Pi_{i,1}(k_i) + \Pi_{i,2}(k_i, x_i^*)\right],$$

where x_i^* is the solution from (28) and (30), and is a function of k_i. The FOC thus is:

$$E_0\left[\left.\frac{\partial \Pi_{i,1}}{\partial p_{i,1}}\right|_{p_{i,1}^*}\frac{\partial p_{i,1}}{\partial k_i} + \left.\frac{\partial[\Pi_{i,1} + E_1(\Pi_{i,1})]}{\partial x_i}\right|_{x_i^*}\frac{\partial x_i}{\partial k_i} + \frac{\partial \Pi_{i,1}}{\partial k_i} + \left.\frac{\partial \Pi_{i,2}}{\partial p_{i,2}}\right|_{p_{i,2}^*}\left(\frac{\partial p_{i,2}}{\partial k_i} + \frac{\partial p_{i,2}}{\partial x_i}\frac{\partial x_i}{\partial k_i}\right) + \frac{\partial \Pi_{i,2}}{\partial k_i}\right] = 0 \text{ .(39)}$$

Assuming that $x_i > 0$, and applying the envelope theorem yields

$$E_0\left[\frac{\partial \Pi_{i,1}}{\partial k_i} + \frac{\partial \Pi_{i,2}}{\partial k_i}\right] = E_0\left\{(1+\iota\eta')\left[\beta w\left(\frac{q_{i,1}+x_i}{z_i k_i}\right)^{\frac{1}{\alpha}} - R'\right] + \beta w\left(\frac{q_{i,2}-x_i}{z_i k_i}\right)^{\frac{1}{\alpha}} - R'\right\} = 0. \quad (40)$$

IV. Conclusion

Connections between the real and financial sectors of a developed economy are complex, and often subtle. This paper shows how the interactions between the two can simultaneously explain three stylized facts regarding trends in real and financial volatility. Over the past two decades, aggregate real output and employment have become less volatile, as has employment at the average firm. On the other hand, aggregate quantities of financial variables have become more volatile. Finally, the covariance of activity among firms and industries has declined, for both real and financial variables.

The analysis starts by positing that the very rapid decline in the price of ICT over the last two decades has reduced the cost of processing information, and thus effectively mitigated the information asymmetry that is the most plausible cause of a convex cost of borrowing external funds. Importantly, this reduction in external borrowing costs acts at three levels: at the level of firms, which borrow to smooth production; at the level of banks, which borrow to fund loans; and at the level of the financial markets, which lend to banks (and also directly to firms).

At the level of individual firms, a lower premium on external funds can explain lower real volatility combined with higher financial volatility. Intuitively, in a situation with asymmetric information, firms have to balance between smoothing production to minimize production costs and smoothing cash flows to minimize borrowing costs. A reduced marginal cost of external finance tilts their decision towards smoothing production and away from smoothing cash flows. Thus, real activity at an individual firm becomes less volatile, while financial activity – the quantity borrowed – becomes more volatile. These predictions fit the observations of recent research on this topic.

But aggregate volatility depends on more than the average of individual volatilities—it also depends on the covariances between individual decisions. The paper thus analyzes how a change in information processing costs will affect covariances for both real and financial variables. It identifies a set of sufficient conditions under which technological progress stemming from cheaper and better ICT will lead financial institutions and markets to set a relatively lower premium on idiosyncratic return volatility at the margin. Under these conditions, the actions of both borrowers and lenders will result in a greater share of funding going to projects that have relatively more exposure to idiosyncratic return risk, and so the covariance across projects will decline. The prediction for aggregate real volatility is thus unambiguous: it will decline, since both individual variances *and* covariances fall. The prediction for aggregate financial volatility, on the other hand, can be ambiguous—it could rise, which is the observed trend.

In summary, the model shows that a clear prediction for the effects of financial innovations on aggregate real activity depends on whether financial institutions have recently begun to assume greater idiosyncratic risk at the margin. Therefore the empirical section of the paper concentrates mostly on showing that this condition is satisfied in the data. It uses stock return data for publicly traded bank holding companies, and finds that the degree of diversification in bank portfolios has indeed declined over time, controlling for asset size. This indicates that, if banks are making smaller loans nowadays, as seems likely, their optimal choice of bank-specific return volatility must have risen more than enough to offset the natural diversification effect of holding more loans in a portfolio. This then implies that the share of idiosyncratic risk has risen for the constituent loans as well.

So far, the paper has analyzed the actions of financial institutions and non-financial firms. The obvious, and important, extension of the analysis is to the household sector. Intuition strongly suggests that the same mechanisms that apply to firms apply to households as well, and with even greater force. Technological advances have enabled banks to lend to more and smaller borrowers, and thus tolerate idiosyncratic volatility better. Small size and high idiosyncratic risk describes loans to households even better than loans to private firms. Hence, improvements in financial technology are likely to have lessened credit constraints on households, enabling them to smooth consumption better. Better consumption smoothing by households facing large idiosyncratic income shocks is likely to lead to less volatile aggregate demand, and reinforce the prediction of lower real output volatility. According to Ramey and Vine (2005) and McCarthy and Zakrajsek (2003), the decline in aggregate output volatility is largely driven by lower sales volatility, which then leads to a greater buffer stock role for inventories. This observation suggests that better access to financial markets on the part of households may be a significant part of the overall explanation for reduced aggregate output volatility.

Table 1. Volatility Trends of Quantity (Q) and Price (P) Growth

	Real variables			**Financial variables**		
	Aggregate (1)	Idiosyncratic[2] (2)	Covariance[2] (3)	Aggregate (4)	Idiosyncratic[2] (5)	Correlation[2] (6)
Q	↓	↓ [3]	↓	↑ [4]	↑	↓ [5]
P [1]	↓	↑ [6]	↓	–	↑	↓

Notes:
1. Growth rate of price of financial variables is equivalent to the rate of return.
2. The direction of trend is for the average idiosyncratic volatility and cross-section covariance. For some variables, there may be cross-section variations, such as between public and private firms. Those cases are noted below.
3. The trends for public vs. private firms seem to have diverged, with the former increasing whereas the latter decreasing. But the trend for private firms dominate the average since they account for the majority of the firm population.
4. The most likely outcome of overall trend. Again the overall behavior of public firms differs from that of private firms.
5. A decline in correlation means that covariance falls *relative* to the (geometric) average variance. So it is not inconsistent with an increase in covariance, as long as individual variance rises even more. Since the correlation between private and public firms has rise to near perfect, in order for overall correlation to fall, the correlation within each sector will have to fall.
6. Mostly conjecture, lacking sufficient evidence.

Figure 1:

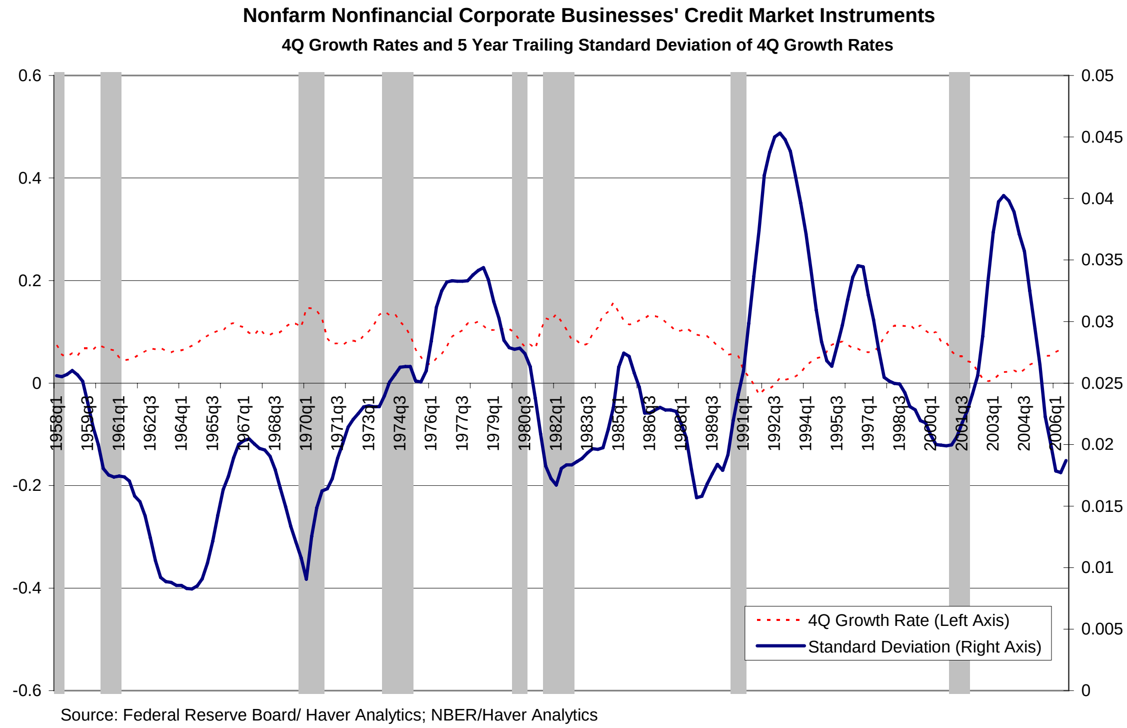

Figure 2:

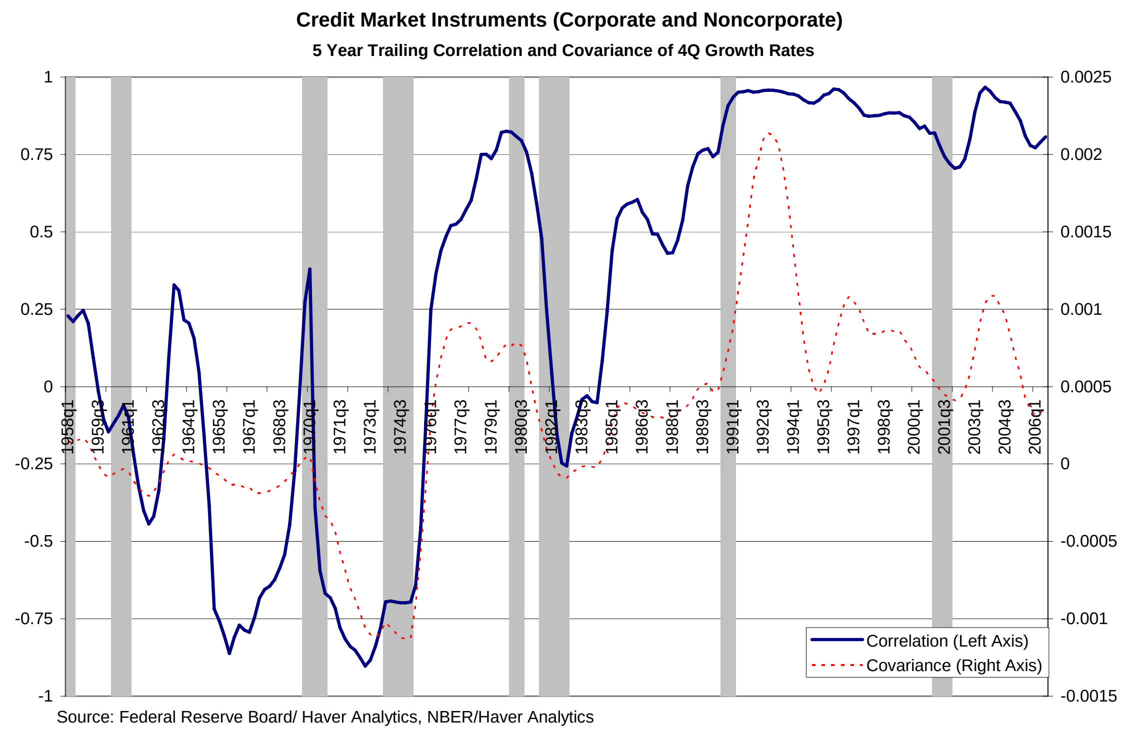

Table 2. Trends in the Degree of Diversification,
(Diversification measure based on the CAPM)

Dependent Variable: Log Adjustment of R-Squared					
Log Real Total Assets	0.122	–	–	0.047	0.39
	(0.111)			(0.128)	(0.153)*
Year	0.006	–	–	0.014	0.383
	(0.015)			(0.018)	(0.089)**
Year X Log Total Assets	–	-0.012	-0.017	–	-0.025
		(0.004)**	(0.005)**		(0.006)**
C&I Loans / Total Assets	–	–	-0.857	-0.919	-0.835
			(1.220)	(1.220)	(1.208)
Real Estate Loans / Total Assets	–	–	-0.959	-1.079	-1.115
			(0.669)	(0.678)	(0.676)
Agricultural Loans / Total Assets	–	–	2.070	0.983	1.900
			(4.945)	(4.949)	(4.947)
Consumer Loans / Total Assets	–	–	-0.442	-0.47	-0.303
			(1.250)	(1.250)	(1.250)
HHI-style Index of Loan Portfolio Concentration	–	–	0.059	0.184	-0.019
			(1.143)	(1.139)	(1.134)
Trading Acct. Assets / Total Assets	–	–	0.566	0.058	1.112
			(2.026)	(2.000)	(2.004)
Total Deposits / Total Assets	–	–	-0.137	0.197	0.191
			(0.690)	(0.712)	(0.707)
Foreign Deposits / Total Deposits	–	–	0.720	0.708	0.682
			(0.511)	(0.512)	(0.510)
Noninterest Bearing Deposits / Total Deposits	–	–	-1.663	-1.672	-1.503
			(0.851)	(0.856)	(0.853)
Notional Principal on Interest Rate Swaps / Total Assets	–	–	0.108	0.042	0.122
			(0.057)	(0.054)	(0.056)*
Notional Principal on FX futures / Total Assets	–	–	0.088	-0.062	0.110
			(0.167)	(0.167)	(0.167)
Noninterest Income / Net Interest Income	–	–	0.047	0.039	0.061
			(0.045)	(0.047)	(0.042)
Log (Equity Capital / Total Assets)	–	–	-0.227	-0.254	-0.076
			(0.185)	(0.187)	(0.190)
Trading Volume / Outstanding Shares	–	–	-0.218	-0.309	-0.232
			(0.156)	(0.154)*	(0.153)
Volatility of Weighted-Average Employment Growth	–	–	0.653	0.762	0.722
			(1.918)	(1.934)	(1.919)
Observations	6756	6756	6187	6187	6187
Number of BHCs	927	927	886	886	886
R-squared	0.07	0.07	0.08	0.08	0.08

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

Table 3. Trends in the Idiosyncratic Risk,
(Diversification measure based on the CAPM)

Dependent Variable: Log S.D. of Idiosyncratic Returns					
Log Real Total Assets	0.053 (0.019)**	–	–	-0.028 (0.021)	0.042 (0.025)
Year	-0.013 (0.003)**	–	–	-0.011 (0.003)**	0.064 (0.015)**
Year X Log Total Assets	–	-0.002 (0.001)**	-0.004 (0.001)**	–	-0.005 (0.001)**
C&I Loans / Total Assets	–	–	0.144 (0.184)	0.130 (0.183)	0.147 (0.185)
Real Estate Loans / Total Assets	–	–	0.112 (0.108)	0.102 (0.109)	0.095 (0.109)
Agricultural Loans / Total Assets	–	–	0.788 (1.012)	0.585 (1.014)	0.770 (1.007)
Consumer Loans / Total Assets	–	–	-0.263 (0.221)	-0.282 (0.221)	-0.248 (0.220)
HHI-style Index of Loan Portfolio Concentration	–	–	0.223 (0.178)	0.255 (0.177)	0.214 (0.178)
Trading Acct. Assets / Total Assets	–	–	-0.742 (0.409)	-0.898 (0.409)*	-0.684 (0.412)
Total Deposits / Total Assets	–	–	-0.453 (0.120)**	-0.416 (0.122)**	-0.418 (0.122)**
Foreign Deposits / Total Deposits	–	–	-0.292 (0.090)**	-0.291 (0.089)**	-0.296 (0.090)**
Noninterest Bearing Deposits / Total Deposits	–	–	-0.143 (0.143)	-0.16 (0.144)	-0.126 (0.143)
Notional Principal on Interest Rate Swaps / Total Assets	–	–	0.005 (0.008)	-0.01 (0.008)	0.006 (0.008)
Notional Principal on FX futures / Total Assets	–	–	0.015 (0.029)	-0.017 (0.029)	0.018 (0.029)
Noninterest Income / Net Interest Income	–	–	-0.007 (0.010)	-0.01 (0.009)	-0.006 (0.011)
Log (Equity Capital / Total Assets)	–	–	-0.282 (0.033)**	-0.302 (0.034)**	-0.266 (0.034)**
Trading Volume / Outstanding Shares	–	–	0.351 (0.026)**	0.334 (0.026)**	0.35 (0.027)**
Volatility of Weighted-Average Employment Growth	–	–	-0.365 (0.379)	-0.349 (0.379)	-0.358 (0.378)
Observations	6756	6756	6187	6187	6187
Number of BHCs	927	927	886	886	886
R-squared	0.19	0.19	0.24	0.24	0.24

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

Table 4. Trends in the Systematic Risk,
(Diversification measure based on the CAPM)

Dependent Variable: Log S.D. of Systematic Returns					
Log Real Total Assets	0.114 (0.055)*	–	–	-0.005 (0.062)	0.237 (0.073)**
Year	-0.010 (0.007)	–	–	-0.004 (0.009)	0.256 (0.043)**
Year X Log Total Assets	–	-0.008 (0.002)**	-0.013 (0.002)**	–	-0.018 (0.003)**
C&I Loans / Total Assets	–	–	-0.284 (0.596)	-0.330 (0.598)	-0.271 (0.590)
Real Estate Loans / Total Assets	–	–	-0.368 (0.333)	-0.437 (0.336)	-0.462 (0.335)
Agricultural Loans / Total Assets	–	–	1.823 (2.438)	1.076 (2.440)	1.72 (2.425)
Consumer Loans / Total Assets	–	–	-0.484 (0.610)	-0.517 (0.611)	-0.400 (0.609)
HHI-style Index of Loan Portfolio Concentration	–	–	0.252 (0.564)	0.347 (0.561)	0.205 (0.560)
Trading Acct. Assets / Total Assets	–	–	-0.459 (0.997)	-0.869 (0.987)	-0.128 (0.984)
Total Deposits / Total Assets	–	–	-0.521 (0.343)	-0.318 (0.352)	-0.322 (0.348)
Foreign Deposits / Total Deposits	–	–	0.068 (0.259)	0.063 (0.259)	0.045 (0.258)
Noninterest Bearing Deposits / Total Deposits	–	–	-0.975 (0.423)*	-0.997 (0.428)*	-0.878 (0.424)*
Notional Principal on Interest Rate Swaps / Total Assets	–	–	0.059 (0.028)*	0.011 (0.027)	0.068 (0.028)*
Notional Principal on FX futures / Total Assets	–	–	0.059 (0.081)	-0.048 (0.082)	0.073 (0.081)
Noninterest Income / Net Interest Income	–	–	0.016 (0.016)	0.009 (0.017)	0.025 (0.016)
Log (Equity Capital / Total Assets)	–	–	-0.395 (0.092)**	-0.428 (0.093)**	-0.303 (0.095)**
Trading Volume / Outstanding Shares	–	–	0.242 (0.073)**	0.179 (0.072)*	0.234 (0.072)**
Volatility of Weighted-Average Employment Growth	–	–	-0.038 (1.086)	0.031 (1.096)	0.003 (1.084)
Observations	6756	6756	6187	6187	6187
Number of BHCs	927	927	886	886	886
R-squared	0.08	0.08	0.10	0.09	0.10

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

Table 5. Trends in the Market Beta,
(Diversification measure based on the CAPM)

Dependent Variable: Beta (Coefficient on Market Return)					
Log Real Total Assets	0.125 (0.041)**	–	–	0.041 (0.048)	0.192 (0.056)**
Year	0.019 (0.005)**	–	–	0.022 (0.006)**	0.184 (0.028)**
Year X Log Total Assets	–	-0.004 (0.001)**	-0.007 (0.002)**	–	-0.011 (0.002)**
C&I Loans / Total Assets	–	–	0.184 (0.460)	0.158 (0.459)	0.194 (0.457)
Real Estate Loans / Total Assets	–	–	-0.214 (0.232)	-0.275 (0.233)	-0.291 (0.233)
Agricultural Loans / Total Assets	–	–	-0.908 (1.430)	-1.395 (1.417)	-0.992 (1.425)
Consumer Loans / Total Assets	–	–	-0.357 (0.458)	-0.363 (0.457)	-0.289 (0.452)
HHI-style Index of Loan Portfolio Concentration	–	–	-0.001 (0.408)	0.05 (0.407)	-0.039 (0.406)
Trading Acct. Assets / Total Assets	–	–	0.130 (1.079)	-0.065 (1.088)	0.399 (1.088)
Total Deposits / Total Assets	–	–	-0.467 (0.254)	-0.303 (0.258)	-0.306 (0.256)
Foreign Deposits / Total Deposits	–	–	-0.002 (0.181)	-0.009 (0.181)	-0.021 (0.181)
Noninterest Bearing Deposits / Total Deposits	–	–	-0.161 (0.351)	-0.157 (0.355)	-0.083 (0.352)
Notional Principal on Interest Rate Swaps / Total Assets	–	–	0.030 (0.025)	0.002 (0.025)	0.037 (0.025)
Notional Principal on FX futures / Total Assets	–	–	0.112 (0.080)	0.047 (0.081)	0.123 (0.081)
Noninterest Income / Net Interest Income	–	–	0.038 (0.022)	0.035 (0.023)	0.045 (0.021)*
Log (Equity Capital / Total Assets)	–	–	-0.326 (0.088)**	-0.329 (0.090)**	-0.251 (0.092)**
Trading Volume / Outstanding Shares	–	–	0.314 (0.068)**	0.273 (0.068)**	0.307 (0.068)**
Volatility of Weighted-Average Employment Growth	–	–	0.554 (0.476)	0.605 (0.476)	0.588 (0.473)
Observations	6756	6756	6187	6187	6187
Number of BHCs	927	927	886	886	886
R-squared	0.07	0.07	0.09	0.08	0.09

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

Table 6. Trends in Total Risk,
(Diversification measure based on the CAPM)

Dependent Variable: Log S.D. of Total Returns					
Log Real Total Assets	0.061 (0.019)**	–	–	-0.023 (0.020)	0.061 (0.024)*
Year	-0.013 (0.003)**	–	–	-0.011 (0.003)**	0.08 (0.014)**
Year X Log Total Assets	–	-0.003 (0.001)**	-0.005 (0.001)**	–	-0.006 (0.001)**
C&I Loans / Total Assets	–	–	0.153 (0.175)	0.136 (0.175)	0.156 (0.176)
Real Estate Loans / Total Assets	–	–	0.077 (0.106)	0.061 (0.106)	0.052 (0.107)
Agricultural Loans / Total Assets	–	–	0.499 (0.959)	0.247 (0.959)	0.472 (0.951)
Consumer Loans / Total Assets	–	–	-0.319 (0.209)	-0.338 (0.210)	-0.297 (0.208)
HHI-style Index of Loan Portfolio Concentration	–	–	0.206 (0.172)	0.244 (0.171)	0.194 (0.172)
Trading Acct. Assets / Total Assets	–	–	-0.663 (0.405)	-0.836 (0.407)*	-0.577 (0.407)
Total Deposits / Total Assets	–	–	-0.477 (0.115)**	-0.424 (0.117)**	-0.425 (0.116)**
Foreign Deposits / Total Deposits	–	–	-0.269 (0.087)**	-0.269 (0.086)**	-0.276 (0.086)**
Noninterest Bearing Deposits / Total Deposits	–	–	-0.145 (0.141)	-0.162 (0.143)	-0.12 (0.141)
Notional Principal on Interest Rate Swaps / Total Assets	–	–	0.014 (0.010)	-0.004 (0.010)	0.016 (0.010)
Notional Principal on FX futures / Total Assets	–	–	0.019 (0.030)	-0.02 (0.031)	0.022 (0.030)
Noninterest Income / Net Interest Income	–	–	-0.002 (0.007)	-0.006 (0.006)	0.000 (0.008)
Log (Equity Capital / Total Assets)	–	–	-0.301 (0.032)**	-0.321 (0.032)**	-0.277 (0.033)**
Trading Volume / Outstanding Shares	–	–	0.336 (0.024)**	0.315 (0.024)**	0.334 (0.025)**
Volatility of Weighted-Average Employment Growth	–	–	-0.325 (0.359)	-0.304 (0.360)	-0.314 (0.358)
Observations	6756	6756	6187	6187	6187
Number of BHCs	927	927	886	886	886
R-squared	0.22	0.22	0.27	0.26	0.27

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

Table 7. Trends in the Degree of Diversification,
(Diversification measure based on the Fama-French Model)

Dependent Variable: Log Adjustment of R-Squared					
Log Real Total Assets	0.159 (0.053)**	–	–	0.115 (0.060)	0.144 (0.070)*
Year	-0.005 (0.007)	–	–	-0.004 (0.009)	0.027 (0.041)
Year X Log Total Assets	–	0.002 (0.002)	0.001 (0.002)	–	-0.002 (0.003)
C&I Loans / Total Assets	–	–	0.328 (0.545)	0.329 (0.544)	0.336 (0.544)
Real Estate Loans / Total Assets	–	–	-0.242 (0.313)	-0.296 (0.314)	-0.299 (0.314)
Agricultural Loans / Total Assets	–	–	-1.851 (2.337)	-1.99 (2.341)	-1.914 (2.346)
Consumer Loans / Total Assets	–	–	-0.787 (0.645)	-0.75 (0.645)	-0.736 (0.645)
HHI-style Index of Loan Portfolio Concentration	–	–	0.157 (0.512)	0.145 (0.511)	0.129 (0.512)
Trading Acct. Assets / Total Assets	–	–	-0.135 (1.253)	-0.022 (1.250)	0.066 (1.251)
Total Deposits / Total Assets	–	–	-0.454 (0.343)	-0.332 (0.351)	-0.333 (0.351)
Foreign Deposits / Total Deposits	–	–	-0.239 (0.258)	-0.251 (0.258)	-0.253 (0.258)
Noninterest Bearing Deposits / Total Deposits	–	–	-0.908 (0.424)*	-0.863 (0.424)*	-0.849 (0.426)*
Notional Principal on Interest Rate Swaps / Total Assets	–	–	0.003 (0.036)	0.001 (0.034)	0.008 (0.036)
Notional Principal on FX futures / Total Assets	–	–	0.092 (0.112)	0.086 (0.109)	0.1 (0.111)
Noninterest Income / Net Interest Income	–	–	0.028 (0.029)	0.032 (0.029)	0.034 (0.029)
Log (Equity Capital / Total Assets)	–	–	-0.138 (0.098)	-0.097 (0.101)	-0.082 (0.103)
Trading Volume / Outstanding Shares	–	–	-0.053 (0.084)	-0.065 (0.083)	-0.058 (0.083)
Volatility of Weighted-Average Employment Growth	–	–	-0.339 (0.969)	-0.311 (0.967)	-0.314 (0.967)
Observations	6756	6756	6187	6187	6187
Number of BHCs	927	927	886	886	886
R-squared	0.05	0.05	0.06	0.06	0.06

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

Table 8. Trends in the Idiosyncratic Risk,
(Diversification measure based on the Fama-French Model)

Dependent Variable: Log S.D. of Idiosyncratic Returns					
Log Real Total Assets	0.034 (0.020)	–	–	-0.043 (0.022)	0.034 (0.027)
Year	-0.012 (0.003)**	–	–	-0.010 (0.003)**	0.073 (0.016)**
Year X Log Total Assets	–	-0.003 (0.001)**	-0.005 (0.001)**	–	-0.006 (0.001)**
C&I Loans / Total Assets	–	–	0.049 (0.194)	0.032 (0.193)	0.051 (0.194)
Real Estate Loans / Total Assets	–	–	0.147 (0.115)	0.142 (0.115)	0.134 (0.115)
Agricultural Loans / Total Assets	–	–	0.906 (1.056)	0.684 (1.061)	0.891 (1.051)
Consumer Loans / Total Assets	–	–	-0.206 (0.235)	-0.232 (0.235)	-0.194 (0.234)
HHI-style Index of Loan Portfolio Concentration	–	–	0.169 (0.186)	0.208 (0.184)	0.162 (0.186)
Trading Acct. Assets / Total Assets	–	–	-0.543 (0.454)	-0.733 (0.454)	-0.495 (0.456)
Total Deposits / Total Assets	–	–	-0.377 (0.129)**	-0.346 (0.131)**	-0.348 (0.131)**
Foreign Deposits / Total Deposits	–	–	-0.211 (0.093)*	-0.208 (0.093)*	-0.214 (0.093)*
Noninterest Bearing Deposits / Total Deposits	–	–	0.038 (0.154)	0.014 (0.155)	0.052 (0.155)
Notional Principal on Interest Rate Swaps / Total Assets	–	–	0.01 (0.009)	-0.007 (0.009)	0.012 (0.009)
Notional Principal on FX futures / Total Assets	–	–	0.005 (0.038)	-0.032 (0.037)	0.007 (0.038)
Noninterest Income / Net Interest Income	–	–	-0.009 (0.010)	-0.013 (0.010)	-0.008 (0.011)
Log (Equity Capital / Total Assets)	–	–	-0.264 (0.035)**	-0.291 (0.035)**	-0.251 (0.036)**
Trading Volume / Outstanding Shares	–	–	0.342 (0.030)**	0.324 (0.029)**	0.341 (0.030)**
Volatility of Weighted-Average Employment Growth	–	–	-0.272 (0.379)	-0.257 (0.381)	-0.266 (0.378)
Observations	6756	6756	6187	6187	6187
Number of BHCs	927	927	886	886	886
R-squared	0.16	0.16	0.21	0.20	0.21

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

Table 9. Trends in the Systematic Risk,
(Diversification measure based on the Fama-French Model)

Dependent Variable: Log S.D. of Systematic Returns					
Log Real Total Assets	0.114 (0.027)**	–	–	0.014 (0.030)	0.106 (0.034)**
Year	-0.014 (0.004)**	–	–	-0.012 (0.004)**	0.087 (0.021)**
Year X Log Total Assets	–	-0.002 (0.001)*	-0.005 (0.001)**	–	-0.007 (0.001)**
C&I Loans / Total Assets	–	–	0.213 (0.267)	0.197 (0.267)	0.219 (0.268)
Real Estate Loans / Total Assets	–	–	0.026 (0.162)	-0.006 (0.162)	-0.016 (0.162)
Agricultural Loans / Total Assets	–	–	-0.020 (1.211)	-0.311 (1.206)	-0.066 (1.203)
Consumer Loans / Total Assets	–	–	-0.60 (0.309)	-0.607 (0.309)*	-0.562 (0.308)
HHI-style Index of Loan Portfolio Concentration	–	–	0.247 (0.260)	0.280 (0.259)	0.226 (0.260)
Trading Acct. Assets / Total Assets	–	–	-0.610 (0.587)	-0.744 (0.591)	-0.462 (0.588)
Total Deposits / Total Assets	–	–	-0.603 (0.170)**	-0.513 (0.174)**	-0.514 (0.174)**
Foreign Deposits / Total Deposits	–	–	-0.330 (0.132)*	-0.333 (0.132)*	-0.340 (0.132)**
Noninterest Bearing Deposits / Total Deposits	–	–	-0.416 (0.211)*	-0.418 (0.213)*	-0.372 (0.212)
Notional Principal on Interest Rate Swaps / Total Assets	–	–	0.012 (0.017)	-0.006 (0.017)	0.015 (0.017)
Notional Principal on FX futures / Total Assets	–	–	0.051 (0.046)	0.011 (0.047)	0.057 (0.046)
Noninterest Income / Net Interest Income	–	–	0.005 (0.010)	0.002 (0.010)	0.009 (0.011)
Log (Equity Capital / Total Assets)	–	–	-0.333 (0.049)**	-0.340 (0.050)**	-0.292 (0.051)**
Trading Volume / Outstanding Shares	–	–	0.316 (0.035)**	0.291 (0.036)**	0.312 (0.035)**
Volatility of Weighted-Average Employment Growth	–	–	-0.442 (0.540)	-0.412 (0.538)	-0.423 (0.537)
Observations	6756	6756	6187	6187	6187
Number of BHCs	927	927	886	886	886
R-squared	0.16	0.15	0.18	0.18	0.18

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

Table 10. Trends in the Market Beta,
(Diversification measure based on the Fama-French Model)

Dependent Variable: Beta (Coefficient on Market Return)					
Log Real Total Assets	0.179 (0.048)**	–	–	0.058 (0.055)	0.163 (0.064)*
Year	0.013 (0.006)*	–	–	0.012 (0.008)	0.124 (0.034)**
Year X Log Total Assets	–	0.000 (0.002)	-0.004 (0.002)*	–	-0.008 (0.002)**
C&I Loans / Total Assets	–	–	0.297 (0.511)	0.281 (0.509)	0.306 (0.510)
Real Estate Loans / Total Assets	–	–	0.007 (0.272)	-0.048 (0.273)	-0.058 (0.273)
Agricultural Loans / Total Assets	–	–	0.942 (2.196)	0.592 (2.177)	0.871 (2.184)
Consumer Loans / Total Assets	–	–	-0.448 (0.495)	-0.441 (0.496)	-0.390 (0.495)
HHI-style Index of Loan Portfolio Concentration	–	–	0.104 (0.477)	0.133 (0.476)	0.071 (0.477)
Trading Acct. Assets / Total Assets	–	–	-0.256 (1.178)	-0.348 (1.189)	-0.028 (1.189)
Total Deposits / Total Assets	–	–	-0.772 (0.306)*	-0.634 (0.310)*	-0.635 (0.309)*
Foreign Deposits / Total Deposits	–	–	-0.152 (0.221)	-0.160 (0.219)	-0.168 (0.220)
Noninterest Bearing Deposits / Total Deposits	–	–	0.256 (0.392)	0.271 (0.394)	0.323 (0.393)
Notional Principal on Interest Rate Swaps / Total Assets	–	–	0.042 (0.029)	0.024 (0.028)	0.048 (0.029)
Notional Principal on FX futures / Total Assets	–	–	0.164 (0.097)	0.121 (0.098)	0.173 (0.099)
Noninterest Income / Net Interest Income	–	–	0.040 (0.025)	0.039 (0.025)	0.046 (0.024)
Log (Equity Capital / Total Assets)	–	–	-0.366 (0.099)**	-0.357 (0.103)**	-0.303 (0.105)**
Trading Volume / Outstanding Shares	–	–	0.416 (0.077)**	0.387 (0.077)**	0.411 (0.078)**
Volatility of Weighted-Average Employment Growth	–	–	0.322 (0.612)	0.363 (0.606)	0.350 (0.606)
Observations	6756	6756	6187	6187	6187
Number of BHCs	927	927	886	886	886
R-squared	0.05	0.05	0.06	0.06	0.06

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

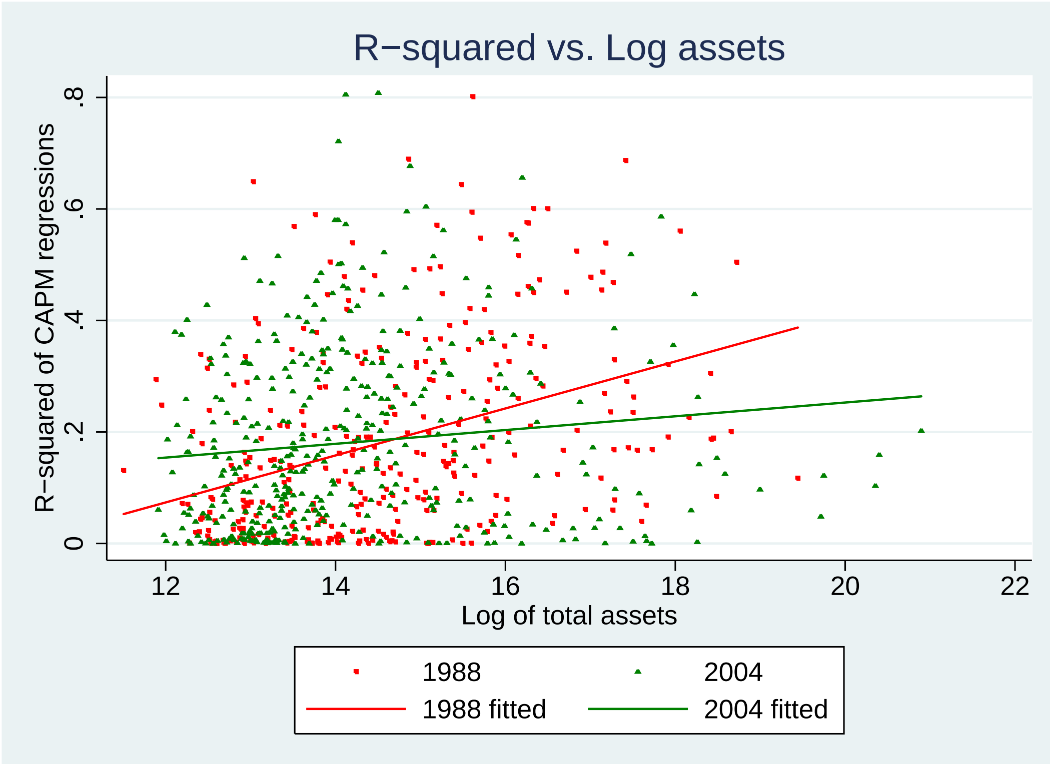

Figure 3. Graphical Representation of Trends in the Degree of Diversification
(Based on the CAPM)

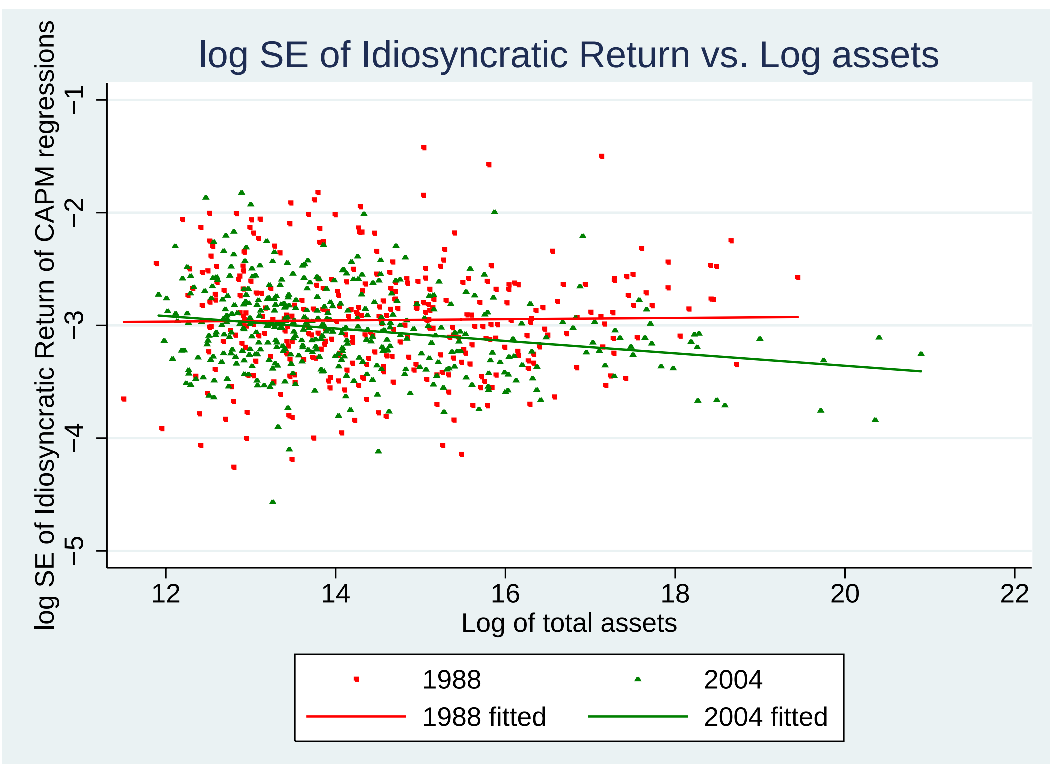

Figure 4. Graphical Representation of Trends in Idiosyncratic Risk
(Based on the CAPM)

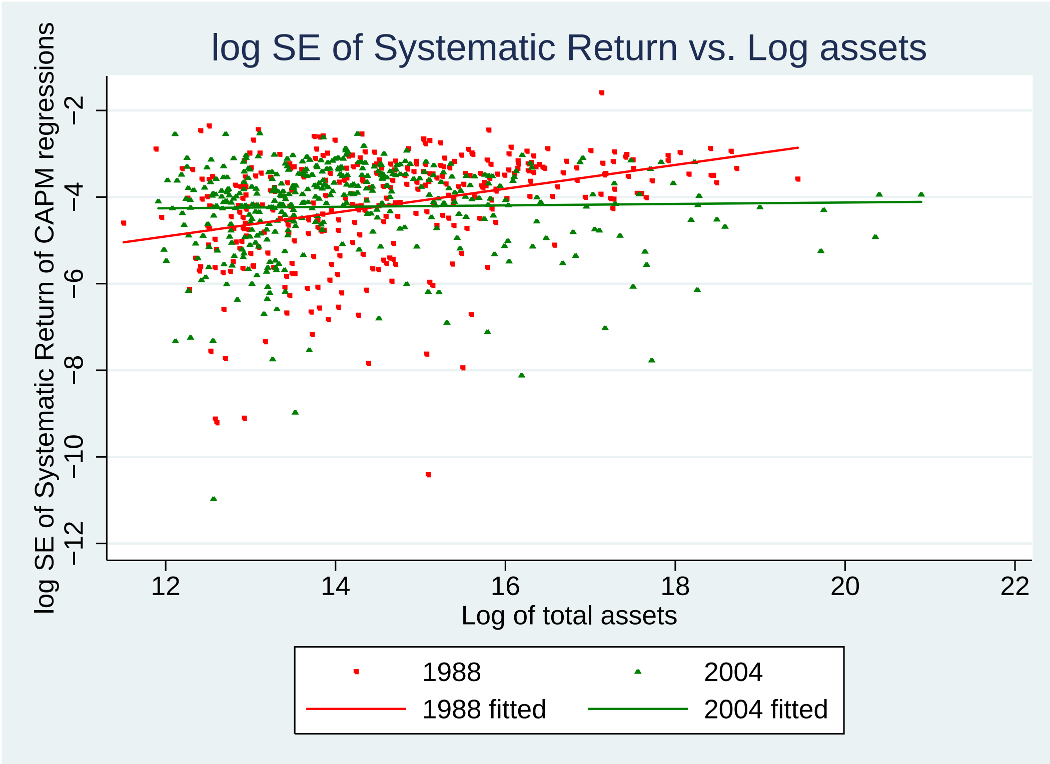

Figure 5. Graphical Representation of Trends in the Systematic Risk
(Based on the CAPM)

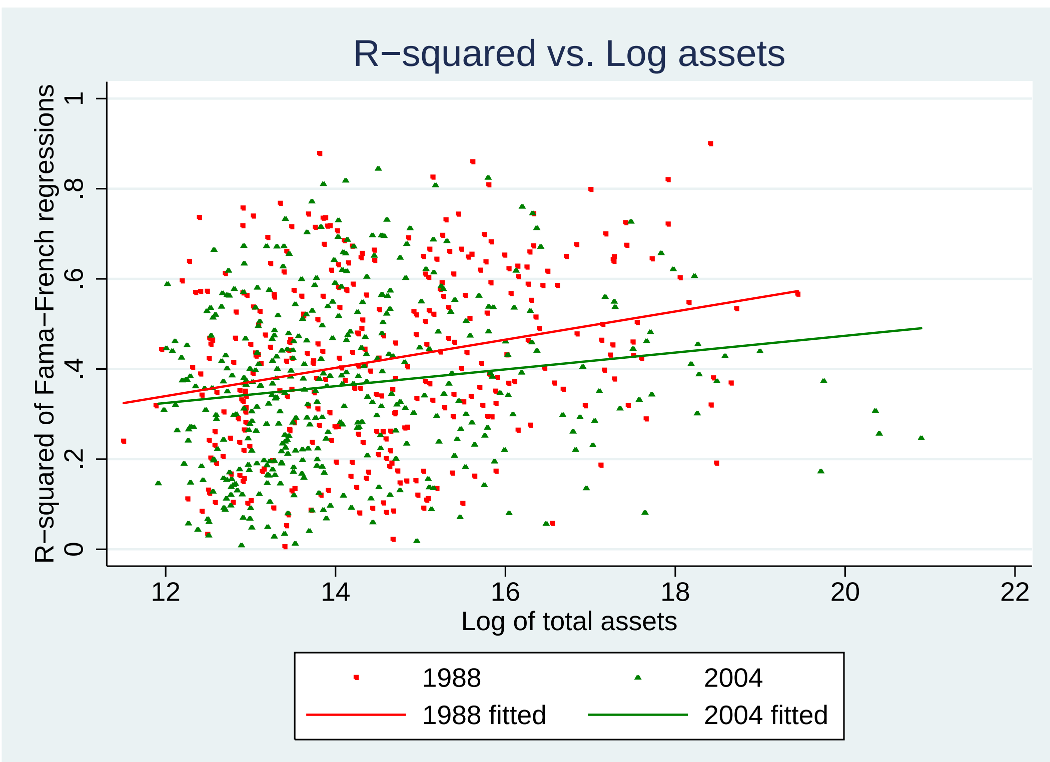

Figure 6. Graphical Representation of Trends in the Degree of Diversification
(Based on the FF model)

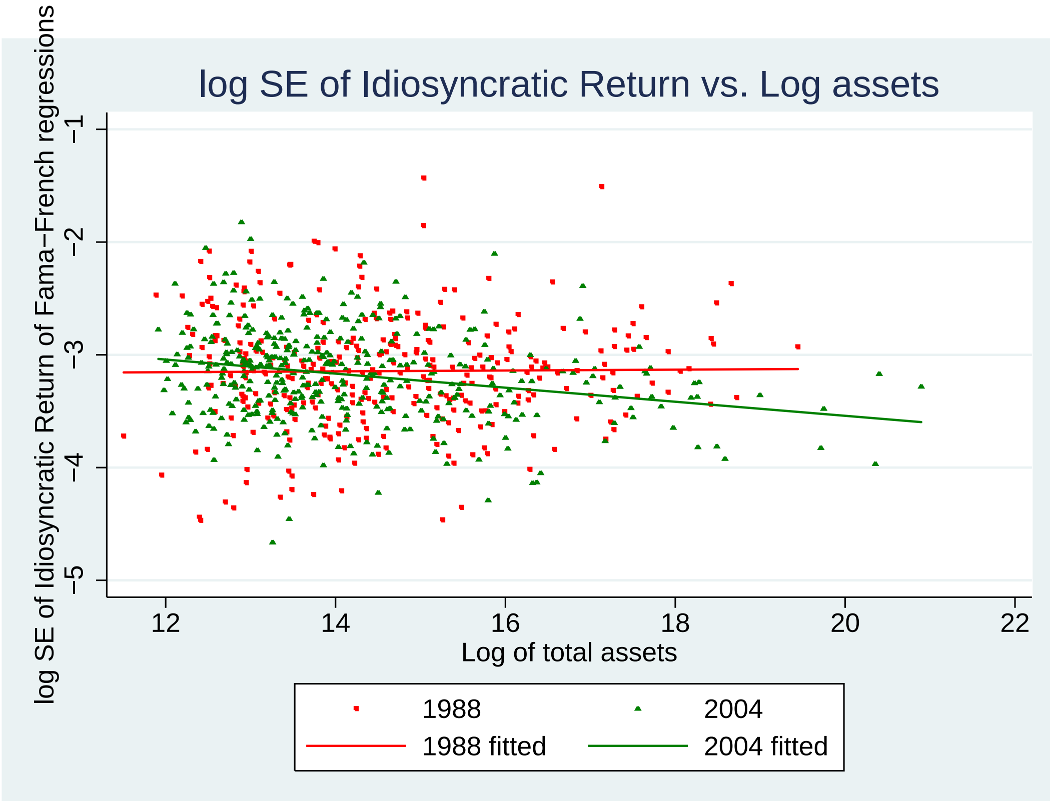

Figure 7. Graphical Representation of Trends in Idiosyncratic Risk
(Based on the FF model)

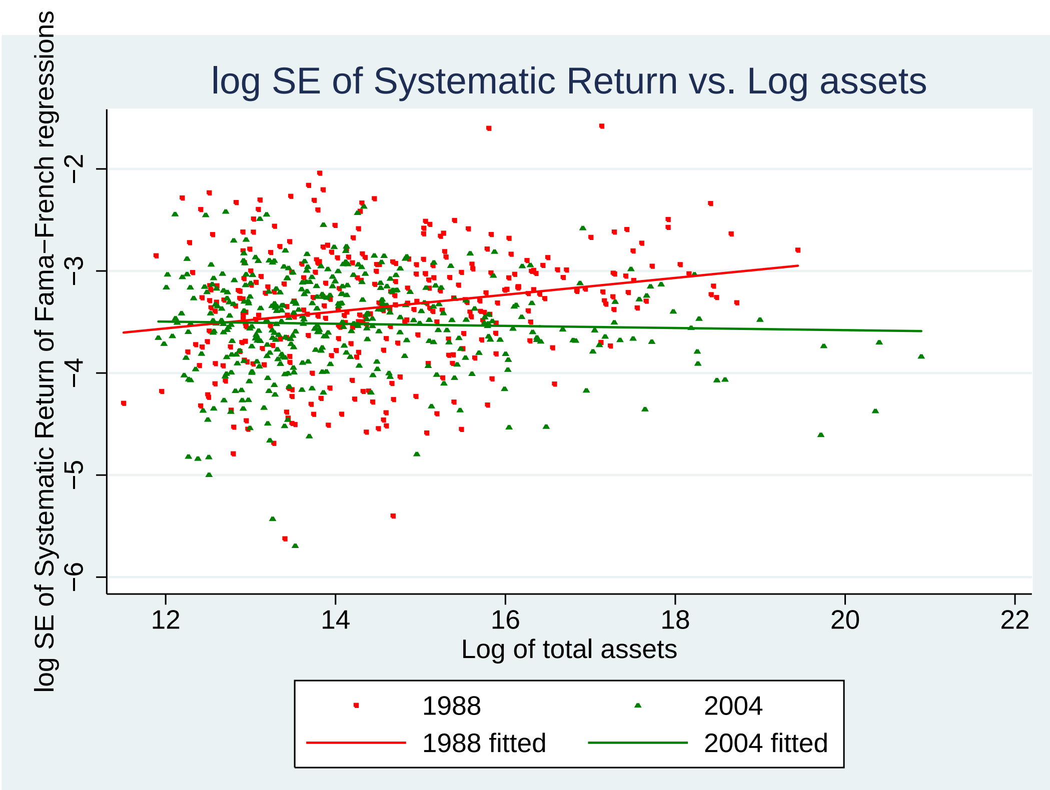

Figure 8. Graphical Representation of Trends in the Systematic Risk
(Based on the FF model)

Appendix 1. Relationship between Diversification and the Risk Components

This appendix details the model's implication for the degree of diversification in financial intermediaries' loan portfolios. According to basic portfolio theories, diversification – defined as dividing a *given* amount of funds among a larger number of assets with imperfectly correlated returns – tends to lower the volatility of a portfolio's total *rate of return* through reduction in the average idiosyncratic volatility. In other words, a reduction in total risk is effected through an increase in the degree of diversification, defined as the *portion* of variations in a portfolio's rate of return that is correlated with the systematic factors.

The condition for a portfolio's degree of diversification to rise with additional assets is that idiosyncratic risk does not account for too much greater a fraction of return variations for the additional assets than for the initial portfolio. To be precise, denote total rate of return on an existing portfolio r_O, and that on an additional asset (or portfolio of assets) r_N. Then the resulting portfolio's rate of return,

$$r_T = \frac{1}{1+\omega} r_O + \frac{\omega}{1+\omega} r_N ,$$

where ω is the weight of the new assets relative to the initial portfolio, whose size is normalized to 1. The respective total rate of return can be decomposed into $r_j = r_j^S + r_j^\varepsilon$,

$j = O$, N and T, where r_j^S denotes the systematic returns and r_j^ε the idiosyncratic returns. By definition,

$\mathrm{var}(r_\cdot) = \mathrm{var}(r_\cdot^S) + \mathrm{var}(r_\cdot^\varepsilon)$, in turn $\mathrm{var}(r_T^\varepsilon) = (1+\omega)^{-2}\left[\mathrm{var}(r_O^\varepsilon) + \omega^2\,\mathrm{var}(r_N^\varepsilon)\right]$ and

$\mathrm{var}(r_T^S) = (1+\omega)^{-2}\left[\mathrm{var}(r_O^S) + \omega^2\,\mathrm{var}(r_N^S) + 2\omega\mathrm{cov}(r_O^S, r_N^S)\right]$.[52]

So, the change in idiosyncratic risk is proportional to $\mathrm{var}(r_N^\varepsilon)/\mathrm{var}(r_O^\varepsilon) - (1+2/\omega)$, as

$$\mathrm{var}(r_T^\varepsilon) - \mathrm{var}(r_O^\varepsilon) = \omega^2\,\mathrm{var}(r_O^\varepsilon)\left[\mathrm{var}(r_N^\varepsilon)/\mathrm{var}(r_O^\varepsilon) - (1+2/\omega)\right]; \quad (41)$$

while the change in the systematic risk is proportional to

[52] Note that, by definition, covariance between returns of any two assets equals the covariance between their systematic returns.

$$\frac{\text{var}(r_N^S)}{\text{var}(r_O^S)} - \left[1+\frac{2}{\omega}-\frac{2\rho}{\omega}\left(\frac{\text{var}(r_N^S)}{\text{var}(r_O^S)}\right)^{1/2}\right], \text{ i.e., } \left(\frac{\text{var}(r_N^S)}{\text{var}(r_O^S)}\right)^{1/2} - \frac{\left[\rho^2+\omega(\omega+2)\right]^{1/2}-\rho}{\omega}. \tag{42}$$

Denote the threshold $\left[\left(\rho^2+\omega(\omega+2)\right)^{1/2}-\rho\right]\big/\omega$ as $S(\omega, \rho)$. It is easily verified that $S(\cdot, 1) = 1$, while $S(\cdot, -1) = 1+2/\omega$, and $\partial S(\omega,\rho)/\partial\rho < 0$. Since $\rho \in [-1, 1]$, then clearly $S(\cdot) \in [1,\ 1+2/\omega]$. This means that, if the new and old assets have the same systematic risk but are not perfectly correlated, then the portfolio's systematic risk falls.

Comparing (41) and (42) also shows that the threshold of the new-to-old variance ratio, above which the combined volatility rises, is almost always higher for idiosyncratic risk. So, in general, idiosyncratic risk is more likely to fall as new assets are added.[53] In addition, when assets are added at the margin (i.e., relatively low values of ω), the lower the new assets' weight, the wider the threshold and hence the more likely both risk components fall.

The change in the degree of diversification is proportional to the value of

$$\left[1+\frac{2\rho}{\omega}\left(\frac{\text{var}(r_O^S)}{\text{var}(r_N^S)}\right)^{1/2}\right]\frac{\text{var}(r_O^\varepsilon)}{\text{var}(r_O^S)} - \frac{\text{var}(r_N^\varepsilon)}{\text{var}(r_N^S)}, \text{ or equivalently } \left[\frac{\text{var}(r_N^S)}{\text{var}(r_O^S)}+\frac{2\rho}{\omega}\left(\frac{\text{var}(r_N^S)}{\text{var}(r_O^S)}\right)^{1/2}\right] - \frac{\text{var}(r_N^\varepsilon)}{\text{var}(r_O^\varepsilon)}. \tag{43}$$

It is intuitive from (43) that a portfolio's degree of diversification can fall as more assets are added if idiosyncratic risk accounts for a sufficiently larger share of the new assets' return variations.

Consider (41), (42) and (43) together, and it becomes obvious that idiosyncratic risk falls, systematic risk remains the same, and the degree of diversification rises when identical assets are added to a portfolio. In fact, for any given asset, it is most likely to reduce idiosyncratic risk and raise diversification if added at the margin, which corresponds to a small value of ω.

More generally, (41), (42) and (43) together imply the feasible combinations of changes in $\text{var}(r_\cdot^\varepsilon)$, $\text{var}(r_\cdot^S)$ and $\text{var}(r_\cdot^\varepsilon)/\text{var}(r_\cdot^S)$. These can be grouped according to the value of $\text{var}(r_N^S)/\text{var}(r_O^S)$

[53] On the other hand, there is some evidence of falling correlation between individual assets since the early 1980s (e.g., Campbell *et al*. (2001) find such a downward trend for publicly traded stocks). This means, over time, the addition of any given asset is more likely to lower a portfolio's systematic risk.

and hence the sign of (42), which in turn determine the sign combination for changes in idiosyncratic risk and diversification. Table A.1 summarizes all these feasible combinations. Rows (a) and (c) report signs of the change in the idiosyncratic risk, while (b) and (d) report signs of the change in the degree of diversification. Not surprisingly, when the systematic and idiosyncratic risks move in the same direction, the degree of diversification can go either way. Note also that for intermediate values of $\mathrm{var}(r_N^\varepsilon)/\mathrm{var}(r_O^\varepsilon)$, all three variables move in the same direction.

One conclusion of the model proposed in the previous section is that, owing to forces such as technological progress and deregulation, over time idiosyncratic risk accounts for an increasing share in the rate of return on each loan in a BHC's portfolio. In the notation above, this can be expressed as $\mathrm{var}(r_N^\varepsilon)/\mathrm{var}(r_N^S) > \mathrm{var}(r_O^\varepsilon)/\mathrm{var}(r_O^S)$. This, however, does not pin down the direction of the change in diversification. (43) can still hold and the degree of diversification rise as a BHC expands its portfolio. This further implies that the sign of changes in either the systematic or the idiosyncratic risk is ambiguous, as can be easily seen in Table A.1.

Nonetheless, the development in individual loans' diversification has one unambiguous implication, and that is, as $\mathrm{var}(r_N^\varepsilon)/\mathrm{var}(r_N^S)$ rises relative to $\mathrm{var}(r_O^\varepsilon)/\mathrm{var}(r_O^S)$, the *rate* at which diversification increases with BHC size will slow. In other words, for BHCs of a *given* size, the degree of diversification declines over time. It is easily seen from (43) that, conditional on it having a positive value, the bigger $\mathrm{var}(r_N^\varepsilon)/\mathrm{var}(r_N^S)$ is relative to $\mathrm{var}(r_O^\varepsilon)/\mathrm{var}(r_O^S)$, the less positive is (43) and hence the slower diversification increases with portfolio size, *ceteris paribus*. The intuition is similar to the usual marginal vs. average argument: the lower the marginal degree of diversification relative to the initial average, the slower the rate of increase. If the marginal falls sufficiently short of the average, the share of systematic risk will in fact fall as new assets are added.

To test this prediction of the model, we measure a portfolio's degree of diversification using the goodness of fit (i.e., R^2) from regressing its rate of return on the relevant systematic factors. Specifically, $\left(R^2\right)^{-1} = 1 + \mathrm{var}(r_\cdot^\varepsilon)/\mathrm{var}(r_\cdot^S)$. Then, if one regresses the goodness of fit on the number of assets in a portfolio, the coefficient indicates both the direction and the rate at which diversification changes with portfolio size. In this setup, the model's prediction is that, if one includes in the set of explanatory variables the *interaction* between a time trend and the real asset value of each BHC, its coefficient is expected to be negative. In other words, controlling for size, the systematic risk accounts for a decreasing share of the rate of return on a BHC's portfolio over time.

Since asset count is hardly ever available, real dollar volume of the portfolio is used as the proxy, implicitly assuming that the average size of assets in each portfolio is comparable in both the cross section and the time series. If, however, the average weight of each asset in the portfolio is falling over time, real dollar value will understate the extent of diversification, and so the coefficient will tend to rise over time. On the other hand, if idiosyncratic risk accounts for a greater share of return variations for small firms, as suggested by previous studies, then it offsets the underestimate of diversification by real dollar value of a portfolio. The extent of the offset is an empirical matter.

If one does not control for the size of BHCs' loan portfolios and simply regress R^2 from asset pricing equations on a time trend, then the sign of the coefficient is ambiguous in theory. The reason is that the average size of BHCs has increased substantially in the past two decades, in large part owing to the large scale consolidation within the banking industry in the late 1980s to late 1990s. In addition, the size distribution has become much more skewed to the right, with the top 20 BHCs account for close to 50% of all bank loans and assets. If one controls for the size of BHCs' portfolios separately (i.e., assuming a constant slope coefficient over time), then the model-implied decline in the slope would load on the time trend and lead to a negative coefficient.

The above effect can be partially or even fully offset if the average size of loans in a BHC's loan portfolio has declined, that is, if a portfolio of a given value now contains more assets. The effect of increasing the number of assets in a portfolio can be deduced by recognizing that it is analogous to lowering the value of ω, since each additional asset on average carries a smaller weight as the number of assets in a portfolio grows. A quick examination of (41) and (43) shows that having a larger number of assets in a portfolio (i.e., smaller ω) makes it more likely for idiosyncratic risk of the portfolio's rate of return to fall, and the degree of diversification to rise, as the thresholds for both variance ratios widen as ω falls. The systematic risk thus is more likely to rise, as can be seen in (42), where the margin for the variance ratio narrows as ω falls, at low levels of ω.

A few more remarks are necessary about diversification and what it means for the risk of intermediaries. The above definition of diversification, defined based on the risk of the *rate* of return, corresponds to true division and sharing of a given amount of return variations. It should not be confused with the effect on the risk of a portfolio's *total returns* from adding assets. Samuelson (1963) terms the latter a "fallacy of large numbers," because it is obvious that total risk– volatility of total payoff on a portfolio – always increases as the number of assets grows, unless returns of the new assets are negatively correlated with that of the initial portfolio sufficiently to more than offset the added return variations due to the new assets' idiosyncratic risk.

It is this second type of "diversification" that results when an intermediary such as a BHC adds more assets to its portfolio (via either "organic" expansions or mergers and acquisitions). This means that, *ceteris paribus*, a BHC's total risk will *rise* as it grows in real size, unless returns of the additional assets correlate negatively with its pre-existing portfolio. In contrast, total return volatility faced by an investor holding a *fixed* amount of stakes in the BHC may well fall. (See Diamond, 1984 for an exposition of the forms of diversification within an intermediary.)

Distinctions between the two notions of diversification mirror the distinct effects of increases in BHCs' size on an individual intermediary's bankruptcy risk vs. its impact on the volatility of the overall economy. Adding assets generally lowers the odds of bankruptcy for an individual BHC, which depends on the volatility of rate of return. In contrast, merely adding assets does not *per se* reduce a BHC's impact on overall economic fluctuations, because it does not lower a BHC's total return variations.

Table A.1. Combinations of Changes in the Systematic and Idiosyncratic Risk, and the Degree of Diversification

Systematic risk		$\frac{\text{var}(r_N^{\varepsilon})}{\text{var}(r_O^{\varepsilon})} < 1+\frac{2}{\omega}$	$\frac{\text{var}(r_N^{\varepsilon})}{\text{var}(r_O^{\varepsilon})} \in \left(1+\frac{2}{\omega}, G\left[\frac{\text{var}(r_N^{S})}{\text{var}(r_O^{S})}\right]\right)$	$\frac{\text{var}(r_N^{\varepsilon})}{\text{var}(r_O^{\varepsilon})} > G\left[\frac{\text{var}(r_N^{S})}{\text{var}(r_O^{S})}\right]$
+ $\left(\frac{\text{var}(r_N^{S})}{\text{var}(r_O^{S})}\right)^{1/2} > \frac{\left[\rho^2+\omega(\omega+2)\right]^{1/2}-\rho}{\omega}$	(a)	−	+	+
	(b)	+	+	−
		$\frac{\text{var}(r_N^{\varepsilon})}{\text{var}(r_O^{\varepsilon})} < G\left[\frac{\text{var}(r_N^{S})}{\text{var}(r_O^{S})}\right]$	$\frac{\text{var}(r_N^{\varepsilon})}{\text{var}(r_O^{\varepsilon})} \in \left(G\left[\frac{\text{var}(r_N^{S})}{\text{var}(r_O^{S})}\right], 1+\frac{2}{\omega}\right)$	$\frac{\text{var}(r_N^{\varepsilon})}{\text{var}(r_O^{\varepsilon})} > 1+\frac{2}{\omega}$
− $\left(\frac{\text{var}(r_N^{S})}{\text{var}(r_O^{S})}\right)^{1/2} < \frac{\left[\rho^2+\omega(\omega+2)\right]^{1/2}-\rho}{\omega}$	(c)	−	−	+
	(d)	+	−	−

Notes:

1. $G(x) = x^2 + (2\rho/\omega)\,x$.
2. The first column lists the conditions corresponding to the two possible signs of changes in the systematic risk.
3. Rows (a) and (c) report possible signs of the change in the idiosyncratic risk, corresponding to the change in the systematic risk as identified in column one.
4. Rows (b) and (d) report corresponding signs of the change in the degree of diversification.

Appendix 2. Data Summaries

First Stage Regression Output (Market Model)	***Obs***	***Mean***	***Median***	***S.D.***	***Min***	***Max***
Beta (Coefficient on Market Return)	6756	0.52	0.45	0.84	-7.38	11.24
Unadjusted R-squared	6756	0.16	0.10	0.18	0.00	0.92
SD of Idiosyncratic Return	6756	0.07	0.06	0.03	0.01	0.31
SD of Systematic Return	6756	0.03	0.02	0.02	0.00	0.21
SD Total Return	6756	0.08	0.07	0.04	0.01	0.31
First Stage Regression Output (CAPM)						
Beta (Coefficient on Market Return)	6756	0.52	0.45	0.84	-7.38	11.24
Unadjusted R-squared	6756	0.16	0.10	0.18	0.00	0.92
SD of Idiosyncratic Return	6756	0.07	0.06	0.03	0.01	0.31
SD of Systematic Return	6756	0.03	0.02	0.02	0.00	0.21
SD Total Return	6756	0.08	0.07	0.04	0.01	0.31
First Stage Regression Output (CAPM with Fama-French Factors)						
Beta (Coefficient on Market Return)	6756	0.70	0.63	1.00	-6.19	7.42
Unadjusted R-squared	6756	0.37	0.35	0.21	0.00	0.96
SD of Idiosyncratic Return	6756	0.06	0.05	0.03	0.01	0.27
SD of Systematic Return	6756	0.04	0.04	0.03	0.00	0.25
SD Total Return	6756	0.08	0.07	0.04	0.01	0.31
Coefficient on FF SMB Factor	6756	0.42	0.34	1.23	-12.95	12.51
Coefficient on FF HML Factor	6756	0.57	0.49	1.46	-10.23	10.11
First Stage Regression Output (CAPM with Fama-French Factors and Momentum Factor)						
Beta (Coefficient on Market Return)	6212	0.71	0.65	1.04	-6.02	7.70
Unadjusted R-squared	6212	0.45	0.44	0.21	0.00	0.99
SD of Idiosyncratic Return	6212	0.05	0.05	0.03	0.01	0.27
SD of Systematic Return	6212	0.05	0.04	0.03	0.00	0.26
SD Total Return	6212	0.07	0.07	0.03	0.01	0.31
Coefficient on FF SMB Factor	6212	0.38	0.30	1.28	-8.63	16.24
Coefficient on FF HML Factor	6212	0.55	0.48	1.65	-13.88	13.61
Coefficient on First Momentum Factor	6212	-0.09	-0.12	0.54	-2.70	3.93

BHC Data	*Obs*	*Mean*	*Median*	*S.D.*	*Min*	*Max*
Log Real Total Assets	6756	14.30	13.92	1.61	11.46	20.90
C&I Loans / Total Assets	6756	0.13	0.12	0.08	0.00	0.53
Real Estate Loans / Total Assets	6756	0.38	0.37	0.16	0.00	0.87
Agricultural Loans / Total Assets	6756	0.01	0.00	0.02	0.00	0.24
Consumer Loans / Total Assets	6756	0.09	0.08	0.07	0.00	0.62
HHI-style Index of Loan Portfolio Concentration	6756	0.38	0.35	0.09	0.24	0.99
Trading Acct. Assets / Total Assets	6756	0.00	0.00	0.02	0.00	0.44
Total Deposits / Total Assets	6756	0.79	0.82	0.10	0.01	0.95
Foreign Deposits / Total Deposits	6756	0.14	0.10	0.13	0.00	0.99
Noninterest Bearing Deposits / Total Deposits	6756	0.16	0.15	0.08	0.00	0.73
Notional Principal on Interest Rate Swaps / Total Assets	6756	0.08	0.00	0.74	0.00	26.60
Notional Principal on FX futures / Total Assets	6756	0.05	0.00	0.35	0.00	5.10
Noninterest Income / Net Interest Income	6756	0.37	0.26	1.09	-2.10	56.41
Log (Equity Capital / Total assets)	6756	-2.50	-2.51	0.30	-4.76	-0.36
Trading Volume / Outstanding Shares	6756	0.36	0.24	0.35	0.01	4.00
SD of Weighted Avg. Emp. Growth	6187	0.02	0.02	0.02	0.00	0.41
Log Real Net Loans	6755	13.80	13.43	1.60	9.90	19.93

Notes on Variable Derivation:

Trading volume: the average number of shares traded divided by the average number of shares outstanding, calculated using daily CRSP data, by BHC and year.

Weighted average monthly employment growth: a weighted average of month-to-month employment growth in every state where the BHC operates. The weights are the shares of total deposits each BHC holds in each state and the District of Columbia (DC), based on the annual SUMD branch-level deposit data. Each monthly observation g_{imy} is calculated as

$$g_{imy} = S_{my} \bullet D_{iy}.$$

S_{my} is the 51-element vector containing the monthly log employment change for each of the states and DC in month m of year y, and D_{iy} is the corresponding 51-element vector containing the share of deposits held by bank i in year y for each state and DC. Volatility of economic activities in the borrowing firms is then calculated as the *standard deviation* of the monthly values by firm and year.

HHI-style index of loan portfolio concentration: a measure of the concentration of a bank's loan portfolio across five different categories of lending: C&I, real estate, agriculture, consumer, and other. It is modeled after the Herfindahl-Hirschman Index used to measure industry concentration. The variable is the sum of the square of the share of loans contained in each of the five categories. Its possible values range from one ($1^2 + 4*0$, or full concentration in one category) to 0.2 ($5*(0.2)^2$, or exactly 20% in each of the five categories).

Log equity capital/total assets: log value of the ratio of shareholder equity (book value) to total assets.

Log total assets and *log net loans* are the natural logarithm of their respective data items. Other ratios of balance sheet data items are simple ratios (no other transformations).

Notes on Data Sources:

BHC Balance Sheet data is taken from the Federal Reserve Bank of Chicago BHC Data web site, which compiles FR Y-9C filings. (http://www.chicagofed.org/economic_research_and_data/bhc_data.cfm)

Stock return and share turnover values are taken from the Center for Research in Security Prices. (http://www.crsp.chicagogsb.edu/)

90-day Treasury bill yields used to calculate excess return are taken from the Federal Reserve Board's historical H15 interest rate data for constant maturity yields. (http://www.federalreserve.gov/releases/h15/data/Monthly/H15_TB_M3.txt)

Monthly Fama-French factors are from Kenneth R. French's Data Library web page. (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

Employment growth is generated using the Bureau of Labor Statistics seasonally-adjusted employment by state based on the households survey. (http://www.bls.gov)

Deposits used to calculate state averaging weights are taken from branch-level data from the FDIC Summary of Deposits data. (http://www2.fdic.gov/sod/dynaDownload.asp?barItem=6) SUMD data from years preceding 1994 are from the Federal Reserve Board's Micro Statistics Section.

Appendix 3. Additional Regression Results

Table A.2 Trends in the Degree of Diversification,
(Diversification measure based on the market model)

Dependent Variable: Log Adjustment of R-Squared					
Log Real Total Assets	0.117	–	–	0.043	0.394
	(0.111)			(0.128)	(0.155)*
Year	0.010	–	–	0.017	0.395
	(0.014)			(0.018)	(0.089)**
Year X Log Total Assets	–	-0.012	-0.018	–	-0.026
		(0.004)**	(0.005)**		(0.006)**
C&I Loans / Total Assets	–	–	-0.813	-0.877	-0.791
			(1.216)	(1.217)	(1.205)
Real Estate Loans / Total Assets	–	–	-0.979	-1.100	-1.136
			(0.664)	(0.673)	(0.671)
Agricultural Loans / Total Assets	–	–	2.053	0.945	1.881
			(4.868)	(4.876)	(4.872)
Consumer Loans / Total Assets	–	–	-0.328	-0.358	-0.187
			(1.239)	(1.239)	(1.239)
HHI-style Index of Loan Portfolio Concentration	–	–	0.106	0.235	0.028
			(1.121)	(1.119)	(1.112)
Trading Acct. Assets / Total Assets	–	–	0.639	0.114	1.191
			(2.030)	(2.006)	(2.006)
Total Deposits / Total Assets	–	–	-0.066	0.272	0.266
			(0.682)	(0.705)	(0.699)
Foreign Deposits / Total Deposits	–	–	0.786	0.774	0.747
			(0.502)	(0.503)	(0.501)
Noninterest Bearing Deposits / Total Deposits	–	–	-1.726	-1.738	-1.565
			(0.859)*	(0.867)*	(0.861)
Notional Principal on Interest Rate Swaps / Total Assets	–	–	0.109	0.041	0.123
			(0.057)	(0.054)	(0.057)*
Notional Principal on FX futures / Total Assets	–	–	0.100	-0.053	0.122
			(0.168)	(0.167)	(0.167)
Noninterest Income / Net Interest Income	–	–	0.045	0.036	0.059
			(0.045)	(0.047)	(0.042)
Log (Equity Capital / Total Assets)	–	–	-0.210	-0.239	-0.057
			(0.182)	(0.186)	(0.188)
Trading Volume / Outstanding Shares	–	–	-0.192	-0.285	-0.206
			(0.156)	(0.153)	(0.153)
Volatility of Weighted-Average Employment Growth	–	–	0.782	0.892	0.851
			(1.912)	(1.928)	(1.912)
Observations	6756	6756	6187	6187	6187
Number of BHCs	927	927	886	886	886
R-squared	0.07	0.07	0.08	0.08	0.08

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

Table A.3 Trends in the Degree of Diversification,
(Diversification measure based on the momentum model)

Dependent Variable: Log Adjustment of R-Squared					
Log Real Total Assets	0.133	–	–	0.141	0.124
	(0.051)**			(0.058)*	(0.069)
Year	-0.023	–	–	-0.023	-0.041
	(0.007)**			(0.009)**	(0.041)
Year X Log Total Assets	–	0.004	0.004	–	0.001
		(0.002)	(0.002)		(0.003)
C&I Loans / Total Assets	–	–	0.879	0.920	0.913
			(0.516)	(0.516)	(0.516)
Real Estate Loans / Total Assets	–	–	-0.006	-0.054	-0.052
			(0.304)	(0.304)	(0.305)
Agricultural Loans / Total Assets	–	–	-2.370	-2.399	-2.431
			(2.593)	(2.594)	(2.597)
Consumer Loans / Total Assets	–	–	-0.924	-0.873	-0.879
			(0.648)	(0.647)	(0.647)
HHI-style Index of Loan Portfolio Concentration	–	–	-0.159	-0.190	-0.179
			(0.492)	(0.492)	(0.492)
Trading Acct. Assets / Total Assets	–	–	-0.595	-0.356	-0.408
			(1.272)	(1.273)	(1.275)
Total Deposits / Total Assets	–	–	-0.364	-0.254	-0.254
			(0.342)	(0.350)	(0.350)
Foreign Deposits / Total Deposits	–	–	-0.223	-0.235	-0.233
			(0.248)	(0.249)	(0.248)
Noninterest Bearing Deposits / Total Deposits	–	–	-0.955	-0.889	-0.898
			(0.411)*	(0.412)*	(0.413)*
Notional Principal on Interest Rate Swaps / Total Assets	–	–	-0.010	-0.002	-0.006
			(0.031)	(0.030)	(0.031)
Notional Principal on FX futures / Total Assets	–	–	0.065	0.079	0.072
			(0.102)	(0.099)	(0.102)
Noninterest Income / Net Interest Income	–	–	0.029	0.035	0.034
			(0.031)	(0.030)	(0.030)
Log (Equity Capital / Total Assets)	–	–	-0.076	-0.015	-0.025
			(0.097)	(0.100)	(0.103)
Trading Volume / Outstanding Shares	–	–	-0.126	-0.124	-0.128
			(0.083)	(0.083)	(0.083)
Volatility of Weighted-Average Employment Growth	–	–	0.282	0.305	0.307
			(0.941)	(0.938)	(0.938)
Observations	6212	6212	5714	5714	5714
Number of BHCs	886	886	847	847	847
R-squared	0.05	0.05	0.06	0.06	0.06

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

Table A.4 Trends in the Degree of Diversification,
(Risk measures based on the CAPM, BHC size based on net loan balance)

Dependent Variable:	Log Adjustment of R-Squared			Log S.D. of Idiosyncratic Returns		
Log Real Total Net Loans	0.107	–	0.443	-0.034	–	0.033
	(0.128)		(0.151)**	(0.021)		(0.025)
Year	0.010	–	0.367	-0.010	–	0.061
	(0.018)		(0.086)**	(0.003)**		(0.015)**
Year X Log Net Loans	–	0.001	-0.025	–	0.000	-0.005
		(0.001)	(0.006)**		(0.000)**	(0.001)**
C&I Loans / Total Assets	-1.038	0.142	-1.033	0.169	0.529	0.170
	(1.223)	(1.184)	(1.212)	(0.185)	(0.193)**	(0.186)
Real Estate Loans / Total Assets	-1.258	-0.900	-1.372	0.145	0.499	0.123
	(0.726)	(0.674)	(0.725)	(0.116)	(0.116)**	(0.117)
Agricultural Loans / Total Assets	0.779	2.999	1.708	0.632	1.599	0.818
	(4.956)	(5.083)	(4.953)	(1.016)	(1.141)	(1.009)
Consumer Loans / Total Assets	-0.548	1.184	-0.474	-0.244	-0.086	-0.229
	(1.253)	(1.271)	(1.251)	(0.222)	(0.240)	(0.221)
HHI-style Index of Loan Portfolio Concentration	0.268	1.233	0.193	0.246	-0.152	0.231
	(1.156)	(1.140)	(1.151)	(0.177)	(0.190)	(0.179)
Trading Acct. Assets / Total Assets	0.187	-0.243	1.257	-0.938	-0.677	-0.725
	(1.999)	(2.306)	(2.000)	(0.411)*	(0.536)	(0.413)
Total Deposits / Total Assets	0.307	-0.630	0.305	-0.433	-0.496	-0.433
	(0.723)	(0.695)	(0.718)	(0.124)**	(0.125)**	(0.124)**
Foreign Deposits / Total Deposits	0.721	0.298	0.673	-0.299	-0.109	-0.308
	(0.512)	(0.526)	(0.510)	(0.089)**	(0.094)	(0.090)**
Noninterest Bearing Deposits / Total Deposits	-1.636	-0.205	-1.367	-0.168	-0.753	-0.115
	(0.857)	(0.853)	(0.856)	(0.144)	(0.160)**	(0.144)
Notional Principal on Interest Rate Swaps / Total Assets	0.041	0.029	0.115	-0.010	0.000	0.005
	(0.053)	(0.052)	(0.056)*	(0.008)	(0.011)	(0.008)
Notional Principal on FX futures / Total Assets	-0.066	-0.150	0.088	-0.018	0.037	0.012
	(0.166)	(0.177)	(0.167)	(0.029)	(0.033)	(0.029)
Noninterest Income / Net Interest Income	0.041	0.042	0.059	-0.011	-0.015	-0.007
	(0.046)	(0.049)	(0.043)	(0.009)	(0.010)	(0.010)
Log (Equity Capital / Total Assets)	-0.241	-0.171	-0.073	-0.299	-0.280	-0.266
	(0.187)	(0.182)	(0.189)	(0.033)**	(0.034)**	(0.034)**
Trading Volume / Outstanding Shares	-0.315	-0.302	-0.236	0.333	0.364	0.348
	(0.154)*	(0.162)	(0.153)	(0.026)**	(0.030)**	(0.027)**
Volatility of Weighted-Average Employment Growth	0.778	-3.353	0.729	-0.348	0.235	-0.358
	(1.936)	(1.881)	(1.918)	(0.379)	(0.377)	(0.378)
Observations	6186	6186	6186	6186	6186	6186
Number of BHCs	886	886	886	886	886	886
R-squared	0.08	0.00	0.08	0.23	0.06	0.24

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

Table A.5 Trends in the Degree of Diversification,
(Risk measures based on the CAPM, BHC size based on net loan balance)

Dependent Variable:	Log S.D. of Systematic Returns			Beta (Coeff. on Market Return)		
Log Real Total Net Loans	0.019	–	0.254	0.045	–	0.184
	(0.062)		(0.072)**	(0.047)		(0.055)**
Year	-0.006	–	0.244	0.022	–	0.170
	(0.009)		(0.042)**	(0.006)**		(0.027)**
Year X Log Net Loans	–	0.000	-0.018	–	0.000	-0.011
		(0.000)	(0.003)**		(0.000)	(0.002)**
C&I Loans / Total Assets	-0.351	0.600	-0.347	0.108	-0.340	0.110
	(0.600)	(0.582)	(0.594)	(0.465)	(0.477)	(0.463)
Real Estate Loans / Total Assets	-0.483	0.049	-0.563	-0.340	-0.244	-0.388
	(0.360)	(0.337)	(0.359)	(0.248)	(0.233)	(0.249)
Agricultural Loans / Total Assets	1.022	3.098	1.672	-1.444	-2.467	-1.058
	(2.442)	(2.661)	(2.428)	(1.419)	(1.514)	(1.425)
Consumer Loans / Total Assets	-0.518	0.506	-0.466	-0.400	-0.548	-0.370
	(0.611)	(0.620)	(0.609)	(0.460)	(0.477)	(0.454)
HHI-style Index of Loan Portfolio Concentration	0.380	0.465	0.327	0.089	0.271	0.058
	(0.568)	(0.567)	(0.567)	(0.408)	(0.415)	(0.407)
Trading Acct. Assets / Total Assets	-0.845	-0.799	-0.097	-0.027	0.193	0.417
	(0.988)	(1.138)	(0.983)	(1.099)	(1.122)	(1.098)
Total Deposits / Total Assets	-0.279	-0.811	-0.281	-0.281	0.062	-0.283
	(0.357)	(0.344)*	(0.353)	(0.260)	(0.249)	(0.258)
Foreign Deposits / Total Deposits	0.062	0.040	0.029	-0.002	-0.049	-0.021
	(0.258)	(0.262)	(0.258)	(0.181)	(0.186)	(0.181)
Noninterest Bearing Deposits / Total Deposits	-0.987	-0.856	-0.798	-0.150	-0.132	-0.038
	(0.428)*	(0.426)*	(0.425)	(0.356)	(0.354)	(0.354)
Notional Principal on Interest Rate Swaps / Total Assets	0.010	0.014	0.062	0.002	-0.005	0.033
	(0.027)	(0.029)	(0.028)*	(0.025)	(0.022)	(0.025)
Notional Principal on FX futures / Total Assets	-0.051	-0.038	0.056	0.048	0.046	0.112
	(0.082)	(0.088)	(0.082)	(0.080)	(0.080)	(0.081)
Noninterest Income / Net Interest Income	0.010	0.006	0.022	0.035	0.039	0.042
	(0.017)	(0.018)	(0.017)	(0.023)	(0.023)	(0.021)*
Log (Equity Capital / Total Assets)	-0.420	-0.365	-0.302	-0.331	-0.310	-0.261
	(0.093)**	(0.091)**	(0.094)**	(0.089)**	(0.086)**	(0.091)**
Trading Volume / Outstanding Shares	0.175	0.213	0.230	0.274	0.265	0.307
	(0.073)*	(0.077)**	(0.072)**	(0.068)**	(0.067)**	(0.067)**
Volatility of Weighted-Average Employment Growth	0.041	-1.442	0.006	0.606	-1.292	0.586
	(1.096)	(1.055)	(1.084)	(0.476)	(0.489)**	(0.473)
Observations	6186	6186	6186	6186	6186	6186
Number of BHCs	886	886	886	886	886	886
R-squared	0.09	0.01	0.10	0.08	0.01	0.09

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

Table A.6 Trends in the Degree of Diversification,
(Risk measures based on the momentum model, 1987 data excluded)

Dependent Variable:	Log Adjustment of R-Squared			Log S.D. of Systematic Returns		
Log Real Total Assets	–	0.058 (0.134)	0.425 (0.163)**	–	0.024 (0.028)	0.098 (0.033)**
Year	–	0.043 (0.019)*	0.429 (0.095)**	–	-0.018 (0.004)**	0.060 (0.020)**
Year X Log Total Assets	-0.017 (0.005)**	–	-0.027 (0.006)**	-0.003 (0.001)**	–	-0.005 (0.001)**
C&I Loans / Total Assets	-1.311 (1.266)	-1.350 (1.267)	-1.282 (1.252)	0.512 (0.246)*	0.507 (0.245)*	0.539 (0.246)*
Real Estate Loans / Total Assets	-1.046 (0.683)	-1.169 (0.691)	-1.196 (0.689)	0.114 (0.151)	0.087 (0.152)	0.078 (0.152)
Agricultural Loans / Total Assets	1.472 (5.211)	0.576 (5.195)	1.415 (5.203)	0.269 (1.339)	0.082 (1.336)	0.220 (1.332)
Consumer Loans / Total Assets	0.049 (1.307)	0.058 (1.307)	0.134 (1.308)	-0.690 (0.315)*	-0.682 (0.315)*	-0.654 (0.313)*
HHI-style Index of Loan Portfolio Concentration	0.282 (1.171)	0.365 (1.167)	0.191 (1.160)	0.115 (0.250)	0.143 (0.250)	0.098 (0.250)
Trading Acct. Assets / Total Assets	1.049 (2.066)	0.504 (2.041)	1.701 (2.041)	-0.607 (0.536)	-0.680 (0.537)	-0.458 (0.538)
Total Deposits / Total Assets	0.068 (0.706)	0.424 (0.729)	0.403 (0.721)	-0.458 (0.161)**	-0.369 (0.166)*	-0.369 (0.165)*
Foreign Deposits / Total Deposits	0.737 (0.511)	0.739 (0.512)	0.697 (0.510)	-0.297 (0.121)*	-0.296 (0.120)*	-0.305 (0.120)*
Noninterest Bearing Deposits / Total Deposits	-1.698 (0.894)	-1.708 (0.902)	-1.527 (0.895)	-0.436 (0.200)*	-0.432 (0.201)*	-0.391 (0.200)
Notional Principal on Interest Rate Swaps / Total Assets	0.099 (0.060)	0.032 (0.056)	0.115 (0.059)	0.009 (0.015)	-0.004 (0.015)	0.012 (0.015)
Notional Principal on FX futures / Total Assets	0.105 (0.165)	-0.049 (0.168)	0.117 (0.165)	0.045 (0.041)	0.017 (0.041)	0.051 (0.041)
Noninterest Income / Net Interest Income	0.049 (0.044)	0.041 (0.046)	0.063 (0.042)	0.004 (0.009)	0.002 (0.009)	0.007 (0.010)
Log (Equity Capital / Total Assets)	-0.292 (0.189)	-0.313 (0.194)	-0.123 (0.197)	-0.314 (0.048)**	-0.317 (0.049)**	-0.274 (0.050)**
Trading Volume / Outstanding Shares	-0.252 (0.164)	-0.349 (0.161)*	-0.266 (0.161)	0.305 (0.034)**	0.287 (0.034)**	0.303 (0.034)**
Volatility of Weighted-Average Employment Growth	0.777 (1.929)	0.854 (1.944)	0.857 (1.929)	-0.115 (0.459)	-0.090 (0.457)	-0.095 (0.456)
Observations	5912	5912	5912	5714	5714	5714
Number of BHCs	864	864	864	847	847	847
R-squared	0.080	0.080	0.080	0.21	0.21	0.21

In parentheses are robust standard errors. * significant at 5%; ** significant at 1%

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