# The Diversification Benefits of Universal Banks

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**Abstract**

We estimate reduced form equilibrium conditions for the markets for outstanding loans, and new issuance of bonds and stocks for the US economy. We find that both the aggregate issuance of bonds, and the volume of loans respond to fluctuations in industrial production and interest rates, but in opposite directions, so that at the aggregate level loans and bonds are substitutes. This result is supported by the finding that the conditional correlation between the two aggregates is negative. We then jointly study different classes of aggregate loans and find that they display a different behavior over the cycle, respond to different macroeconomic determinants, and their conditional correlations are time-varying and all consistently lower than one. These results suggest that universal banks can potentially reduce the cyclical fluctuations of their revenues by providing direct lending to different classes of borrowers, and by jointly providing both lending and security underwriting services.

*Keywords:* Universal Banking, Diversification.

*JEL classification:* G21, G24.

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# 1 Introduction

The development of capital markets over the last decades has reduced the role of traditional commercial banks and increased that of investment banks, as bonds have become a fundamental source of finance for large firms in the US. Many commercial banks have reacted by developing, or purchasing, their own investment banking activities, becoming universal banks. Conversely, investment banks have often acquired commercial banks in order to get access to deposits, a cheap and stable source of finance, and to benefit from the guarantee provided by deposit insurance schemes. Since the immediate aftermath of the Subprime Crisis, however, an ongoing debate has taken place regarding the systemic risks generated by universal banking. Many commentators have proposed the adoption of a regulatory framework imposing a rigid segmentation of the industry, in the spirit of the Glass-Steagall Act. This view, however, implicitly overlooks the possibility that universal banks can benefit from the diversification of their activities into security underwriting and direct lending.

Several studies, which we review in a separate session, have analyzed empirically the impact of the diversification benefits obtained from the observed shift toward activities that generate fees, trading revenues, and other non-interest income, on the profitability and risk profile of banks in the U.S. and Europe. Although these studies have allowed a far better understanding of the relevance of the diversification benefits generated by economies of scope in banking activities, most of these analyses are of a limited relevance to asses the diversification benefits of universal banks. The large samples of banks used in these studies, in fact, include mainly commercial banks, and since these panels give equal weight to banks of different size, investment banking activities, conducted almost exclusively by large banks, play an almost negligible role. Furthermore, while a large part of the revenues of investment banks consists of fees and commissions, commercial banks have not only increased significantly the share of non-interest income produced by retail banking activities such as portfolio management or payment services, but also generate a significant share of the remuneration for lending activities in the form of fees, since now commitment loans represent the vast majority of commercial and industrial loans.[1] As a result, even in the case of large universal banks, non interest income is generated by a large variety of different sources of revenues, and most of them have nothing to do with investment banking activities.

We investigate this issue by conducting an empirical analysis of the impact of macroeconomic factors on the aggregate volume of securities issuance, and on the level of loans outstanding. Aggregate data make it possible to shed light on the link between macro variables and aggregate revenues of the banking system. By placing shares and bonds, in fact, banks earn fees proportional to the sums raised, while fees from commitment loans are proportional to the amount granted and, for given interest margins, net interest revenues are proportional to the amount of loans outstanding.[2] We thus do not analyze the actual diversification benefits that banks achieve, but rather the potential benefits that universal banks can achieve. Since banks revenues are an increasing function of the quantity placed or lent, whenever exogenous factors produce innovations on the equilibrium quantity of securities issued that are poorly correlated, potential diversification benefits for the intermediaries that trade such securities may be relevant.

We initially study the equilibrium conditions in the market for primary placements of shares and bonds, together with that of total outstanding loans. The analysis is carried out by means of reduced form equations, by regressing the rate of growth of equilibrium aggregate quantities on factors different from their prices, and focusing in particular on secondary market prices, short-term interest rates, and business condition indicators. We find that both the aggregate issuance of bonds, and the volume of total loans outstanding, respond to fluctuations in the industrial production and short-term interest rates, but they move in opposite directions, so that, at the aggregate level, loans and bonds are substitutes. We then undertake a different kind of analysis whose aim is to measure how conditional

[1] Stiroh (2004) suggests that the largest share of the non-interest income of US banks is obtained from commitment lending activities.

[2] The literature on bank interest margins suggests that interest margins a pro-cyclical.

correlations among the different classes of securities and total loans evolve over time. Such analysis is carried out by means of standard multivariate GARCH models. Our results shows that such correlations are time-varying and consistently lower than one over time. The conditional correlation between bonds and loans is negative for protracted periods, and its average value is negative. We thus conclude that diversification benefits for universal banks that undertake both underwriting and lending activities can be sizeable.

We then conduct a second empirical study in which we decompose Total Loans into four smaller aggregates, i.e. Consumer, Commercial and Industrial, Real Estate and Other loans. By jointly analyzing the above aggregates as a system, we obtain results that suggest that the four classes display a substantially different behavior over the cycle, as they respond to different macroeconomic determinants. Moreover, also in this case the pairwise conditional correlations for the four classes of loans are time-varying and their average values are close to zero. Diversification benefits for commercial banks that provide simultaneously different classes of loans can be important, so that specialized banks may have more volatile revenues over the cycle.

An important limitation of our work is the focus on factors affecting bank revenues, while neglecting the cyclical profile of bank costs, since we lack similar aggregate data providing indications regarding the behavior over the cycle of these last. The main concern is that changes over the cycle of bank costs may offset the changes in revenues that we try to identify. However, industrial costs such as labor are not likely to display a cyclical profile in commercial banking activity significantly different from that of revenues, since they are normally far less volatile and similarly pro-cyclical. Furthermore, in the case of investment banks, labor costs are to a large extent variable, and linked to performance, so that they should track revenues closely. The main potential problem is caused by loan loss provisions, which display sharp cyclical fluctuations, and whose cycle might not be perfectly synchronous with that of revenues. Our arguments, however, would substantially be challenged only if the cyclical peaks in loan loss provisions would coincide with the periods when security issuance dries up. Although we have no data to study formally these dynamics, it seems unlikely for this to be the case, as securities issuance is extremely forward looking, while loans loss provisions normally fluctuate with a time lag over the cycle. Finally, although loan loss provisions may be perfectly correlated with losses on the portfolios of long term securities, this is not necessarily the case, in particular if the portfolio is actively managed. Asset and liabilities management activities can be very effective in reducing the volatility of both revenues and costs. Similarly, it is quite unlikely for loan loss provisions of different classes of loans to be perfectly correlated, as different sectors display poorly correlated dynamics.

The paper is organized as follows: Section 2 discusses the relevant literature, Section 3 presents the dataset employed for the empirical analysis, Section 4 introduces the empirical models and econometric methodologies used, Sections 5 and 6 comment on the results while Section 7 concludes.

# 2 The literature

Benefits and costs of universal banking have been mainly analyzed on theoretical ground (e.g. Boyd et al. (1998)) whereas the empirical literature is much less developed. In his studies of the US banking system before the introduction of the Glass-Steagall Act, White (1986) finds that universal banks were not more unstable and risky than other banks during the 1930s. Moreover, Vennet (2002) has provided evidence that in Europe universal banks benefit from higher levels of efficiency relative to specialized banks. On the contrary, Kwast (1989) suggests that diversification benefits between investment in securities and bank lending are limited.

A large literature has studied empirically the impact of diversification on the market value as well as on the cost of debt of banks, by using large panels of bank balance-sheet data. These studies define the diversification by means of an Herfindal-type index, measuring the weight of different sources of non-interest income with respect to total income, and include the index in regressions explaining the market-to-book value or adjusted measures of Tobin's Q. Non-interest income, in fact, has become an extremely important source of revenues for commercial banks, as the data reported by Stiroh (2004) highlight. [3] The results yielded by this literature, however, are somewhat mixed. On the one hand, Laeven and Levine (2007), find the presence of a diversification discount for US financial conglomerates. On the other hand, Elsas et al. (2010) find evidence against a diversification discount for European and US banks.[4] Similarly, Deng et al. (2007) find evidence that the diversification of banking activities leads to a lower cost of market debt, thus reflecting diversification benefits. On the contrary, De Young and Roland (2001) find that the shift in product mix generating a substitution of traditional lending with fee-based activities is associated with higher earnings volatility, due to both higher revenue volatility and higher leverage. The empirical analysis by Stiroh (2004) suggests that the volatility of non-interest income is much higher than that of interest income, that non-interest income is affected by the business cycle, and that as its share of income has grown over time, also its correlation with interest income has risen. The author explains the above findings as the result of the development of commitment lending, since commitment loans in the US represent nowadays more than 80% of all industrial and commercial lending. He concludes that the declining volatility of net operating revenue observed during the period reflects reduced volatility of net interest income, not diversification benefits from non interest income. Similarly, Mercieca et al. (2007) analyze a sample of small European banks by regressing measures of diversification on risk-adjusted returns on equity, and find no inverse relationship between non-interest income and bank performance. Adopting a similar framework, Stiroh and Rumble (2006) find evidence of diversification benefits in the case of financial holding companies of the U.S. but these gains are offset by costs implied by the increased exposure to non-interest activities, since these last are more volatile than interest-generating activities but not necessarily more profitable.

The issuance of shares and bonds have been the subject of extensive research. The

[3] According to data from the FDIC the share on non-interest income for US banks has increased from 20% in 1980 to 43% in 2000.

[4] Elsas et al. (2010) suggest that the difference in the results largely depends on the indicators used to measure bank values and diversification.

aim of this literature is to explain the underlying determinants of the dramatic swings in the volume of primary placements of securities observed in developed financial markets. The literature has evolved into two different strands. In the first strand, issuance is normally analyzed in the context of the optimal decision of the firm, and the main undisputed conclusion is that stock and bond market returns are a fundamental driving force behind primary placements. The second strand, which is more relevant for our analysis, has developed a substantial body of empirical evidence which suggests that macroeconomic factors are important driving forces for the external finance of firms. Researchers have put forward a number of different explanations of the cyclical nature of IPOs based on changing business conditions, investor sentiments, and asymmetric information between owners and outside investors (e.g. Lowry (2003) and Ivanov and Lewis (2008)).[5] These factors, in fact, could directly influence stock and bond market prices, and indirectly the amount raised, as well as the timing of the issuance. For instance, Lamont and Stein (2006) find that equity issuance of existing firms is substantially more sensitive to aggregate stock prices than firm-level prices, thus supporting the hypothesis that macro factors affecting stock markets are fundamental to understand the dynamics of primary placements. This hypothesis is also supported by a number of other studies. The survey of the literature by Ritter and Welch (2002) shows that market conditions are the most important factor influencing the decision to go public, and that the stage of the firm in its life cycle may be relevant, although to a much lesser extent. Finally, Casalin and Dia (2009) find that stocks and bonds issuance is not directly affected by the volatility of secondary markets.

[5]These studies differ in terms of findings and dataset employed. In terms of dataset, these studies conduct their empirical analysis by using annual and quarterly data on IPO volumes (e.g. Lowry (2003)). When monthly data are employed, the analysis makes use of the number of IPO transactions instead of IPO volumes (e.g. Ivanov and Lewis (2008)). Both these types of datasets gather data for US IPOs and cover periods from 1970 to 2002.

# 3 Dataset

The dataset gathers monthly aggregate data for the volumes of primary placements of shares (STOCKS) and bonds (BONDS), and the volume of total loans (LOANS) for the US economy.[6] Total loans are then partitioned, following the classification adopted by the FED, in four broad categories, namely Commercial and Industrial (that we label CORP and represent 19% of total aggregate loans at the end of 2009), Consumer (CONS, 14% of the total), Real Estate (REE, 56% of the total) and Other loans (OTHER, 11% of the total).[7] The dataset includes also series for the Industrial Production Index (IPI), the Composite Index of Leading Indicators (CLI), yields on three-month T-bills (TB3M), yields on the ten-year government bond (BOND10Y), a yield spread between ten- and three-year government bonds (YD), returns on the S&P500 and Barclays Corporate Bonds Index (BCBI).[8] The period under analysis spans from January 1970 to June 2007 for all the series. We choose not to include the period after June 2007 as it is characterized by abnormal financial distress and severe volatility in all the above series.[9]

Table 1 reports the Augmented Dickey-Fuller (ADF) as well as the Phillips-Perron (PP) tests for the null of unit-roots in the levels of the series taken in log. While LOANS are unequivocally non-stationary, when the two tests are applied to STOCKS and BONDS they reject the null of non stationarity. This last result, however, must be taken with caution as the distribution of standard unit root tests critically depends on the assumption that the underlying process is purely autoregressive. In fact, Schwert (1987) shows that if the

[6]The placements of shares and corporate bonds include both financial and non financial institutions.

[7]Real estate loans include revolving home equity loans (16% of the total at the end of 2009), closed-end residential loans (40%), and commercial real estate loans (44%). Consumer loans include credit cards and other revolving plans (44%) and other consumer loans, consisting of student loans, loans for purchasing automobiles and other personal loans (56%). Other loans loans and leases include Fed funds and reverse repurchase agreements with non banks (27%), and all other loans and leases (73%), consisting of loans for purchasing or carrying securities, loans to finance agricultural production, loans to foreign governments and foreign banks, obligations of states and political subdivisions, loans to nonbank depository institutions, loans to nonbank financial institutions, unplanned overdrafts, loans not elsewhere classified, and lease financing receivables.

[8]These series are obtained from the Federal Reserve Bulletin, Federal Reserve Bank of St Louis, OECD, and Datastream.

[9]The extension beyond June 2007 would make problematic the empirical estimation of our econometric models as even specifications which include a large number of parameters and lags would fail to account for the severe degree of serial correlation induced in standardized and squared standardized residuals.

process is an ARIMA(0,1,1) with a large moving average parameter $\theta$, most of the tests depart from the original distribution calculated by Dickey and Fuller, and the bias becomes more and more severe as the parameter $\theta$ becomes larger.[10] To investigate whether this is the case for our series, we fit ARIMA(0,1,1) models to the placements of stocks and bonds and find that the moving average parameters $\theta$ are equal, respectively, to 0.568 and 0.754.[11] Given these values of the parameters $\theta$, the corrected critical values for the ADF and PP statistics are, respectively, -8.883 and -8.472 for the series STOCKS, and -13.84 and -14.25 for BONDS.[12] By comparing the ADF and PP statistics reported in Table 1 with these critical values we obtain convincing evidence that the null of unit root cannot be rejected at the 5% level. The ADF and PP tests are then applied to the five different loan aggregates. Both the tests clearly suggest that when the loan aggregates LOANS, CORP, REE and OTHER are taken in levels, the null of unit-root cannot be rejected at standard significance levels. This evidence, however, becomes more mixed when the ADF and PP tests are applied to the aggregate CONS. The two tests, in fact, provides conflicting results with the former suggesting the series to be trend stationary. In order to keep consistency in the way we treat the five aggregates we choose to compute the log first differences for all the five series.[13]

Table 1 reports also some descriptive statistics for all the series taken in log first differences. The sample moments indicate empirical distributions with fat tails relative to the normal distribution as the null of zero excess kurtosis is soundly rejected at standard significance levels. This result holds for all the series except the issuance of stocks. The Ljung-Box Q statistics applied to the raw series suggest the presence of strong serial correlation in all the series. The Q statistics are then applied to detect serial correlation in the squared series. Also in this case they consistently reject the null suggesting the presence of nonlinear dependence, possibly due to changing conditional volatility over time. We

[10]By conducting Monte Carlo experiments the same author provides corrected critical values which accounts for the presence of the moving average component.

[11]Empirical estimates of ARIMA(1,0,1) models provides similar values for the parameters $\theta$.

[12]These critical values are calculated by interpolating the values reported in Schwertz (1987) pag. 89.

[13]The results obtained for the seven series are robust for different specifications of both the ADF and PP tests.

then compute the Q statistics for leads and lags of raw and squared series in order to test for the presence of lead/lag serial correlation in first and second moments. The result of these tests (not reported to save space) indicates the presence of weak interactions among the first moments of the series.[14]

**Table 1:** Summary Statistics for the Monthly Volumes of Placements of Stocks (STOCKS) and Bonds (BONDS), and Total (LOANS), Consumer (CONS), Commercial and Industrial (CORP), Real Estate (REE) and Other (OTHER) loans.

| | **STOCKS (i=1)** | | **BONDS (i=2)** | | **LOANS (i=3)** | | **-** | |
|---|---|---|---|---|---|---|---|---|
| | **statf** | **p-value** | **stat** | **p-value** | **stat** | **p-value** | **stat** | **p-value** |
| **ADF†** | -4.668 | (0.001) | -3.697 | (0.026) | 2.249 | (1.000) | - | - |
| **PP‡** | -8.227 | (0.000) | -8.905 | (0.000) | 2.113 | (1.000) | - | - |
| **Mean** | 0.004 | - | 0.007 | - | 0.003 | - | - | - |
| **Std Dev** | 0.436 | - | 0.369 | - | 0.007 | - | - | - |
| **Skewness** | -0.368 | (0.001) | -0.077 | (0.510) | -0.278 | (0.016) | - | - |
| **Kurtosis** | 0.355 | (0.125) | 5.597 | (0.000) | 0.703 | (0.003) | - | - |
| **Obs** | 445 | - | 445 | - | 445 | - | - | - |
| **Q(4)** | 65.82 | (0.000) | 88.34 | (0.000) | 136.1 | (0.000) | - | - |
| **Q(8)** | 67.12 | (0.000) | 97.71 | (0.000) | 206.4 | (0.000) | - | - |
| **$Q^2$(4)** | 18.75 | (0.000) | 52.24 | (0.000) | 18.88 | (0.001) | - | - |
| **$Q^2$(8)** | 28.58 | (0.000) | 52.85 | (0.000) | 34.53 | (0.000) | - | - |
| | **CONS (i=1)** | | **CORP (i=2)** | | **REE (i=3)** | | **OTHER (i=4)** | |
| | **statf** | **p-value** | **stat** | **p-value** | **stat** | **p-value** | **stat** | **p-value** |
| **ADF†** | -5.683 | (0.000) | -3.006 | (0.132) | 1.447 | (1.000) | -0.347 | (0.989) |
| **PP‡** | -2.353 | (0.404) | -2.187 | (0.495) | 3.729 | (1.000) | -0.239 | (0.992) |
| **Mean** | 0.002 | - | 0.002 | - | 0.005 | - | 0.002 | - |
| **Std Dev** | 0.009 | - | 0.007 | - | 0.006 | - | 0.020 | - |
| **Skewness** | 0.346 | (0.003) | 0.168 | (0.148) | 0.745 | (0.000) | -0.076 | (0.510) |
| **Kurtosis** | 1.623 | (0.000) | 0.656 | (0.005) | 6.044 | (0.000) | 0.729 | (0.002) |
| **Obs** | 445 | - | 445 | - | 445 | - | 445 | - |
| **Q(4)** | 199.2 | (0.000) | 427.3 | (0.000) | 341.8 | (0.000) | 12.24 | (0.016) |
| **Q(8)** | 289.2 | (0.000) | 646.3 | (0.000) | 467.8 | (0.000) | 44.06 | (0.000) |
| **$Q^2$(4)** | 27.91 | (0.000) | 46.68 | (0.000) | 20.48 | (0.000) | 10.54 | (0.032) |
| **$Q^2$(8)** | 83.32 | (0.000) | 48.87 | (0.000) | 24.22 | (0.000) | 17.07 | (0.029) |

Notes: Sample period 1970:01-2007:06. † and ‡ indicate Augmented Dickey-Fuller and Phillips-Perron unit-root tests applied to the log of the series in levels. Q(n) and $Q^2$(n) are Ljung-Box statistic for serial correlation in raw and squared log first differences up to lag n. P-values in parenthesis.

[14] Moreover, the interaction substantially disappears among the second moments. This last result implies the absence of volatility spill-overs among the series considered.

# 4 Empirical Model

The empirical analysis makes use two different models that we apply to two different sets of data. We initially carry out a system estimation of equilibrium conditions of the markets, in order to isolate the impact of macroeconomic variables on these equilibria. We then make use of GARCH techniques to analyze the behavior of the second moment of these aggregate variables, and, in particular, to study their conditional covariances. In the first set of data we jointly consider the markets for different securities, namely stocks, bonds and loans. In the second, we focus our analysis on the different classes of loans.

We estimate systems of simultaneous equations, but we do not aim to explore a detailed structural model of the banking industry or of the markets for securities. We rather focus on reduced form equilibria, by regressing the equilibrium quantities on variables different from the respective market prices, capturing the cyclical behavior of aggregate demand and interest rates. Similar reduced form equilibria can be obtained from standard theoretical models. In particular, when analyzing loan aggregates, the dynamic structure we assume can obtained from dynamic models of banking under the assumptions that interest rates and aggregated demand can be described as random walk processes, so that the expectation of future values are captured by the current values of the variables (e.g. Cosimano (1988), and Dia and Giuliodori (2011)). The equations describing the market for securities are standard in the literature on primary placements (e.g. Lowry (2003).)

We adopt a general-to-specific approach by initially estimating a model including all the exogenous variables in each equation, together with several lags of the dependent variables. We then obtain a specific nested model, after the exclusion of variables that are not statistically significant and after running a set of diagnostic controls. We study the variables in log first differences since they are non-stationary, and we deflate the data using the CPI, in order not to capture the dynamics of inflation.[15]

The first model we consider is a system of simultaneous equations in which each equa-

[15]The result for the nominal variables are qualitatively very similar, but characterized by stronger statistical significance.

tion models the dynamics of the equilibrium quantities of the securities under analysis. Assuming N different securities the model takes the following structure:

$$\Delta S_t^1 = \alpha_0^1 + \alpha_2^1 \Delta S_t^2 + ... + \alpha_N^1 \Delta S_t^N + \underline{\beta}^1 \underline{x}_t + \sum_{j=1}^{N} \sum_{i=1}^{L_j^1} \gamma_i^{1j} \Delta S_{t-i}^j + \varepsilon_t^1 \tag{1}$$

$$\Delta S_t^2 = \alpha_0^2 + \alpha_1^2 \Delta S_t^1 + ... + \alpha_N^2 \Delta S_t^N + \underline{\beta}^2 \underline{x}_t + \sum_{j=1}^{N} \sum_{i=1}^{L_j^2} \gamma_i^{2j} \Delta S_{t-i}^j + \varepsilon_t^2 \tag{2}$$

........

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$$\Delta S_t^N = \alpha_0^N + \alpha_1^N \Delta S_t^1 + ... + \alpha_{N-1}^N \Delta S_t^{N-1} + \underline{\beta}^N \underline{x}_t + \sum_{j=1}^{N} \sum_{i=1}^{L_j^N} \gamma_i^{Nj} \Delta S_{t-i}^j + \varepsilon_t^N \tag{3}$$

where $\Delta S_t^i$ is the first log differences in the volumes of the security i (for i=1,2,..,N), the vector $\underline{x}_t$ contains a set of predetermined variables that captures, for the different types of securities, the dynamics of GDP and interest rates, and $L_j^i$ defines the number of lags included in the RHS of each equations of the system for each type of security.[16]

The statistics reported in Table 1 suggest the presence of both strong serial correlation and changing conditional volatility in the series under analysis. The second model we employ aims to account for these features of the data. More specifically, we make use of standard multivariate GARCH frameworks to model the growth rates of the different aggregates as well as the their conditional covariances matrix. In line with the standard literature, we assume that the mean equations follow a VAR(p) stochastic process in which each equation is specified as follows (for i=1,2,..,N):

$$\Delta S_t^i = \mu_i + \sum_{j=1}^{N} \sum_{p=1}^{P_j^i} \gamma_{i,p} \Delta S_{t-p}^i + \varepsilon_{i,t} \tag{4}$$

The growth rates $\Delta S^i(t)$ depend on a constant $\mu_i$ and on their own $P_i^i$ lags and $P_j^i$ cross lags.

[16]The inclusion of lagged dependent variables is in line with what suggested by Granger and Newbold (1974), and with previous studies in the literature, such as that of Lowry (2003) on IPOs, as they can capture the effects of omitted factors.

Finally, the terms $\varepsilon_{i,t}$ capture the "unexpected shocks" that affect the dependent variables. The conditional covariances matrix $\Sigma(t)$ is assumed to follow a standard Diagonal VECH GARCH(1,1) model which can be written as follows:

$$vech(\Sigma_t) = \mathbf{C} + \mathbf{A}\ vech(\varepsilon_{t-1}\varepsilon_{t-1}^{'}) + \mathbf{B}\ vech(\Sigma_{t-1}) \tag{5}$$

where the matrices $\Sigma(t)$ and $\varepsilon(t)\varepsilon^{'}(t)$ are symmetric of dimension (N $\times$ N), the vector **C** has dimension (N(N+1)/2 $\times$ 1) and both the matrices **A** and **B** are symmetric of dimension (N(N+1)/2 $\times$ N(N+1)/2).[17] In order to reduce the large number of parameters under estimation we introduce the assumption that the matrices **A** and **B** are diagonal.[18] Thus, Eq.(5) can be rewritten, after conveniently rearranging the parameter indices, as follows:

$$\sigma_{ij}(t) = c_{ij} + a_{ij}\ \varepsilon_{i,t-1}\varepsilon_{j,t-1} + b_{ij}\ \sigma_{ij,t-1} \tag{6}$$

for (i,j)=1,2,..,N. By collecting the series $\Delta S_t^i$ into a vector of dimension N and gathering a sample of $T$ observations, maximum likelihood estimates can be obtained by making use of the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm. In Section 5 the analysis is carried out by considering the aggregates STOCKS, BONDS and LOANS, whereas in Section 6 the same type of analysis is conducted for the aggregates CONS, CORP, REE and OTHER.

# 5 The diversification benefits of universal banks

The hypotheses we want to investigate involve linear relationships among the difference in logarithm of the aggregate volumes raised by means of primary placements of shares (STOCKS) and corporate bonds (BONDS), and of the aggregate volume of Total outstanding loans (LOANS), plus a set of pre-determined explanatory variables taken

[17]The VECH denotes the operator that stacks columns of the lower triangle of the matrices $\Sigma_t$ and $\varepsilon_t\varepsilon_t^{'}$ in (N(N+1)/2 $\times$ 1) vectors.

[18]This restriction enables us to drastically reduce the number of parameters under estimation in Eq.(5).

from the literature on the determinants of IPOs of shares and bonds and that on banking. These last include: current and lagged values of stock (S&P500) and bond (BCBI) market returns, the first differences of three-month T-bill yields (TB3M) and of yields on ten-year government bonds (BOND10Y) as proxies for the expected cost of capital (following Lowry (2003), and Mayfield (2004)), the log differences of the Composite Index of Leading Indicators (CLI), and of the Industrial Production Index (IPI). The model we estimate is the following:

$$\begin{aligned}
STOCKS_t &= \alpha_0^1 + \alpha_1^1 BONDS_t + \alpha_2^1 LOANS_t + \beta_1^1 S\&P500_t + \beta_2^1 CLI_t + \beta_3^1 S\&P500_{t-1} \\
&\quad + \sum_{i=1}^{4} \gamma_i^{11} STOCKS_{t-i} + \sum_{i=1}^{3} \gamma_i^{12} BONDS_{t-i} + \gamma_1^{13} LOANS_{t-1} + \varepsilon_t^1 \qquad (7) \\
BONDS_t &= \alpha_0^2 + \alpha_1^2 STOCKS_t + \alpha_2^2 LOANS_t + \beta_1^2 BCBIt + \beta_2^2 IPI_t + \beta_3^2 TB3M_t + \\
&\quad + \gamma_1^{21} STOCKS_{t-1} + \sum_{i=1}^{8} \gamma_i^{22} BONDS_{t-i} + \gamma_1^{23} LOANS_{t-1} + \varepsilon_t^2 \qquad (8) \\
LOANS_t &= \alpha_0^3 + \alpha_1^3 STOCKS_t + \alpha_2^3 BONDS_t + \beta_1^3 IPI_t + \beta_2^3 TB3M_t + \\
&\quad + \beta_3^3 BOND10Y_t + \gamma_1^{31} STOCKS_{t-1} + \sum_{i=1}^{5} \gamma_i^{33} LOANS_{t-i} + \varepsilon_t^3 \qquad (9)
\end{aligned}$$

In order to identify the model we follow a general-to-specific approach, the system is supplemented with seasonal dummies, and we add a structure of lags and cross-lags in order to avoid serial correlation in the residuals.[19] Table 2 reports the empirical estimates for both the Three Stage Least Squares system estimation (3SLS) and the GMM estimation with White's heteroscedasticity consistent covariance matrix.[20] The results under the two estimation techniques are very similar.[21]

In line with the literature, we find that current and lagged values of the return of the

[19] The model has been supplemented with dummy variables to account for idiosyncratic shocks, such as the Stock Market Crash of October 1987 and the collapse of LTCM of 1998. The number of lags is initially set to 12, then the lags not statistically significant are progressively removed. The results are not dependent on the structure of the dynamic chosen, but their omission induces serial correlation in the residuals of the three equations.

[20] We do not report the results for the lags and cross lags beyond the first, as we are not interested in the long-run responses of the variables.

[21] We do not present the results for the Maximum Likelihood estimations because the residuals are not normally distributed. However, these empirical estimates are not substantially different from those obtained by applying 3SLS and GMM.

S&P500 as well as the Composite Index of Leading Indicator (CLI) drive primary placements of shares. We also find that changes in bond issuance significantly and positively influence share issuance, and vice-versa. The link between issuance of stocks and bonds is thus bi-directional, suggesting that common factors, such as technological shocks, can drive the issuance of both types of securities (in line with the findings of Lowry (2003)).

**Table 2:** 3SLS and GMM Empirical Estimates of the Model of Eqs. (7)-(9).

| | **3SLS** | | | **GMM** | | |
|---|---|---|---|---|---|---|
| | **STOCKS** | **BONDS** | **LOANS** | **STOCKS** | **BONDS** | **LOANS** |
| $\text{STOCKS}_t$ | | $0.21^{***}$ (0.05) | $0.004^{***}$ (0.001) | | $0.18^{***}$ (0.06) | $0.004^{***}$ (0.001) |
| $\text{BONDS}_t$ | $0.49^{***}$ (0.080) | | -0.0004 (0.001) | $0.45^{***}$ (0.080) | | -0.0002 (0.001) |
| $\text{LOANS}_t$ | $15.98^{***}$ (4.61) | $-8.93^{***}$ (3.62) | | $15.01^{***}$ (4.47) | $-7.80^{**}$ (3.77) | |
| $\text{STOCKS}_{t-1}$ | $-0.51^{***}$ (0.05) | $0.09^{***}$ (0.04) | $0.0016^{**}$ (0.001) | $-0.51^{***}$ (0.05) | $0.09^{**}$ (0.03) | $0.0016^{**}$ (0.001) |
| $\text{BONDS}_{t-1}$ | $0.24^{***}$ (0.080) | $-0.74^{***}$ (0.040) | | $0.24^{***}$ (0.008) | $-0.75^{***}$ (0.050) | |
| $\text{LOANS}_{t-1}$ | $-12.30^{***}$ (3.16) | $11.55^{***}$ (2.41) | $0.37^{**}$ (0.04) | $-12.08^{**}$ (3.47) | $10.52^{**}$ (2.43) | $0.36^{***}$ (0.05) |
| $\text{CLI}_t$ | 5.70 (3.52) | | | $7.51^{*}$ (4.30) | | |
| $\text{IPI}_t$ | | $-4.22^{**}$ (1.81) | $0.062^{*}$ (0.035) | | -2.94 (2.29) | $0.083^{**}$ (0.041) |
| $\text{TB3M}_t$ | | $-0.14^{***}$ (0.030) | $0.002^{***}$ (0.001) | | $-0.14^{***}$ (0.032) | $0.002^{***}$ (0.001) |
| $\text{BCBI}_t$ | | $1.85^{***}$ (0.63) | | | $2.14^{***}$ (0.68) | |
| $\text{BONDS10Y}_t$ | | | -0.0014 (0.001) | | | -0.0014 (0.001) |
| $\text{S\&P500}_t$ | $1.47^{***}$ (0.39) | | | $1.25^{***}$ (0.45) | | |
| $\text{S\&P500}_{t-1}$ | $1.61^{***}$ (0.380) | | | $1.73^{***}$ (0.430) | | |
| $\text{R}^2$ | 0.39 | 0.55 | 0.44 | 0.41 | 0.56 | 0.45 |
| $Q(4)$ | 0.4 (0.98) | 3.8 (0.43) | 2.8 (0.59) | 0.3 (0.99) | 3.0 (0.56) | 3.0 (0.56) |
| $Q(8)$ | 10.2 (0.25) | 12.3 (0.14) | 4.3 (0.83) | 9.1 (0.20) | 11.1 (0.28) | 4.5 (0.80) |
| $Q(12)$ | 13.5 (0.34) | 14.8 (0.25) | 11.3 (0.51) | 12.2 (0.43) | 13.3 (0.35) | 11.5 (0.49) |
| $Q(16)$ | 17.1 (0.38) | 18.1 (0.32) | 14.9 (0.53) | 15.8 (0.48) | 16.6 (0.41) | 15.3 (0.50) |

Notes: Sample period 1970:01 - 2007:06. GMM is estimated with White's heteroscedasticity consistent covariance matrix. Standard errors are in parenthesis. $^{*}$= significant at 10%, $^{**}$= at 5% and $^{***}$= at 1%. Adjusted $R^2$ calculated as $1-(1-R^2)/(T-1/T-k)$. Q(n) are the Ljung-Box Q-statistics for serial correlation in the residuals and cross-products of residuals up to lag n. P-values in parenthesis.

We find that primary placements of shares and bonds are complementary, mutually reinforcing processes, as both the contemporaneous and lagged coefficients measuring the dynamic links of one aggregate to the other are positive, statistically significant at the 1% level, and of a relevant sizes. On the contrary, we find that bond issuance and changes in the outstanding level of loans have a negative contemporaneous impact on each other. Nevertheless, the long-run impact, after including just one lag, becomes positive also in the case of the relationship between loans and bonds.

Primary placements of bonds are associated with positive returns on the bond index (indicating lower interest rates), and declining T-Bill rates. Corporate bond issuance thus rises following expansionary monetary policy. The Industrial Production Index is also significant, and the sign of the attached coefficient is negative, indicating that the issuance of corporate bonds is counter-cyclical.

The main driving force behind the issuance of loans is the short-term interest rate, as loans outstanding grow as interest rates rise. This result is in line with the findings of Den Haan et al. (2007) that, in the case of large banks, loans issuance rises following a monetary tightening. Loans outstanding are also positively influenced by the industrial production, indicating that the issuance of loans is pro-cyclical (while provisions for loan losses are anti-cyclical, so that also profits from lending are cyclical).

While bank lending declines in economic downturns, the issuance of corporate bonds grows. In a similar fashion, when monetary policy is expansionary, bond issuance grows, whereas direct lending decreases. In this case, a one standard deviation increase in short-term interest rates (equivalent to 51 basis points) is expected to accelerate the growth rate of outstanding loans by 0.2% and to decrease that of the issuance of bonds by 14.1%.[22] To provide an example of the economic relevance of the figures involved, loans outstanding in real terms (base year 1983) for January 2000 were 2,069 billions (equivalent in nominal terms to 3,502 billions of US dollars), whereas the issuance of bonds in the same period was of 26.1 billions (equivalent in nominal figures to 44.2 billions). As a consequence, a one standard deviation positive shock in short-term interest rates generates an increase

[22]It is important to notice that an increase of 0.2% on monthly basis corresponds to an annual increase of 2.24%.

of 2.43 billions in the level of loans outstanding (equivalent to 4.12 billions in nominal terms), and a decline of 1.84 billions for bonds (equivalent to 3.14 billions in nominal terms). These values are thus remarkably similar.[23]

These results suggest that corporate borrowers may take advantage of a low interest-rate environment to issue new bonds and restructure existing debt, but as rates rise and corporate balance sheets improve, companies are expected to explore alternative sources of funding. However, we find no evidence that changes in interest rates drive firms to issue equity, since the change in interest rates is not significant in the equation describing the equilibrium level of share issuance.[24]

Similarly, a one standard deviation increase in the Industrial Production Index is expected to accelerate the rate of growth of outstanding loans by 6.2% and to decrease that of the issuance of bonds by a factor equal to 4.22. The magnitudes involved in this case are an increase of loans outstanding of 932 millions of 1983 dollars (1.56 billions in nominal terms), and a decline of 789 millions in the issuance of bonds (equivalent to 1.34 billions in nominal terms). Also in this case the decline in bond issuance is almost perfectly offset by the increase in the issuance of loans.[25]

The picture emerging from our empirical estimates is that loans and bonds are substitutes at the aggregate level, and thus banks providing both may significantly reduce the volatility of their revenues. Investment banks, on the contrary, may not get similar benefits by intermediating both equity and bonds, since primary placements of bonds and shares do not respond differently to macro variables, and reinforce each other.[26] Universal banks can thus benefit from an additional level of diversification and they may potentially be safer and more efficient than institutions providing separate banking activities.

To further investigate the issue we make use of the GARCH model of Eqs.(4)-(5) to

[23] For these calculations we used the parameters obtained from the 3SLS estimation of Table 2. A measure of the average monthly issuance od bonds for the same year would provide very similar results.

[24] We have omitted this variable in the final version of our empirical results.

[25] Also these figures measure the impact on a monthly basis.

[26] In terms of volumes the issuance of corporate bonds is much larger than the issuance of shares. However, fees charged for the underwriting of shares are, on average, much higher than those charged for the underwriting of corporate bonds.

analyze the statistical properties of the the second moments of the aggregate quantities of securities issued (STOCKS and BONDS) and total outstanding loans (LOANS). Because shocks in the mean equations are the main actors in GARCH models, it is paramount that the mean equations for the three aggregates are properly specified. We initially estimate a VAR(p) to evaluate how important are the cross interactions among the levels of the three series. Since we find evidence of cross interaction we choose to fit the three series with processes that keep the same lag structures as those already defined in Eqs.(7)-(9). Following this criteria we find that the best fitting models are an AR(4,3,1)-GARCH(1,1) for the STOCKS, an AR(1,7,1)-GARCH(0,1) for BONDS, and an AR(1,0,6)-GARCH(1,1) for the series LOANS.[27]

These specifications are then employed to estimate the multivariate AR Diagonal VECH model of Eqs.(4)-(5). The empirical results are reported in Table 3.[28] The likelihood ratio (LR) test for the null of constant covariance matrix strongly suggests that time varying conditional covariances are important when modeling the variance-covariance matrix $\Sigma(t)$.[29]

The estimates of the coefficients attached to the product of the shocks $\varepsilon_i(t-1)\varepsilon_j(t-1)$ range from 0.200 to 0.030, whereas those attached to lagged volatilities span from 0.886 to 0.358. These parameters are in large part statistically significant at the 10% level with the notable exception of those that govern the conditional variance of BONDS. The null $H_0 : a_{ij} = b_{ij} = 0$ is soundly rejected at standard significance levels for i,j={(2,1), (3,1), (3,2)}. The above results suggest that both the variances and covariances tend to cluster over time. When comparing the conditional volatilities of the different aggregates, past shocks seem somewhat more important for LOANS. Past volatility, on the other hand, plays a more relevant role for STOCKS.

[27] The notation AR($L_1^i, L_2^i, L_3^i$) with i=1,2,3 defines the structure of lags and cross lags in each of the three equations (7)-(9). Thus, for instance, Eq.(9) includes 6 own lags, no lags for the series BONDS and 1 lag for the series STOCKS. The Ljiung-Box Q statistics applied to standardized and squared standardized residuals generated by the above models suggest absence of serial correlation and GARCH effects.

[28] To save space the empirical estimates of the mean equations (4) for i=1,2,3 are not reported.

[29] The null is $H_0 : a_{11} = a_{12} = a_{22} = a_{13} = a_{23} = 0$. The LR statistic is 12.9, and with the degrees of freedom being equal to 5, the null is rejected at standard significance levels.

**Table 3:** Maximum Likelihood Estimates of the Diagonal VECH GARCH Model of Eqs.(4)-(5) for Monthly Volumes of Issuance of Stocks (STOCKS), Bonds (BONDS) and Total Outstanding Loans (LOANS).

| | STOCKS (i=1) | | BONDS (i=2) | | LOANS (i=3) | |
|---|---|---|---|---|---|---|
| | **coeff** | **s.e.** | **coeff** | **s.e.** | **coeff** | **s.e.** |
| $\mathbf{const}_1$ | 0.008$^{**}$ | 0.004 | | | | |
| $\mathbf{const}_{21}$ | 0.002 | 0.002 | | | | |
| $\mathbf{const}_{31}$ | 0.9e$^{-4}$ | 0.6e$^{-4}$ | | | | |
| $\mathbf{const}_2$ | | | 0.088$^{***}$ | 0.006 | | |
| $\mathbf{const}_{32}$ | | | -0.30e$^{-4}$ | 0.31e$^{-4}$ | | |
| $\mathbf{const}_3$ | | | | | 0.16e$^{-4}$ | 0.13e$^{-4}$ |
| $\sigma^2_{1,t-1}$ | 0.886$^{***}$ | 0.036 | | | | |
| $\sigma^2_{21,t-1}$ | 0.861$^{***}$ | 0.091 | | | | |
| $\sigma^2_{31,t-1}$ | 0.588$^{***}$ | 0.221 | | | | |
| $\sigma^2_{2,t-1}$ | | | – | – | | |
| $\sigma^2_{32,t-1}$ | | | 0.766$^{***}$ | 0.172 | | |
| $\sigma^2_{3,t-1}$ | | | | | 0.358 | 0.433 |
| $\varepsilon^2_{1,t-1}$ | 0.057$^{***}$ | 0.022 | | | | |
| $\varepsilon_{2,t-1}\ \varepsilon_{1,t-1}$ | 0.034 | 0.023 | | | | |
| $\varepsilon_{3,t-1}\ \varepsilon_{1,t-1}$ | 0.101$^{*}$ | 0.057 | | | | |
| $\varepsilon^2_{2,t-1}$ | | | 0.030 | 0.039 | | |
| $\varepsilon_{3,t-1}\ \varepsilon_{2,t-1}$ | | | 0.041 | 0.033 | | |
| $\varepsilon^3_{3,t-1}$ | | | | | 0.200$^{**}$ | 0.089 |
| $\mathbf{R}^2$ | 0.22 | | 0.34 | | 0.23 | |
| **Q(4)** | 0.109 | (0.990) | 0.534 | (0.911) | 0.525 | (0.913) |
| **Q(8)** | 2.091 | (0.954) | 5.117 | (0.645) | 2.575 | (0.921) |
| **LM(4)**$^\flat$ | 1.471 | (0.831) | 7.290 | (0.121) | 4.655 | (0.324) |
| **Q$^2$(4)** | 8.895 | (0.031) | 0.356 | (0.949) | 1.660 | (0.645) |
| **Q$^2$(8)** | 9.503 | (0.218) | 2.050 | (0.957) | 8.551 | (0.286) |
| **ARCH(4)**$^\natural$ | 7.702 | (0.103) | 0.361 | (0.985) | 1.815 | (0.769) |

Notes: Sample period 1970:01 - 2007:06. $^*$= significant at 10%, $^{**}$= at 5% and $^{***}$= at 1%. Adjusted $R^2$ calculated as $1-(1-R^2)/(T-1/T-k)$. $\flat$ LM test for serial correlation in standardized residuals up to lag 4. $\natural$ ARCH LM test for heteroscedasticity in standardized residuals up to lag 4. Q(n) and Q$^2$(n) are Ljung-Box statistics for serial correlation up to lag n in the standardized and squared standardized residuals. P-values in parenthesis.

The lower panel of Table 3 reports some diagnostic tests for the Diagonal VECH GARCH model of Eqs.(4)-(5). The Ljung-Box Q statistics at lags 4 and 8 for the standardized residuals, as well as the LM Breush-Godfrey test at lag 4 suggest negligible presence of serial correlation. The Ljung-Box Q statistics calculated for the standardized squared residuals suggest that our model adequately captures also the serial correlations in the second moments.[30]

[30]The stationary conditions for the Diagonal VECH GARCH model are fulfilled as the largest eigenvalue of the matrix $\mathbf{A}+\mathbf{B}$ is 0.944. This implies that for all the three aggregates the unconditional covariance

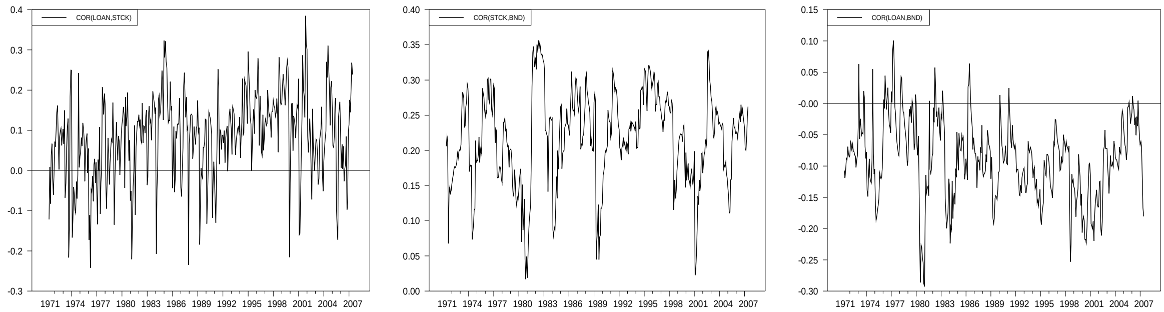


**Fig. 1:** Conditional correlations between LOANS and STOCKS (left diagram), between STOCKS and BONDS (center), and between LOANS and BONDS (right).

Figure 1 displays the conditional correlations based on the estimation results of our AR Diagonal VECH model. They all vary over time, but they follow significantly different patterns. To examine whether the time variability in the conditional covariances is solely due to the variation in the variances, we consider the conditional correlation indices. Let $\rho_{ij}(t)$ denote the conditional correlation index between the growth rates of aggregates $i$ and $j$ at time $t$ (for $i, j$=1,2,3 with $i \neq j$). If $\rho_{ij}(t)$ is constant over time, then the variability in the conditional covariances is solely due to variation in the variances. In that case, the modeling of the time-varying covariances would not be interesting as all the dynamics are already captured by the variances. Tests for the constancy of the conditional correlation indices are carried out by estimating AR(1) regressions of the correlation indices and checking the statistical significance of the AR coefficients. These tests clearly suggest that the correlation indices are not constant over time.[31] The conditional correlations between stocks and bonds fluctuates and consistently assumes positive values over time between 0 and 0.35, while its average value is equal to 0.21. This suggests that the two classes of securities are strictly interconnected, and their respective dynamics tend to reinforce each other. We obtain a similar but much weaker result for the conditional correlation between stocks and loans. This time the index fluctuates from positive to negative over time and, although its mean value fairly low to 0.085, it is characterized by clusters in

matrix exists. Moreover, the matrix **C** is positive definite whereas the matrices **A** and **B** are semi-definite. Thus, the conditions that ensure that the covariance matrix $\Sigma(t)$ is positive definite hold.

[31] The AR coefficients span from 0.874 (with t-stat equal to 39.28) for the correlation between STOCKS and BONDS to 0.567 (with t-stat equal to 14.47) for the correlation between LOANS and STOCKS.

which the values are largely positive of the order of 0.2, as in the period from the early 90s to mid-2000s. The conditional correlation between bonds and total loans is consistently negative, especially in the second half of the sample period with peaks of the order of -0.2, and its average value is equal to -0.089. These last results further support the thesis that investment banks can exploit sizable diversification benefits by managing both equity and debt. Even more importantly, they provide substantial evidence that universal banks providing both investment banking activities and direct lending can substantially mitigate the pro-cyclicality of their revenues. Since both interest revenues and fees in the US are largely dependent on the volume of the portfolio of outstanding loans, these revenues are pro-cyclical, while, on the contrary, the fees from underwriting bonds, which depend on the volumes of bonds issued, are counter-cyclical.

# 6 Diversification benefits of commercial banks

In this section we decompose the aggregate Total Loans (LOANS) into four smaller components, i.e Consumer (CONS), C&I (CORP), Real Estate (REE) and Other (OTHER) loans and we analyze simultaneously the market equilibria for each of them. We aim to study the relevance of several cyclical factors influencing the components of bank credit, to investigate the potential diversification benefits for banks providing different lending services jointly, rather than acting as specialized institutions. In particular, we investigate the hypothesis that different classes of loans react to different macroeconomic variables, and are thus subject to different dynamics. For example, the demand for C&I loans is presumably dependent on the cyclical behavior of the industrial production, whereas that for Consumer loans is likely to be more significantly influenced by the unemployment.

We study the market for the different type of loans as a system to take into account the possibility that supply-side factors, such as capital requirements, or the availability of deposits, are binding constraints on the market for loans, since in this case the optimal portfolio of one class of loans would not be independent from those of the other ones. The system is supplemented with seasonal dummies and we add a structure of lags, in order to avoid serial correlation in the residuals. The model we estimate is the following:[32]

$$CONS_t = \alpha_0^1 + \alpha_1^1 CORP_t + \alpha_2^1 REE_t + \alpha_3^1 OTHER_t + \beta_1^1 UNEMP_t + \beta_2^1 CLI_t + \tag{10}$$

$$+ \sum_{i=1}^{12} \gamma_i^{11} CONS_{t-i} + \gamma_1^{12} CORP_{t-1} + \gamma_1^{13} REE_{t-1} + \gamma_1^{14} OTHER_{t-1} + \varepsilon_t^1 \tag{11}$$

$$CORP_t = \alpha_0^2 + \alpha_1^2 CONS_t + \alpha_2^2 REE_t + \alpha_3^2 OTHER_t + \beta_1^2 IPI_t + \beta_2^2 TB3M_t + \tag{12}$$

$$+\gamma_1^{21} CONS_{t-1} + \sum_{i=1}^{6} \gamma_i^{22} CORP_{t-i} + \gamma_1^{23} REE_{t-1} + \gamma_1^{24} OTHER_{t-1} + \varepsilon_t^2 \tag{13}$$

$$REE_t = \alpha_0^3 + \alpha_1^3 CONS_t + \alpha_2^3 CORP_t + \alpha_3^3 OTHER_t + \beta_1^3 YD_t + \tag{14}$$

$$+\gamma_1^{31} CONS_{t-1} + \gamma_1^{32} CORP_{t-1} + \gamma_1^{33} REE_{t-1} + \gamma_1^{34} OTHER_{t-1} + \varepsilon_t^3 \tag{15}$$

$$OTHER_t = \alpha_0^4 + \alpha_1^4 CONS_t + \alpha_2^4 CORP_t + \alpha_3^4 REE_t + \beta_1^4 BOND10Y_t + \varepsilon_t^4 \tag{16}$$

Table 4 reports the empirical estimates for both the Three Stage Least Squares (3SLS) and the GMM system estimation.[33] The results obtained from the two methodologies are similar and suggest that there is no evidence of substitution among the different classes of loans while, on the contrary, there is strong evidence of complementarity among C&I, Consumer and Real Estate loans. The growth rate of Real Estate loans (which is half of the total) has a statistically significant and positive impact on the other two classes, and it is of a relevant economic magnitude. Similarly, an increase in the growth of C&I loans has a strong reinforcing effect on both Real Estate and Other loans, whereas it has a negative impact on the growth of consumer loans. On the other hand, an increase in the growth rate of Consumer loans has a positive impact on Real Estate and negative on C&I loans. The picture that emerges is that the equilibria in the markets for loans are

[32]In the estimation process the model of Eqs.(11)-(16) is supplemented with significant lags of the endogenous variables, namely lags 3, 8, 9, and 12 for CONS, lags 2, 3, 4, 5, and 6 for CORP, and lags 2, 3, 4, 5, 6, 7, and 8 for REE, while OTHER loans is not significantly influenced by the dynamics of its own lag and lagged values of the other types of loans. The model is also supplemented with monthly and seasonal dummies. However, to make the notation more tractable we do not report the complicated lag structure. The omission of the entire dynamic structure, or of the seasonal dummies, does not modify our basic results. However, it induces serial correlation and heteroscedasticity in the residuals.

[33]We do not report the results for the Maximum Likelihood (ML) estimations because the residuals are not normally distributed. However, ML estimates are not substantially different from those obtained by applying 3SLS and GMM.

mutually linked. For instance, positive shocks on Real Estate loans have a reinforcing impact on the other categories of loans, and vice versa, so that the processes reinforce each other. On the contrary, C&I and Consumer loans are clearly substitutes, indicating that the availability of bank credit may be constrained. One possible explanation for the first result is that the value of collateral, endogenous with respect to the quantities of loans, acts as an accelerating mechanism. However, we found no evidence that changes in the prices of houses had any significant impact, so that this explanation is not supported by the data. Overall, these results suggest that constraints on the availability of credit, at the aggregate level, are binding for those categories of loans where collateral plays a minor role, so that more risky unsecured lending is a larger share of the total. On the contrary, for all kinds of real estate lending, normally backed by collateral, these constraints do not generate a substitution with other classes of loans. Or at least this was the case before the recent Subprime Crisis.

We find that the macroeconomic factors that significantly influence C&I loans are the Industrial Production Index (IPI) and short-term interest rates (TB3M). In both cases, positive innovations in the two variables are associated with rising volumes of loans. While the first result can be easily explained, the second is less obvious. The impact of short-term rates is significant at the 1% level, it is robust to almost any change of the model specification, and it survives also when splitting the sample period. A possible explanation is that since most C&I loans are issued as commitment loans, as short-term rates rise, borrowers make extensive use of the credit lines previously obtained at predetermined interest rates, and reduce the issuance of commercial papers instead.[34] While this interpretation is supported by the result that the impact of short-term rates is stronger in the second half of the sample, the result holds also for the first half in which commitment lending was a less widespread practice.

As expected, the issuance of consumer loans is significantly reduced when unemployment rises, and it increases following positive innovations in the consumer leading

[34] In fact, the link between the volumes of corporate bonds issued (BONDS) and short-term interest rates (TB3M) is negative and statistically significant, as reported in Table 2.

**Table 4:** 3SLS and GMM Empirical Estimates of the Model of Eqs.(11)-(16).

| | 3SLS | | | | GMM | | | |
|---|---|---|---|---|---|---|---|---|
| | **CONS** | **CORP** | **REE** | **OTHER** | **CONS** | **CORP** | **REE** | **OTHER** |
| $\text{CONS}_t$ | | -0.135** (0.061) | 0.134*** (0.051) | 0.141 (0.166) | | -0.116** (0.052) | 0.149*** (0.040) | 0.044 (0.133) |
| $\text{CORP}_t$ | -0.227* (0.128) | | 0.380*** (0.105) | 0.281 (0.172) | -0.254** (0.121) | | 0.358*** (0.073) | 0.364*** (0.149) |
| $\text{REE}_t$ | 0.654*** (0.170) | 0.592*** (0.137) | | 0.234 (0.244) | 0.669*** (0.187) | 0.489*** (0.108) | | 0.383 (0.150) |
| $\text{OTHER}_t$ | 0.041 (0.050) | -0.013 (0.027) | 0.036 (0.024) | | -0.003 (0.044) | -0.031 (0.023) | 0.021 (0.018) | |
| $\text{CONS}_{t-1}$ | 0.4787*** (0.043) | 0.0936** (0.041) | -0.095*** (0.036) | | 0.484*** (0.037) | 0.097*** (0.036) | -0.122*** (0.032) | |
| $\text{CORP}_{t-1}$ | 0.1152 (0.092) | 0.5128*** (0.049) | -0.172** (0.067) | | 0.134* (0.081) | 0.516*** (0.046) | -0.147*** (0.051) | |
| $\text{REE}_{t-1}$ | -0.3671*** (0.104) | -0.368*** (0.087) | 0.495*** (0.046) | | -0.415*** (0.121) | -0.323*** (0.069) | 0.550*** (0.060) | |
| $\text{OTHER}_{t-1}$ | 0.002 (0.018) | -0.029 (0.014) | 0.026** (0.012) | | -0.002 (0.014) | 0.035 (0.012) | 0.017* (0.010) | |
| $\text{UNEMP}_t$ | -0.004** (0.002) | | | | -0.003** (0.001) | | | |
| $\text{CLI}_t$ | 0.114* (0.064) | | | | 0.131*** (0.044) | | | |
| $\text{IPI}_t$ | | 0.061 (0.037) | | | | 0.070** (0.032) | | |
| $\text{TB3M}_t$ | | 0.002*** (0.0005) | | 0.004** (0.002) | | 0.002*** (0.0004) | | 0.003** (0.001) |
| $\text{BOND10Y}_t$ | | | | -0.009*** (0.003) | | | | -0.009*** (0.002) |
| $\text{YD}_t$ | | | 0.001*** (0.0004) | | | | 0.001*** (0.0003) | |
| $\text{S\&P500}_t$ | | | | 0.044** (0.019) | | | | 0.052*** (0.019) |
| $\text{R}^2$ | 0.57 | 0.42 | 0.43 | 0.31 | 0.54 | 0.42 | 0.45 | 0.30 |
| $Q(4)$ | 1.0 (0.95) | 3.1 (0.56) | 3.0 (0.57) | 0.9 (0.93) | 1.5 (0.83) | 1.7 (0.78) | 3.1 (0.54) | 0.9 (0.92) |
| $Q(8)$ | 5.5 (0.70) | 5.6 (0.68) | 4.3 (0.83) | 6.2 (0.62) | 6.9 (0.55) | 4.4 (0.82) | 3.5 (0.90) | 6.8 (0.56) |
| $Q(12)$ | 7.5 (0.82) | 7.7 (0.80) | 8.7 (0.73) | 12.8 (0.83) | 7.5 (0.83) | 7.1 (0.85) | 7.6 (0.81) | 3.3 (0.35) |
| $Q(16)$ | 13.6 (0.63) | 20.5 (0.20) | 13.4 (0.64) | 15.9 (0.46) | 14.5 (0.56) | 18.7 (0.28) | 11.5 (0.77) | 16.6 (0.41) |

Notes: Sample period 1970:01 - 2007:06. GMM is estimated with White's heteroscedasticity consistent covariance matrix. Standard errors are in parenthesis. *= significant at 10% level, **= at 5% and ***= at 1%. Adjusted $\text{R}^2$ calculated as $1-(1-R^2)/(T-1/T-k)$. Q(n) are the Ljung-Box Q-statistics for serial correlation in the residuals and cross-products of residuals up to lag n. P-values in parenthesis.

indicator (CLI), a measure of consumers' expectations. More surprisingly, we find that innovations in neither short-term, nor long-term interest rates have any significant impact on both consumer and real estate loans. However, we find that real estate lending is strongly influenced by the term structure of interest rates. A number of different yield spreads which differ in terms of maturities of both the long and short rates have been taken into consideration as regressors. The yield spread between ten and three-year US government bonds is the spread with the greatest explanatory power. This result shows that the long-end of the term structure's spectrum has more information content than the short-end, which is valuable to explain variations in the volume of Real Estate loans. This result can be interpreted in the light of the findings of Ang and Piazzesi (2003) that while the short and medium-end of the US term structure is characterized by macroeconomic factors like current GDP growth and inflation, unobservable factors account for a large share of the variance of movements in the long-end of the term structure. Thus, our empirical evidence implies that these unobservable factors are important to explain the issuance of real estate loans. However, Dewachter et al. (2006) have further developed the framework, finding that the central tendencies of inflation and the real interest rate display the dynamics able to explain the long-end of the term structure. They conclude that "the variability at the long-end of the yield curve is mostly explained by shocks to the central tendency of inflation". Thus, our finding of a positive relationship between real estate lending and the slope of the term structure suggests that real estate loans grow with expected future inflation, confirming that banks would benefit from expected inflation, in line with the findings of Bordes et al. (1991).

Finally, the issuance of other loans is affected by interest rates and stock market returns, as loans to non-bank financial institutions and loans for purchasing securities are a large component of the aggregate, and presumably the most volatile. Higher issuance is associated with both higher stock market returns and higher short-term rates, while a declining issuance is associated with higher long-term rates. Since lower long-term rates imply higher bond prices, and thus higher returns for the bondholders, these findings are quite homogeneous, since higher issuance of loans is associated with higher returns on both stocks and bonds, pushing agents to increase leverage. In parallel with C&I loans, a larger issuance is also associated with rising short-term interest rates.

We then proceed to analyze the statistical properties of the second moments of the outstanding quantities of the different classes of loans. As in Section 5 we initially estimate a VAR(p) and find weak evidence of cross interaction. Thus, in order to reduce the numer of parameters under estimation we choose to fit the four series with simple AR processes. We find that the best fitting models are an AR(11)-GARCH(1,1) for CONS, AR(3)-GARCH(1,1) processes for CORP and REE, and an AR(3)-GARCH(0,1) for OTHER loans.[35] These specifications are then employed to estimate the multivariate AR Diagonal VECH model of Eqs.(4)-(5).

The empirical results are reported in Table 5.[36] The estimates of the coefficients attached to the product of the shocks $\varepsilon_{i,t-1}\varepsilon_{j,t-1}$ range from 0.433 to 5.97e-3 for the variances, and from 0.194 to -5.04e-3 for the covariances. These parameters are all statistically significant at the 5% level except for those that govern the covariances between consumer and C&I loans, and between consumer and other loans.[37] Finally, the estimates for the coefficients attached to lagged volatilities are all statistically significant and range from 0.527 to 0.105 for the variances, whereas for the conditional covariances they span from 0.578 to -0.216. Thus, both variances and covariances tend to cluster over time. The results suggest that when comparing the conditional volatility of the different aggregates, past shocks seem somewhat more important for C&I loans, whereas past volatility seems to have a stronger impact on real estate and consumer loans. On the contrary, past volatility does not play any role in OTHER loans as their volatility is modeled by means of an ARCH(1).

The lower panel of Table 5 reports the Ljung-Box Q statistics at lags 4 and 8 for the standardized residuals, as well as the LM Breush-Godfrey test for serial correlation at lag 12. These tests suggest that negligible degrees of serial correlation remain unexplained by the model. The Q statistics, in fact, always fail to reject the null of absence of serial correlation. The LM test soundly rejects the null for the aggregates CONS and OTH, whereas

[35] The Ljiung-Box Q statistics applied to standardized and squared standardized residuals generated by the AR-GARCH models suggest absence of serial correlation and GARCH effects.

[36] To save space the empirical estimates of the mean equations (4) for i=1,2,3,4 are not reported.

[37] However, the null $H_0 : a_{ij} = b_{ij} = 0$ for i,j=(2,1) and (4,1) is rejected at standard significance levels. The LR statistics when i,j=(2,1) and (4,1) are respectively 4.61 and 20.92 with p-values 0.099 and 0.000.

for the aggregates CORP and REE the null is still rejected but only at the 10% level. A similar analysis is then carried out for the standardized squared residuals. Also in this case the Q statistics provide convincing evidence that our model adequately captures the serial correlations in the second moments. However, there is still some significant serial correlation at lags 4 and 8 for the aggregate Other (OTH) loans. This evidence is confirmed by the results provided by the ARCH LM tests. Overall, the above results suggest that the our AR Diagonal VECH GARCH model provides an adequate description of the stochastic properties of the four loan aggregates.[38]

The likelihood ratio (LR) test for the null of constant covariance matrix strongly suggests that time varying conditional covariances are important when modeling the matrix $\Sigma(t)$ of the different loan aggregates.[39] To examine whether the time variability in the conditional covariances is solely due to the variation in the variances, we consider the conditional correlation indices $\rho_{ij}(t)$ between the growth rates of aggregates $i$ and $j$ at time $t$ (for $i, j$=1,2,3,4 with $i \neq j$) and we carry out the same tests as those implemented in Section 5. These tests clearly suggest that the correlation indices are not constant over time.[40] Figure 2 depicts the conditional correlations based on the empirical estimates of the model of Eqs.(4)-(5). All the conditional correlations appear to be highly clustered over time.

The most important result of this analysis is that for the entire sample all the conditional correlations are consistently lower than 1. For instance, OTHER loans are poorly correlated with any of the other classes of loans, and this result holds for the entire sample period. More specifically, the correlations of OTHER with CORP and REE loans, always very small, turns negative during several subperiods. The correlation between CORP and CONS is always positive, but very small for the entire sample as it is never greater than

[38]The stationary conditions for the Diagonal VECH GARCH model of Table 5 are fulfilled as the largest eigenvalue of the matrix $\mathbf{A}+\mathbf{B}$ is 0.854. Moreover, both the matrices $\mathbf{C}$ and $\mathbf{B}$ are positive definite whereas the matrix $\mathbf{A}$ is semi-definite. Thus, the conditions that ensure that the covariance matrix $\Sigma(t)$ is positive definite hold.

[39]The null is $H_0 : a_{12} = a_{13} = a_{14} = a_{23} = a_{24} = a_{34} = 0$. The LR statistic is 5,194.9, and with the degrees of freedom being equal to 6, the null is soundly rejected at standard significance levels.

[40]The AR coefficients span from 0.769 (with t-stat equal to 25.2) for the correlation between CONS and REE to -0.093 (with t-stat equal to -1.96) for the correlation between REE and OTHER.

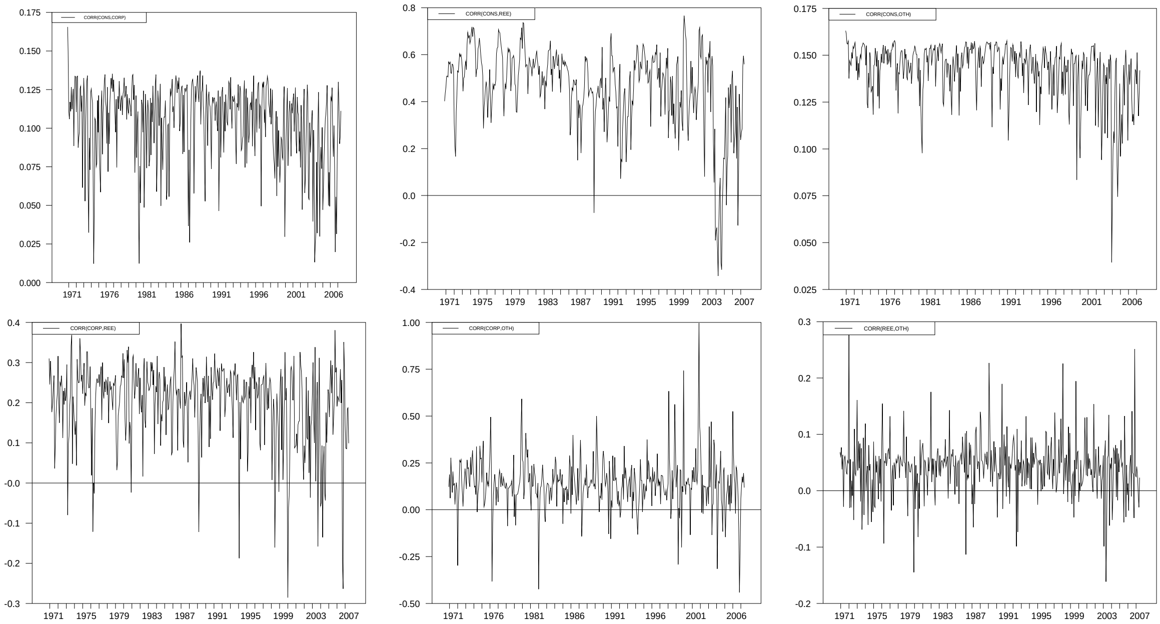

**Fig. 2:** Conditional correlation indices between Consumer (CONS) and C&I loans (CORP) (upper left panel), CONS and Real Estate loans (REE) (upper center), CONS and Other loans (OTHER) (upper right), CORP and REE (lower left), CORP and OTHER (lower center), REE and OTHER (lower right).

0.15. The correlation between REE and both CONS and CORP is greater, but it displays a much higher variability over time. More specifically, the correlation between REE and CORP is never larger than 0.4, and it shows substantial variability over time, so that it often becomes negative. Similarly, the correlation between REE and CONS never exceeds 0.8 and it remains lower than 0.5 for large parts of the sample. Interestingly enough, both the correlations tend to decline over the last part of the sample, reaching the minimum in the months between 2003 and 2006, when they become negative for a protracted period. Not surprisingly, during the booming period for real estate lending the correlations have been consistently declining, indicating that liability-side constraints may have begun to play a role. This evidence is also strongly against the hypothesis that the positive effect that real estate lending has on other types of loans is due to the value of collateral, since during the period of strongest growth in house prices the correlation actually became negative.

The picture that emerges is thus that average correlations among the aggregate equilibrium levels of different classes of loans is fairly low, so that diversification benefits can be

**Table 5:** Maximum Likelihood Estimates of the AR Diagonal VECH GARCH Model of Eqs.(4)-(5) for Monthly Volumes of Consumer (CONS), C&I (CORP), Real Estate (REE) and Other (OTHER) loans.

| | **CONS (i=1)** | | **CORP (i=2)** | | **REE (i=3)** | | **OTH (i=4)** | |
|---|---|---|---|---|---|---|---|---|
| | **coeff** | **s.e.** | **coeff** | **s.e.** | **coeff** | **s.e.** | **coeff** | **s.e.** |
| $\mathbf{const}_1$ | 2.78e-5*** | 2.84e-6 | | | | | | |
| $\mathbf{const}_{21}$ | 3.92e-6** | 1.68e-6 | | | | | | |
| $\mathbf{const}_{31}$ | 4.92e-6*** | 1.23e-6 | | | | | | |
| $\mathbf{const}_{41}$ | 2.28e-5*** | 4.48e-6 | | | | | | |
| $\mathbf{const}_2$ | | | 2.02e-5*** | 1.43e-6 | | | | |
| $\mathbf{const}_{32}$ | | | 3.53e-6*** | 5.97e-7 | | | | |
| $\mathbf{const}_{42}$ | | | 8.37e-6*** | 1.23e-6 | | | | |
| $\mathbf{const}_3$ | | | | | 5.38e-6*** | 7.30e-7 | | |
| $\mathbf{const}_{43}$ | | | | | 3.87e-6* | 2.03e-6 | | |
| $\mathbf{const}_{44}$ | | | | | | | 3.12e-4*** | 7.52e-6 |
| $\sigma^2_{1,t-1}$ | 0.383*** | 0.030 | | | | | | |
| $\sigma^2_{21,t-1}$ | 0.116** | 0.054 | | | | | | |
| $\sigma^2_{31,t-1}$ | 0.578*** | 0.030 | | | | | | |
| $\sigma^2_{41,t-1}$ | -0.216*** | 0.049 | | | | | | |
| $\sigma^2_{2,t-1}$ | | | 0.105*** | 0.014 | | | | |
| $\sigma^2_{32,t-1}$ | | | 0.189*** | 0.052 | | | | |
| $\sigma^2_{42,t-1}$ | | | 0.222*** | 0.008 | | | | |
| $\sigma^2_{3,t-1}$ | | | | | 0.527*** | 0.023 | | |
| $\sigma^2_{34,t-1}$ | | | | | -0.107*** | 0.035 | | |
| $\sigma^2_{4,t-1}$ | | | | | | | – | – |
| $\varepsilon^2_{1,t-1}$ | 0.150* | 0.081 | | | | | | |
| $\varepsilon_{2,t-1}\ \varepsilon_{1,t-1}$ | -0.012 | 0.042 | | | | | | |
| $\varepsilon_{3,t-1}\ \varepsilon_{1,t-1}$ | 0.194*** | 0.042 | | | | | | |
| $\varepsilon_{4,t-1}\ \varepsilon_{1,t-1}$ | -0.005 | 0.055 | | | | | | |
| $\varepsilon^2_{2,t-1}$ | | | 0.433*** | 0.0423 | | | | |
| $\varepsilon_{3,t-1}\ \varepsilon_{2,t-1}$ | | | 0.160*** | 0.024 | | | | |
| $\varepsilon_{4,t-1}\ \varepsilon_{2,t-1}$ | | | 0.161*** | 0.003 | | | | |
| $\varepsilon^2_{3,t-1}$ | | | | | 0.160*** | 0.024 | | |
| $\varepsilon_{4,t-1}\ \varepsilon_{3,t-1}$ | | | | | -0.064** | 0.029 | | |
| $\varepsilon^2_{4,t-1}$ | | | | | | | 0.006** | 0.003 |
| $\mathbf{R}^2$ | 0.451 | – | 0.414 | – | 0.367 | – | 0.215 | – |
| **Q(4)** | 3.626 | (0.304) | 1.633 | (0.651) | 3.626 | (0.304) | 2.218 | (0.528) |
| **Q(8)** | 8.639 | (0.279) | 8.521 | (0.288) | 8.639 | (0.279) | 6.627 | (0.468) |
| **LM(12)**♭ | 13.25 | (0.351) | 20.24 | (0.062) | 19.21 | (0.084) | 14.72 | (0.257) |
| $\mathbf{Q}^2$**(4)** | 0.232 | (0.972) | 2.108 | (0.550) | 2.976 | (0.395) | 10.26* | (0.016) |
| $\mathbf{Q}^2$**(8)** | 0.599 | (0.988) | 3.125 | (0.873) | 12.96 | (0.073) | 14.97* | (0.036) |
| **ARCH(4)**♮ | 0.341 | (0.986) | 2.201 | (0.698) | 4.334 | (0.362) | 11.43* | (0.022) |

Notes: Sample period 1970:01 - 2007:06. *= significant at 10%, **= at 5% and ***= at 1%. Adjusted $R^2$ calculated as $1-(1-R^2)/(T-1/T-k)$. ♭ LM test for serial correlation in standardized residuals up to lag 12. ♮ ARCH LM test for heteroscedasticity in standardized residuals up to lag 4. Q(n) and $Q^2$(n) are Ljung-Box statistics for serial correlation up to lag n in the standardized and squared standardized residuals. P-values in parenthesis.

substantial. Large banks providing different types of loans are likely to experience more stable revenues, so that regulatory constraints segmenting the industry, as those limiting saving banks and Savings & Loan associations to noncommercial investments, may not contribute to promote a safer and more stable banking system.

## 7 Conclusions

In this paper we have carried out two different empirical analysis. In the former we have jointly studied the aggregate volumes of shares and corporate bonds issued, along with the aggregate level of total outstanding bank loans. In the latter we have studied how the different classes of loans that the banking systems issue relate to each other. We have neglected the long-run trends, and focused instead on the short-term cyclical dynamics. We have thus identified the driving forces of their cyclical fluctuations, evaluating the potential benefits that universal banks may obtain from diversification.

Our results suggest that the equilibrium aggregate volumes of the different securities are interrelated, and that macroeconomic indicators which proxy business conditions explain sizeable proportions of their variability. More specifically, we find that the issuance of shares and total loans are weakly interdependent, that the issuance of stocks and bonds are mutually reinforcing processes, and that primary placements of corporate bonds and total loans are substitutes. We also find that these last respond in opposite ways to changes in the current level of economic activity, as well as to changes in the monetary policy stance. Higher levels of industrial production are, in fact, associated with larger issuance of loans, as industrial firms finance inventories by resorting to unused commitment loans. On the contrary, bond issuance rises when the level of economic activity declines. A plausible explanation is that in periods of economic expansion the cyclical component of the supply declines, as firms benefit from larger cash flows and need less external finance. Moreover, bond volumes quickly respond to an expansionary monetary policy, while, on the contrary, bank lending, and commercial and industrial lending in particular, rises when the monetary policy is tightened. Thus, as a recessions lurks, industrial firms need to rely on bank lending because financial markets freeze, but as the FED reacts by slashing interest rates, corporate bonds become cheaper, even if risk premia remains substantial, so that firms proportionally reduce their recourse to bank lending.

By making use of standard multivariate GARCH models, we also measure the conditional correlation among the different securities. Our results highlight that the correlations between stocks and bonds, and that between stocks and loans, vary over time in a range between 0 and 0.4. Even more strikingly, the correlation between bonds and loans is negative for most of the sample under analysis. The above results suggest that universal banks can substantially mitigate the pro-cyclicality of revenues from lending activities, with the fees from underwriting bonds, which are counter-cyclical. These benefits are potentially important whenever systemic, macroeconomic shocks occur. Such shocks, in fact, generate risks that are difficult to hedge by purchasing derivatives or other sophisticated financial instruments, since they are strongly correlated across different classes of assets and geographies. As a consequence, the diversification benefits that universal banks can achieve cannot be easily obtained by the banking system through other instruments, and a system based on universal banking can potentially be safer and more efficient than one in which institutions undertake separate banking activities.

In the second part of our analysis we decompose Total Loans into the four aggregates Consumer, Commercial and Industrial, Real Estate and Other loans, and we analyze them as a system. Our results suggest that the four aggregates display a substantially different behavior over the cycle, and that they respond to different macroeconomic determinants. Moreover, the empirical results suggest that also in this case the conditional correlations among the four aggregates are time-varying and consistently lower than the unity over time. We thus conclude that diversification benefits for commercial banks that provide different classes of loans simultaneously are sizeable, questioning the opportunity of any kind of regulatory constraints segmenting the industry into specialized entities.

An important limitation of our work is that time-varying cost factors, such as loan loss provisions, may potentially offset the benefits that we have identified. However, there are reasons to believe that this is not the case, as loan loss provisions typically peak after the bottom of a recession, when most of the dynamics that we have identified have already taken place. The presence of these diversification benefits, however, does not necessarily imply that a system composed of universal banks is safer and more stable than one where investment and commercial banks are strictly separate, since the lower cost of funding may potentially push universal banks to take more risks than their separate counterparts. In presence of market distortions providing incentives for risk taking, universal banks may thus respond much more aggressively than commercial banks, making the moral hazard problems caused by state guarantees even more serious.

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