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FINANCIAL MARKETS, BANKS' COST OF FUNDING, AND FIRMS' DECISIONS:
LESSONS FROM TWO CRISES

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Financial Markets, Banks' Cost of Funding, and Firms' Decisions: Lessons from Two Crises

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ABSTRACT

We test whether financial fluctuations affect firms' decisions through their impact on banks' cost of funding. We exploit two shocks to Italian banks' CDS spreads and equity valuations: the 2007–2009 financial crisis and the 2010–2012 sovereign debt crisis. Using newly available data linking over 3,000, mostly privately held, non-financial firms to their bank(s), we find that increases in banks' CDS spreads, and decreases in their equity valuations, lead younger and smaller firms to cut investment, employment, and borrowing. We conclude that financial market fluctuations affect even private firms through their banks' cost of funding.

JEL # D92, G21, J23

Keywords: Financial crisis, sovereign-debt crisis, banks, credit-default swaps, volatility, investment, employment, borrowing

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Introduction

Do financial market fluctuations affect the real economy? This question is central to our understanding of how market economies work and has become even more pressing in light of the recent financial and sovereign-debt crises. We address this research question by investigating whether market-driven fluctuations of banks' cost of funding affected firms' decisions during the two crises. We measure banks' cost of funding with their CDS spread and Tobin's Q, and we focus on the investment, employment, and borrowing of client firms.[1] The CDS spread captures banks' cost of debt over and above the risk-free rate, and Tobin's Q reflects the cost of equity capital.[2] Both measures, although not necessarily to the same degree, are likely to affect the credit conditions faced by client firms. In summary, we study a new form of the bank-lending channel through which financial market fluctuations affected the real economy during the two crises.

Our empirical analysis focuses on the Italian experience. There are several reasons why the Italian experience is important. First, both crises can be viewed as shocks that were largely exogenous to the Italian non-financial corporate sector. Second, the two crises generate *heterogeneous* time variation in banks' cost of funding, depending upon their exposure to U.S. banks and Italian sovereign debt. This differential response allows us to estimate the effect of changes in banks' cost of funding on client firms' real decisions. Third, Italian banks rely heavily on bond issuance as a source of funding and, hence, are severely exposed to changes in the cost of debt.[3] Fourth, Italian firms are predominantly small and privately held, and are largely unable to cushion shocks to the cost and availability of bank lending by resorting to the capital markets. Finally, Italian firms mainly finance themselves with variable-rate credit, a substantial fraction of which is short-term,

[1] Note that the amount of bank borrowing on the part of the firms in our sample is, in fact, the result of the interaction between demand and supply decisions—more discussion of this issue in Section 3.6.

[2] An important additional source of medium-term funding, the ECB's Long Term Re-financing Operations, or LTRO, was introduced only in December 2011, at the very end of our sample.

[3] Note, though, that our sample includes two foreign banks, in addition to Italian banks: Deutsche Bank and Crédit Agricole.

and, hence, are especially vulnerable to changes in the cost and availability of bank funding.

Figures 1–3 characterize the recent Italian experience at the aggregate level. Figures 1 and 2 plot the behavior of aggregate financial valuations for Italian banks during the 2006–2011 period. As it is apparent from the figures, banks' cost-of-funding conditions worsened following the Lehman crisis and, especially, following the sovereign debt crisis, as reflected by higher CDS spreads, lower stock valuations, and higher volatility of CDS spreads and stock prices. Furthermore, the evolution of banks' market valuations has not been uniform, as can be seen from the widening of the one-standard deviation bands: different banks have fared differently, particularly at the times of the two crises. Indeed, it is the time variation of the cross-sectional heterogeneity in firms' and banks' behavior that enables us to identify the effects of interest. Figure 3 plots the behavior of aggregate investment, employment, and bank loan growth, and documents their deterioration in times of crisis. In summary, the aggregate evidence in Figures 1–3 raises the question of whether there is a *causal* nexus linking banks' cost of funding to the real economy, through the effects banks exert on the decisions of client firms.

In addressing this issue, we use a newly available data set, covering a representative sample of over 3,000 Italian firms. This data set includes a large number of privately held micro and small firms, and provides information on the identity of the bank(s) each firm has a relationship with. Another distinguishing feature of our analysis is that we quantify banks' financial market conditions with several indicators—level and volatility of banks' CDS spreads and equity valuations—and we quantify their relative importance for firms' decisions. Moreover, we allow for the effects of banks' financial market valuations on firm's decisions to depend on the likelihood of the firm being financially constrained, as measured by age and size. We also develop a novel instrumenting strategy where we use the *pre-crisis* banks' exposure to dollar-denominated assets or sovereign bonds, interacted with *lagged* spreads on CDS contracts written on U.S. banks and Italian sovereign debt, as instruments for contemporaneous banks' financial valuations (more on this below). Although our main focus is on investment, we show that our basic results also hold for firms' employment and borrowing. Finally, we investigate whether other bank-related variables, in addition to our cost-of-funding measures, impact firms' decisions. We do so by including in the investment equation controls for bank balance-sheet variables (Tier 1 capital ratio, liquidity, etc.), as well as expectations of banks' fundamentals based on analyst earnings forecasts. Indeed, all existing literature on the real effects of the financial crisis through the bank-lending channel has focused on *balance-sheet* variables as indicators of bank health.

The need to instrument banks' financial valuations arises because of their potential endogeneity due to omitted variables and reverse-causality effects: banks' financial market conditions could be correlated with omitted variables in the investment, employment, and borrowing equations, and could be themselves affected by the choices of client firms.[4] Therefore, we control for a rich menu of variables capturing firms' demand and balance-sheet conditions, and we go beyond the standard use of internal instruments in a dynamic-panel context (see, for example, Arellano and Bond, 1991; and Blundell and Bond, 1998). As mentioned above, we instrument banks' valuations with their pre-crisis exposure to dollar-denominated assets—interacted with the *lagged* CDS spread on U.S. banks—and with their exposure to sovereign bonds—interacted with the *lagged* CDS spread on Italian Treasury bonds. Our identifying assumption is that these instruments are orthogonal to the *idiosyncratic* shocks to firms' decisions. The use of *pre-crisis* exposures deals with possible feedback from firms' decisions to bank portfolio choices. Furthermore, even though the financial and sovereign debt crises originated outside the Italian non-financial corporate sector, the use of lagged—as opposed to contemporaneous—CDS spreads represents an extra degree of caution in instrument selection.

[4] A detailed discussion of our econometric strategy is contained in Section 1.

The main results of the empirical analysis are easily summarized: an increase in a bank's CDS spread, CDS volatility, and stock price volatility, and a decline in Tobin's Q, all affect the investment activity of client firms. These effects are negative (positive) for younger and smaller (older and larger) firms, and are statistically and economically significant. For example, after controlling for firm-specific effects and common year effects, a one-standard deviation increase in a bank's CDS spread *decreases* the investment activity of a client firm at the 10th percentile of the age distribution—a five-year old firm—by 0.5 standard deviations, while it *increases* investment for a firm at the 90th percentile—a 38-year old firm—by 0.2 standard deviations. We also document significant negative effects of changes in the CDS spread on employment and borrowing of younger and smaller firms. Therefore, there is evidence of a bank-lending channel in the transmission of adverse financial shocks, characterized by a (relative) flight-to-quality away from the riskier and more opaque borrowers.

The results above are robust to the inclusion of a large menu of variables capturing: i) firms' creditworthiness; ii) banks' balance-sheet conditions and profitability; and iii) analyst bank earnings forecasts. Among the cost-of-funding measures used in our empirical work, banks' CDS spreads impact firms' decisions more than Tobin's Qs, suggesting that debt, rather than equity, is the marginal source of funding for the banks in our sample. Moreover, both the level and the (orthogonalized) volatility of CDS spreads seem to matter. Finally, adverse financial shocks also have a negative impact on the employment and borrowing of young and small firms.

While our econometric analysis is performed at the firm level, we also investigate the *aggregate* implications of our results. Specifically, we compute the deviation of actual firm investment and employment from the counterfactual investment and employment, had the CDS spread of the lender bank(s) stayed at the previous year's level. We then aggregate across firms to compute the aggregate effect of CDS changes. Furthermore, we compute indicators of allocative efficiency for both investment and net employment changes, based on the marginal-revenue product of actual investment (net employment change) relative to the counterfactual benchmark. In most years, changes in banks' CDS spreads relative to the previous year's level lead to net reductions in aggregate investment activity, and the effect is the largest and substantial in 2011, when banks' valuations were severely affected by the sovereign debt crisis. Across all years, actual investment is allocated less efficiently than counterfactual investment, with sizable efficiency losses in 2008 and 2011. As to employment decisions, changes in banks' CDS spreads lead to net reductions in aggregate employment in all years, with the largest effects occurring in 2008 and 2011. In all years, the allocation of net employment changes is less efficient than the counterfactual one, with the largest efficiency loss in 2011.

The present paper is related to and extends the recent literature on the effects of shocks to banks' health on bank lending and firms' real decisions during the recent financial crisis. Ivashina and Scharfstein (2010), for example, document that U.S. banks reduced their lending more during the crisis, if they had a less stable deposit base or if they were more exposed to credit-lines drawdowns because of co-syndicated loans with Lehman Brothers (see also Cornett, McNutt, Strahan, and Tehranian, 2011). Chodorow-Reich (2013) presents evidence that firms with pre-crisis relationships with less healthy lenders faced worse credit conditions and reduced employment more.[5] In an international context, Puri, Rocholl, and Steffen (2011) show that more loan applications were rejected by German banks, if these banks were affected by the U.S. financial crisis through their holdings in Landesbanken with substantial subprime exposure.[6] Jiménez, Ongena, Peydró, and

[5]See also Montoriol-Garriga and Wang (2011), who document the deterioration of access to credit for small firms during the Great Recession. A critical view of the importance of lending shocks in the aftermath of the post-Lehman crisis in the U.S. is provided by Khale and Stulz (2012), who find that bank-dependent publicly traded firms, or firms with high initial leverage, do not experience a greater fall in net debt issuance or in investment early on during the crisis. Indeed, Adrian, Colla, and Shin (2012), and Becker and Ivashina (2014), find evidence that, for U.S. firms, the fall in bank credit is compensated by bond issuance. Focusing on *firms'* balance-sheet conditions, Duchin, Ozbas, and Sensoy (2010), and Almeida, Campello, Laranjeira, and Weisbenner (2012), show that U.S. firms with low cash reserves and high short-term debt, or with long-term debt maturing in late 2007, respectively, reduce their investment more in the aftermath of the financial crisis.

[6]Also see Beltratti and Stulz (2012) for a *cross-country* study of the factors affecting bank performance in the

Saurina (2012a,b) use Spanish data to show that banks' capitalization and liquidity matter for the probability of obtaining a loan in time of crisis and for the transmission of monetary policy. Bentolila, Jansen, Jiménez, and Ruano (2013) also use Spanish data to show that firms attached to weak banks suffered an additional fall in employment between 3 and 6 percentage points. Focusing on the Italian experience, Albertazzi and Marchetti (2010) and Bonaccorsi and Sette (2012) document that the supply of loans drops more after the Lehman default, for less well-capitalized and less liquid banks, and for banks more reliant on non-bank sources of funding. Bofondi, Carpinelli, and Sette (2012), show that during the sovereign crisis the supply of credit of foreign banks drops less than that of Italian banks.[7] Finally, Cingano, Manaresi, and Sette (2013) find that firms borrowing from banks with higher exposure to the interbank market reduced investment and employment more, during the 2007–2010 period.[8]

The papers mentioned above, in their emphasis on banks' balance-sheet variables, build on the earlier contributions on the importance of the lending channel of monetary policy by Kashyap, Stein, and Wilcox (1993), and Kashyap and Stein (2000). They also build on Peek and Rosengren (1997, 2000), who studied the international transmission of bank-credit supply shocks following the stock market and real estate crashes in Japan.[9]

Gilchrist and Zakrajšek (2012) analyze similar issues as this paper, but at the aggregate level. They show that the risk-premium component of U.S. aggregate corporate bond spreads has great predictive power for future aggregate economic activity. More importantly, they find that aggregate corporate bond spreads are closely correlated with the CDS spreads of broker-dealers,

aftermath of the financial crisis.

[7] See also Presbitero, Udell, and Zazzaro (2012), who find that the effect of the credit crunch is greater in provinces with more distantly headquartered banks; and D'Aurizio, Oliviero, and Romano (2012), who find that lending to family firms falls less than lending to non-family firms following the 2008 crisis.

[8] See also Gaiotti (2013), who shows that the impact of bank credit quantities on firms' investment is more pronounced in periods of contraction of economic activity, particularly at the beginning of a recession, because alternative sources of funding also dry up.

[9] More recently, Adrian, Moench, and Shin (2010) relate financial intermediaries' balance-sheet conditions to future stock and bond returns and economic activity in the U.S.

supporting the notion that changes in financial intermediaries' market valuations impact credit supply conditions and, hence, real activity.

Our paper differs from and extends the existing literature by being the first to study the effect of market-based measures of banks' funding costs—both their level and volatility—on the real decisions of the firms they lend to, and to do so for both the post-Lehman and sovereign debt crises. The information on firm-bank relationships allows us to exploit the time variation of the *cross-sectional heterogeneity* of banks' cost of funding to identify the real effects of financial volatility on individual firms. This paper uncovers an important channel through which financial market shocks can affect the real economy. Indeed, even in countries where the fraction of firms with publicly traded financial instruments is small, financial market fluctuations are likely to have a powerful impact on firms' real decisions, through their effect on banks' cost of funding.

Furthermore, our results suggest that banks' cost of funding matters for firms' investment, over and above banks' balance-sheet conditions and earnings forecasts. Previous papers provide evidence that stock market fluctuations have an effect on firms' investment, even if one controls for fundamentals (e.g., Morck, Shleifer, Vishny, Shapiro, and Poterba, 1990; and Blanchard, Rhee, and Summers, 2000). The crucial difference between this earlier literature and our contribution is that we focus on banks', not firms', financial valuations. In addition, we show that banks' CDS spreads impact firms' investment decisions more than banks' equity valuations. Finally, our paper presents evidence that *both* the level *and* volatility of bank CDS spreads affect firms' decisions. The focus on the role of volatility for firms' real decisions is also shared by a different literature that uses firms' stock return volatility as a proxy for uncertainty.[10] We differ from those contributions because we place the volatility of banks', not firms', financial valuations at the center of our analysis.

The structure of the paper is as follows. Section 1 discusses the empirical methodology

[10]See, for instance, Bloom, Bond, and Van Reenen (2007), in the context of a model with irreversibility. See also the early paper by Leahy and Whited (1996), and Stein and Stone (2012), where the effects of stock volatility are analyzed using the implied volatility from equity options.

we use, with an emphasis on how we deal with possible endogeneity issues. Section 2 describes the data and, in particular, the novel survey data set containing firm-bank information. Section 3 discusses the empirical results. Section 4 concludes the paper.

1 Empirical methodology

This section describes the empirical strategy used in identifying the effect of banks' cost of funding on client firms' decisions. We first discuss the financial variables employed and why they contain information on the credit conditions of client firms. We then illustrate the econometric issues we face, and present the model-specification and instrumental-variable strategy employed in addressing them.

1.1 Banks' financial valuations and credit supply conditions

There are several reasons why banks' financial valuations measure their cost of funding and, hence, are likely to affect the credit-supply conditions of client firms.[11] First, CDS spreads are tightly correlated with the rates at which banks borrow in the bond markets—in a frictionless economy, arbitrage activity ensures that bond credit spreads are the same as CDS spreads.[12,13] Importantly, Italian banks rely heavily on bond issuance as a source of funding. Indeed, in 2009, Italian banks displayed a bond-to-deposit ratio of 40%, the highest among European banks (Grasso, Linciano,

[11] Banks' cost of funding may also reflect credit demand conditions. The next section discusses how to address this issue.

[12] Obviously, arbitrage activity may be subject to frictions, especially at times of high volatility, and the differential between CDS spreads and bond credit spreads—the CDS "basis"—may deviate significantly from zero. Fontana (2009) and Bai and Collin-Dufresne (2010) document a negative CDS basis during the financial crisis. In our setting, the presence of a non-zero CDS basis does not invalidate the CDS spread as a measure of the cost of funding, as long as the basis has only constant bank-specific and common time-varying components, since these components are captured by the firm and time fixed effects that we control for in the empirical analysis.

[13] Note that, in turn, banks' CDS spreads are likely correlated with sovereign CDS spreads, and, hence, there may be a transmission of sovereign-debt shocks to the real economy through banks' cost of funding. Indeed, Neri (2013) documents how tensions in the sovereign debt markets had a substantial impact on bank lending rates in the peripheral countries of the Eurozone—Italy, Spain, Greece, and Portugal—during 2011. Furthermore, Del Giovane, Nobili, and Signoretti (2013) show that credit-supply effects in Italy were more pronounced during the sovereign debt crisis, than during the financial crisis. These considerations motivate our choice of instruments discussed in the next section.

Pierantoni, and Siciliano, 2010). Banks' cost of debt is likely to be passed on to their customers, possibly more than in a one-to-one fashion.[14] Second, equity valuations reflect the expected rates of return required by stockholders and, hence, the cost of issuing equity capital. This cost should be factored in when the bank makes investment—i.e., lending—decisions. Finally, changes in banks' financial valuations are likely to be driven by investors' risk aversion.[15] These changes in investors' risk aversion may affect bank managers' own risk aversion and, hence, their lending policies.

In addition to the level of banks' valuations, the *volatility* of valuations is also likely to impact bank managers' risk aversion, willingness to lend, and the credit conditions offered to client firms. This is an additional reason why the volatility of banks' valuations is likely to translate into volatility of the credit conditions offered to client firms, which may also affect investment.

Also noteworthy is the fact that Italian firms mainly finance themselves with adjustable-rate credit, a large fraction of which is short-term. Indeed, Casolaro, Eramo, and Gambacorta (2006) document how 90% of Italian firms borrow at rates that are either variable or adjustable within the year. Moreover, the 2011 Bank of Italy Bulletin reports how 38% of bank credit has a term of less than 12 months. Hence, both the cost and availability of bank credit to Italian firms has the potential to be highly variable.[16]

In summary, there are good reasons why we would expect banks' financial valuations to capture banks' cost of funding and, hence, the credit-supply conditions of client firms. To formalize the economic mechanisms at work, denote with c_{it} the the firm-specific discount factor, or cost

[14] Note that CDS spreads reflect a *risk-adjusted* probability of default, which incorporates the objective probability of default, as well as compensation for risk. While we do not take a stand as to the drivers of CDS spread variation in our analysis, we do show that the effects of banks' CDS spreads on firm investment are robust to the inclusion of variables capturing banks' fundamentals.

[15] See Cochrane (2011) for a discussion of the role of expected discount rates versus expected cash growth as drivers of financial valuations.

[16] This general picture has been confirmed by private conversations with bank managers, who have also emphasized the recent widespread recourse to overdraft as a source of funding. The rate on overdraft is typically indexed to the short-term Euribor rate, with a variable spread, where the amount of overdraft available is also variable. The use of overdraft is partly motivated by the lack of financial expertise on the part of Italian firms, but also by the lack of available longer-term bank credit.

of capital, affecting investment decisions by firm i at time t, inclusive of all financial frictions in accessing external funds. We assume that c_{it} can be written as

$$c_{it} = \gamma_{1i}^{\top}\text{FINVAR}_{it} + \gamma_{2i}^{\top}x_{it}^{b} + \gamma_{3i}^{\top}x_{it}^{1,f} + \mu_t + \omega_i + \varepsilon_{it}, \tag{1}$$

where FINVAR_{it} denotes the vector of market-based measures of banks' cost of funding—CDS spreads and equity valuations, and their volatility.

Note, though, that if bond markets are the more common marginal source of funds for the bank, it is likely that CDS spreads are more informative than stock market valuations in determining banks' cost of funding. Firms' credit conditions are also likely to be related to other indicators of bank health obtained from bank balance sheets or from analysts' expectations of banks' profitability, denoted by x_{it}^{b}. We explore their role as well, and compare it to that of banks' market-based measures of their cost of funding. All bank-level variables may have a different effect on the overall credit conditions faced by the firm, depending upon the degree of bank dependence. Young (small) firms, for instance, are likely to be more informationally opaque, short of collateralizable assets and, therefore, less likely to be able to substitute bank funds with market funds. As a result, adverse changes in the health of the bank a firm borrows from are likely to have a larger negative effect on its cost of capital if the firm is young (small). This is why we allow γ_{1i} and γ_{2i} to vary by firm type in equation (1).

Finally, firms' credit conditions may also depend directly upon observable time-varying firm characteristics, x_{it}^{f}—such as balance-sheet conditions—unobservable firm-specific and time-invariant characteristics, ω_i, a common time-specific effect, μ_t, and an idiosyncratic error component, ε_{it}. Since it is possible that some of the firm's balance sheet conditions included in $x_{it}^{1,f}$ may have a different effect depending upon firm type, we index γ_3 by i. The error term has the standard error-component structure: ω_i, and ε_{it} are mean zero and uncorrelated with each other; moreover, ε_{it} is uncorrelated over time and in the cross-section. Finally, in some specifications, the time effect, μ_t, is permitted to vary by firm type or bank type.

1.2 Model specification and instrumenting strategy

There are three main interrelated issues that we must address in assessing the effect of banks' financial valuations on firms' decisions. The first issue is the need to control for credit-demand factors, which, in turn, affect firms' expected returns from investing. Not controlling properly for demand conditions gives rise to an omitted-variable bias in evaluating the effect of market-induced credit supply shocks on firms' decisions.[17]

The second related issue has to do with the problem of reverse causality, whereby banks' financial valuations do not cause investment, but are the result themselves of factors affecting firms' investment activity, which, in turn, affect banks' bottom line and valuations. Positive shocks to investment are associated with a healthier firm's balance sheet and result in improved banks' profitability (reflected in their valuations), because, for instance, of a reduction in the amount of non-performing loans. It is true that most of our firms are small, so that idiosyncratic shocks to their investment prospects have a negligible effect on a bank's bottom line, but this effect may be substantial if firms borrowing from the same bank are hit by correlated shocks and these shocks are not controlled for. All these issues would render banks' valuations econometrically endogenous in the estimating equations and must be addressed in model specification, by using extensive controls for firms' investment opportunities and balance-sheet strength, and through an appropriate instrumenting strategy.

A final issue is one of selection: a firm with better investment prospects at a given time may

[17] Obviously, the firm-level controls for demand effects are likely to be econometrically endogenous and need to be instrumented; more on this issue below.

choose to borrow from banks with more favorable market valuations. If permanently better firms have associations with permanently better banks, this problem is easily addressed by controlling for the time-invariant component of the error term. Indeed, firm-bank relationships in Italy are rather stable and most firms have long-term associations with a single bank.[18]

We discuss our econometric approach in the context of a simple specification of the investment equation. Assume that the investment rate $\frac{I_{it}}{K_{i,t-1}}$ depends upon covariates capturing firm profitability, x_{it}^{2f}, and friction-adjusted cost of capital, c_{it}:[19]

$$\frac{I_{it}}{K_{i,t-1}} = \beta_1^\top x_{it}^{2,f} + \beta_2 c_{it} + \tilde{\lambda}_t + \tilde{\eta}_i + \widetilde{u}_{it}. \tag{2}$$

As in equation (1), the time effects are allowed to vary by firm or bank type in some specifications. Substitute (1) into (2) and assume that the effect of bank-level variables on firms' credit conditions differs by age (or size). We obtain our estimating equation:

$$\frac{I_{it}}{K_{i,t-1}} = \alpha_{1i}^\top \text{FINVAR}_{it} + \alpha_{2i}^\top x_{it}^b + \alpha_{3i}^\top x_{it}^f + \eta_i + \lambda_t + u_{it}, \tag{3}$$

where $\alpha_{1i} = \alpha_{10} + \alpha_{11} \ln(1 + \text{age}_{it})$, $\alpha_{2i} = \alpha_{20} + \alpha_{21} \ln(1 + \text{age}_{it})$, and $\alpha_{3i} = \alpha_{30} + \alpha_{31} \ln(1 + \text{age}_{it})$.

We allow the effect of FINVAR_{it} to differ according to the age of the firm, to account for the fact that market-generated changes in bank-credit conditions are likely to have a different impact depending on firm type. As an alternative to age, we also use firm size, measured by beginning-of-

[18] It is possible, however, that some firms with improved (unobservable) prospects may be able to more easily diversify the portfolio of their bank relationships, which may be reflected in the average valuations of the multiple banks a firm has a relationship with. This issue is interrelated with the fact that we observe the bank-firm relationship only at the end of the sample and is discussed below in Section 2.3.

[19] One way to rationalize our investment equation is to think of a firm facing quadratic adjustment costs. In that case, the investment rate can be written as a function of the expected discounted sum of the marginal revenue products of capital. To a first-order approximation, the latter term can be expressed as the sum of the present value of the expected marginal revenue products (with a fixed common discount rate) and the present value of the firm- and time-specific discount factor summarizing all the possible financial frictions faced by the firm. Assuming that expectations about marginal revenue products and the discount factors are formed on the basis of the variables contained in x_{it}^{2f} and c_{it} respectively, yields equation (2); see Gilchrist and Himmelberg (1998).

period logarithm of total assets in the interaction terms. In addition, investment may depend upon the other bank-level variables, x_{it}^{b}, capturing the effect of other bank characteristics on the firm's cost of capital, c_{it} (balance-sheet variables, measures of profitability, and expected earnings). Their coefficients can also vary by firm age or size. Investment is also a function of the union (denoted by x_{it}^{f}) of all the firm-level variables $x_{it}^{1,f}$ and $x_{it}^{2,f}$ that affect either the firm's cost of capital or its expected profitability. In all specifications, we include in x_{it}^{f} the output-to-capital ratio and the cash-flow-to-capital ratio, in addition to age or size.[20] We also check the robustness of our results to the addition of other variables, such as the firm's Altman Z-score (Altman, 1968). In principle, the effect of the firm's balance-sheet variables may also vary by firm type.

Most of the literature has focused on the role of a firm's balance-sheet variables in determining the firm's discount factor. Some other contributions, old and recent, have focused, instead, on banks' balance-sheet conditions. Our novel contribution is to emphasize the effect of banks' financial valuations on firm investment through their impact on the (unobservable) firm's discount factor. However, banks' financial valuations not only measure banks' cost of funding and, hence, credit supply conditions, but they may also capture credit demand factors. Therefore, in addition to firm-level demand factors, it is important to control for common factors that may have affected firms' investment opportunities during the turbulent years of our sample. The year effect, $\lambda_t(= \tilde{\lambda}_t + \beta_2\mu_t)$, is assumed common to all firms in our basic specification; but, in our robustness exercises, it is allowed to vary by firm industry, region or size, or bank size, to account for shocks to profit opportunities (or the cost of capital) that are specific to particular groups of firms. Finally, in our estimating equation, the firm-specific, time-invariant component of the error term, $\eta_i(= \tilde{\eta}_i + \beta_2\omega_i)$, and the idiosyncratic component, $u_{it}(= \widetilde{u}_{it} + \beta_2\varepsilon_{it})$, are assumed to satisfy the

[20] With a Cobb-Douglas production function and log-linear demand, the marginal revenue product of capital for an imperfectly competitive firm is proportional to the capital-output ratio; see Gilchrist and Himmelberg (1998). A firm's cash flow is likely to contain information *both* about a firm's demand *and* cost of capital, but we do not attempt to identify these separate effects here.

standard assumptions $E(\eta_i) = E(u_{it}) = 0$, $E(\eta_i u_{it}) = 0$, and $E(u_{js} u_{it}) = 0$ for $j \neq i$ or $s \neq t$.

In estimation, we use the Two-step System GMM (Blundell and Bond, 1998, building on Arellano and Bond, 1991, and Arellano and Bover, 1995) as implemented in Stata by Roodman (2009). In the calculation of the standard errors we use the Windmeijer (2005) finite-sample correction. The basic idea of the system estimator is to combine the orthogonality conditions for the differenced and the level models. The differenced equation uses appropriately lagged levels of the variables as instruments, while the level equation is instrumented with lagged first differences of the included variables. More specifically, we use values of the output-to-capital ratio and cash-flow-to-capital ratio (or other included firm-level variables or bank-fundamental variables) lagged twice or more for the differenced model.[21] For the level equations, we use their difference lagged once, which is legitimate given the appropriate assumptions about initial conditions discussed in Blundell and Bond (1998), and Blundell, Bond, and Windmeijer (1993).[22]

Given the rich set of controls included in the investment equation, one could argue that the variables in FINVAR_{it} are likely to be orthogonal to the idiosyncratic component of the error term. Yet, in our main analysis, we instrument FINVAR_{it} and we go beyond the conventional option of using its value lagged (twice or more) as instrument in the differenced equation. Our choice of instruments emphasizes the crucial role of the two main shocks that have buffeted financial markets in the recent past: the post-Lehman financial crisis and the sovereign debt crisis. More specifically, we use as instruments the 2006 (pre-crisis) exposure to dollar-denominated assets interacted with the CDS spread for U.S. banks—lagged two and three periods—and the 2006 exposure to sovereign bonds interacted with the value of the CDS spread for Italian Treasury bonds, also lagged lagged

[21]The error term in the difference equation is Δu_{it}, so that variables dated $t-2$ are legitimate instruments, if u_{it} is serially uncorrelated. We provide, therefore, the results of the serial correlation test proposed by Arellano and Bond (1991).

[22]More precisely, we assume that all the firm- or bank-level variables follow mean-stationary processes. This means that the deviation of the initial observation for each variable from its steady state value is uncorrelated with η_i.

two and three periods.[23]

The use of the pre-crisis exposure to dollar-denominated assets and sovereign bonds virtually eliminates the problem of anticipatory behavior of banks in determining their bond portfolio. Moreover, the use of lagged values of the CDS spread for U.S. banks and for Italian government bonds is motivated by an extra degree of caution in the (unlikely) case that our common or group-specific time effects have not fully controlled for aggregate shocks to the economy that affect firms' investment opportunities, which may be correlated with contemporaneous values of the CDS spreads (particularly the one for Italian government bonds).[24] In other words, our identification strategy requires that the level of the CDS spread for U.S. banks and for Italian sovereign debt in 2008 and 2009 (interacted with the 2006 bank-portfolio allocations) is not correlated with the changes in the idiosyncratic component of the shock in the firm's investment equation between 2010 and 2011.[25] We regard this as highly plausible. The combination of extensive controls for a firm's investment opportunities and our instrumenting strategy leaves us confident that what we are capturing is the effect of fluctuations in banks' financial valuations on investment through a bank-lending channel.

2 Data

The final estimation sample is the result of matches and transformations of several data sets containing information on firm-bank relationships, firm balance-sheet data, bank balance-sheet data and annual reports, banks' cost-of-funding measures, and analyst bank-earnings forecasts.[26] In the

[23]Indeed, Albertazzi, Ropele, Sene, and Signoretti (2013) document that, even when controlling for the standard economic variables that influence bank activity, a rise in the spread on Italian sovereign bonds is followed by an increase in the cost of funding for Italian banks.

[24]Chodorow-Reich (2013) uses an instrumenting strategy similar to the one used here. In estimating the effect of credit supply shocks on employment, he instruments the chosen measure of bank health (lending during the crisis by a firms' pre-crisis syndicate to all of its *other* borrowers) with the pre-crisis exposure to Lehman brothers and to toxic mortgage-backed securities, and with balance-sheet items not related to the corporate loan portfolio.

[25]We also add the interactions between the 2006 exposures and the change (lagged once) in the average value of the U.S. banks and Italian government debt CDS spreads to the instruments for the level equation.

[26]The Appendix contains detailed definitions of all the variables used in the analysis.

following, we describe the different data sources employed.

2.1 The MET dataset

The source of data on firm-bank relationships is the Monitoraggio Economia e Territorio (MET) 2011 survey on Italian firms. The sample size is about 25,000 observations per wave, including both corporations and partnerships, belonging to the manufacturing (about 60%) and service (about 40%) sectors. The sampling design is studied to have representativeness at size, region, and industry levels, while at the same time allowing for an oversampling on some characteristics of interest.[27] Differently from other Italian datasets, the sample contains information on firms of all size classes, even very small firms with less than ten employees.[28] In addition to polling firms on a very rich set of firm characteristics and behaviors, the survey asks each firm to specify the financial institutions it has a relationship with. This is the crucial piece of information that makes our analysis possible.

2.2 Other sources

Several different data sets are matched to the firm-bank identifier. Firm balance sheets, available only for corporations, are from CRIBIS D&B. Bank balance-sheet variables are from the Bankscope Bureau van Dijk dataset, while data on the exposures to the U.S. economy and to sovereign debt are hand-collected from banks' annual reports. Analyst earning forecasts are from the I/B/E/S (Thomson Reuters) database.

A relevant part of the dataset refers to banks' cost-of-funding measures. Individual bank CDS spreads, stock prices, and Tobin's Qs are from Bloomberg. We have CDS spreads for ten banking groups, covering a total of 96 banks, and equity valuations for 21 banking groups, covering

[27]The large size of the sample is compatible with an oversampling of more innovative firms in the manufacturing sector, and of companies in certain geographical regions. The sampling scheme is performed with Bayesian methods exploiting the observed frequencies of previous waves.

[28]Note that our data set covers a very different sample of firms from those covered by the Centrale dei Rischi (CdR) data set, not openly available to researchers. In 1993, for example, the median number of employees for the firms covered by the CdR data set was 277 (D'Auria, Foglia, and Reedtz, 1999), while it is 12–14 in our data set.

a total of 123 banks; see the Appendix for details. CDS spreads for U.S. banks and Italian Treasury bonds are from Datastream.

All the financial variables used in the estimations are the result of aggregations from higher frequency data. CDS spreads and Tobin's Qs are computed as the average of daily observations over the fiscal year. Equity volatilities and CDS volatilities are, respectively, the standard deviations of daily continuously compounded equity returns and daily changes of CDS spreads over the same period. Expected earnings are computed as the discounted sum of analyst earnings forecasts for years $t-1$, t, and $t+1$.[29]

The panel structure of the sample is obtained by assuming stability over time of the firm-bank relationship.[30] From the observed relationships in 2011, we project the firm-bank connections backwards to 2006. In the case of local banks belonging to a banking group, we attribute to the local bank the cost-of-capital measure of the group, in order to match as many cases as possible. Depending on the specification, the final sample contains 10 (for CDS and CDS volatility) to 21 (for Tobin's Q and stock price volatility) banking groups covering 90% to 97% of the overall firm-bank relationships in the survey. Finally, for firms that borrow from multiple institutions, bank variables are computed as the equally-weighted averages across the related financial institutions.[31]

Overall, the dataset includes roughly 15,000 to 19,000 observations, for a total number of 3,000 to 3,400 firms for the years between 2006 and 2011. The main loss of observations is due to the absence of balance-sheet data for partnerships. We further impose a minimum of three observations in the time series in order to implement our GMM estimation. Finally, all quantitative variables

[29] From monthly earnings forecasts at different horizons we compute their averages over the first three months of the year and we aggregate them assuming a discount rate of 0.967. As a robustness check, we also try different values of the discount rate and we include a perpetuity in the expectation from $t+2$ forward—see (Vuolteenaho, 2002)—with very similar results.

[30] See the next section for a discussion of this issue.

[31] On the other hand, for banking groups that resulted from mergers taking place during the sample, we constructed 2006 values for dollar and sovereign exposures by taking the *weighted* average of the exposures of each individual bank in the group, where the weights are the ratios of the total assets of the individual bank over the total assets of the banking group.

are expressed in units of standard deviation and winsorized at the 1% level in order to reduce the influence of outliers.

2.3 Summary statistics and the nature of banking relationships

Tables 1–2 present summary statistics for our panel data set. The patterns in Table 1 are consistent with the graphs in Figures 1–2: the financial and sovereign debt crises lead to a marked increase in the level and volatility of bank CDS spreads and in the volatility of bank equity prices. The two crises also brought about a reduction in banks' stock market valuations.

Table 2 highlights the reduction in the investment rate between the 2006–2008 and 2009–2011 periods. Also marked is the reduction in the growth rate of bank debt. These patterns are consistent with the graphs in Figure 3.

Table 3 documents the number of banking relationships by firm age and firm size. It is evident the prevalence of single bank relationships, ranging between 80.5% (76.7%) and 87.5% (86.4%) of the sample across age (size) quartiles.[32] Also evident, though, is how older (larger) firms tend to have more banking partners.

One issue that the evidence above raises is the possibility of "switchers" among the firms in our sample, i.e., firms that change banking partners over the sample. If a firm switches bank over the sample, this introduces measurement error in the bank financial variables: we attribute to the firm the financial variables of a bank that differs from the bank that the firm was actually doing business with, prior to 2011. We respond to this potential criticism in *three* ways. First, D'Auria, Foglia, and Reedtz (1999) document the tendency of Italian firms to *add*, rather than switch, banking partners. Hence, the possibility of mis-measuring the bank-firm relation arises mainly

[32]Similar percentages of single and multiple banking relationships are documented for firms with less than 20 employees (the vast majority in our sample and in Italy) in the CdR database; see Mistrulli and Vacca (2011). Albertazzi and Marchetti (2010), and Bofondi, Carpinelli, and Sette (2012) (among others), find a higher percentage of multiple banking relationships because of their focus on a sample of larger firms.

for firms that, in 2011, had multiple banking relations, which are a small fraction of the sample. Second, we estimated our basic specification of the investment function also for the subsamples of firms with a single banking relationship in 2011, firms that, based on the evidence of D'Auria, Foglia, and Reedtz (1999), are unlikely to have changed bank over the sample. Our basic results are unchanged for this sample of firms (see discussion in Section 3.1 below). Third, since our instruments only include *lagged* values of the variables of interest, the measurement error generated by mis-measurement of the firm-bank relations gives rise to an asymptotic bias only if it leads to persistent regression residuals, potentially correlated with the lagged instruments. Our diagnostics indicate no persistence in the idiosyncratic component of the error term in the level equation and, thus, indicate as unlikely the correlation between residuals and lagged instruments.

3 Empirical results

In this section, we discuss the empirical results of the analysis. We first provide results for investment decisions. We then turn to employment and borrowing.

3.1 Investment

The core results of the paper are presented in Table 4. An increase in a bank's CDS spread reduces the investment rate of client firms, but this effect is attenuated as the age or size of the firm increases. The same effect occurs as the volatility of the CDS spread and the volatility of the stock price increases. The bank's Tobin's Q, on the other hand, has effects of the opposite sign. We also extract the first principal component (PC) of the four financial market indicators, which loads positively on the CDS spread, the volatility of the CDS spread, and the stock volatility, and loads negatively on Tobin's Q. The first PC affects negatively the investment rate, with an effect that is attenuated by age and size.

Figures 4–5 plot the impact of the four financial variables on the investment rate as a function of a firm's age. For the CDS spread, the effect is negative (positive) and significant (at the 5% level) for firms with age of 10–15 years or less (35–40 years or more). A one-standard deviation increase in a bank's CDS spread *decreases* the investment activity of a client firm at the *10th percentile* of the age distribution—a five-year old firm—by 0.5 standard deviations, while it *increases* investment by 0.2 standard deviations for firms at the *90th percentile*—a 38-year old firm. We see similar patterns for the volatility of the CDS spread and of the stock price. The pattern is reversed for Tobin's Q, as one would expect. These results support the presence of a *relative* flight-to-quality effect towards older (larger) firms. We use the word "relative" because the year dummies absorb the negative effect of an increase in the banks' CDS spread common to all firms.

In all specifications, there is no evidence of misspecification of the model. The Arellano-Bond test for serial correlation for the residuals in the difference equation does not reject the hypothesis of no second-order correlation, making variables lagged twice or more legitimate instruments. The Hansen test of over-identifying restrictions is also not suggestive of model mis-specification.

There are no simple first-stage regression statistics available for the difference and system GMM estimator to assess the "strength" of the instruments. However, it is informative for the difference GMM estimator to calculate the F statistics on our key instruments in an pooled OLS regression of the change in banks' CDS spreads on our instruments in levels (plus values of the firm cash-flow-to-capital and sales-to-capital ratio, lagged two and three periods, and year dummies).[33] Similarly, for the system GMM estimator, we have also regressed the level of banks' CDS spreads on the once-lagged lagged change of our instruments (plus once-lagged changes of the firm cash-flow-to-capital and sales-to-capital ratio and year dummies). We find that our key instruments are strongly significant in predicting both changes and levels of banks' CDS spreads—the p-values of

[33]Recall that the key instruments are the 2006 exposures to dollar-denominated assets and sovereign bonds, interacted with the twice-lagged change of the CDS spread for U.S. banks and Italian Treasury bonds.

the corresponding F-statistics are essentially zero.[34]

We implement several checks to verify the robustness of our results, focusing on the case where the banks' cost of funding is measured by the CDS spread (see Table 5). First, we implement our analysis on the subsample of firms with a *single* banking relationship in 2011. As explained earlier, this addresses the concern that changes in the firm-bank relationship may introduce measurement error in the cost-of-funding variables. Second, we consider *three* alternative instrumenting strategies for the CDS spread: i) we assume that the CDS spread is exogenous; ii) we instrument the CDS spread with its own lagged values (internal instruments); iii) we instrument it with the 2006 dollar-denominated exposure to other financial intermediaries and the 2006 holdings of sovereign bonds, interacted with the *contemporaneous* CDS spread on U.S. banks and Italian Treasuries, respectively. Third, we address the concern that banks' financial valuations may reflect, in part, firms' creditworthiness, by introducing as an additional regressor the Altman Z-score as well as the first principal component of several firm-level financial ratios (see the Appendix for details).[35] Fourth, we control for industry-specific (12 industries), region-specific (20 regions), firm-age specific (young and old), firm-size specific (large and small), and bank-size specific (large and small) time fixed effects. This approach allows us to deal, for instance, with demand shocks that are industry or region specific, or that vary by firm or bank size, and increases the likelihood that our instruments are uncorrelated with the idiosyncratic component of the error term in the investment equation. Finally, we implement the GMM estimator on the differenced specification alone. The results of all these robustness checks are qualitatively and quantitatively similar to those of reported in Table 4, thus confirming our main conclusions.

We have also experimented with allowing the effect of banks' financial variables to depend

[34] Lagged firm-specific variables—cash-flow and sales-to-capital ratios—have little or no explanatory power, providing no evidence that individual firms' observables impact banks' financial valuations.

[35] In computing the Z-score, we use the coefficients employed by Altman, Danovi, and Falini (2012), in their analysis of Italian firms.

on the cash flow of the firm, the lagged stock of liquid assets relative to total assets (or capital), and the Altman Z-score. The coefficient of these interaction terms is never significant. This suggesting that other factors beside creditworthiness may be driving the allocation of credit to Italian firms.

3.2 Controlling for banks' fundamentals

Having established our main results, we now test their robustness when we control for banks' fundamentals. It is possible that the effects that we document, while taking place through the impact of banks' cost of funding on firms' discount factors, are driven by the banks' fundamentals: balance-sheet variables, profitability measures, and analyst earnings forecasts. Our analysis below shows that the effects of banks' financial valuations on firms' investment decisions are robust to the inclusion of variables capturing banks' fundamentals.

In Table 6, we control for the banks' dollar-denominated exposure to other financial intermediaries and the exposure to sovereign risk. In addition, we also control for the liquidity of bank assets, the Tier 1 capital ratio, the stability of the sources of funding, and the amount of loan losses. The additional controls are largely insignificant, whereas the effects of our market-based measures of banks' cost of funding do not change.

In Table 7, we control for bank profitability. Specifically, we control for capital gains on dollar-denominated claims on other financial intermediaries and on holdings of sovereign bonds. In addition, we also control for the bank's ROE. Again, the additional controls are mainly insignificant, whereas the size and significance of the coefficient of our banks' cost-of-funding measures remain unaffected. We attribute this result to the forward-looking nature of market valuations and the fact that they contain information not only on cash flow fundamentals, but also on expected future discount rates.

In Table 8, we control for the banks' earning forecasts formulated by sell-side analysts.[36]

[36]See also Cummins, Hassett, and Oliner (2006) for the use of analysts' forecasts of *firms*' earnings in investment

Specifically, we aggregate the earnings forecasts formulated during the first three months of the year pertaining to the previous year, the current year, and the next year. The earnings forecasts are then standardized by the bank's assets at the end of the previous year to construct an ROA measure. The analysis in Table 8 shows how an increase in a bank's expected earnings leads client firms to invest significantly more, but that this effect is attenuated by age and size. At the same time, the effects of the banks' cost-of-funding measures do not change. Therefore, banks' cost of funding appears to matter over and above banks' balance-sheet conditions and expectations of fundamentals.

This result bears a resemblance with the evidence in Morck, Shleifer, Vishny, Shapiro, and Poterba (1990), and Blanchard, Rhee, and Summers (2000), who document that stock market fluctuations have an effect on firms' investment even after one controls for fundamentals.[37] Our result is also related to the aggregate evidence in Gilchrist and Zakrajšek (2012), who partition an index of credit spreads into a component reflecting information on firms default risk and a residual component—the excess bond premium—and show that the latter has greater predictive power for aggregate economic activity.

3.3 CDS spreads versus equity prices

One of our contributions is to test which of banks' cost-of-funding measures is empirically more important for firm's investment decisions. Table 9 compares the effects of CDS spreads to those of equity valuations, when both these variables are included in the equation. We first consider the level of the CDS spread and equity valuations. While the effect of the CDS spread is strongly significant, the effect of Tobin's Q is insignificant. We obtain the same results when we include both CDS and equity volatility; or both the first principal component of the level and volatility

equations. We focus instead on analyst forecasts of *banks'* earnings.

[37]The crucial difference, however, is that these papers focus on *firms*' market valuations, whereas we focus on *banks'* cost of funding and its effect on credit conditions.

of the CDS spread, and the first principal component of Tobin's Q and equity volatility. This is consistent with debt being the marginal source of funding for the banks in our sample.

3.4 Levels v. volatility

Table 10 explores whether both the level and the volatility of CDS spreads matter. In this analysis, given the high correlation between the level and volatility of CDS spreads, we use as regressors the level of the CDS spread and the residual of a regression of the volatility of the CDS spread on the level. We find that both the level and the volatility of CDS spreads matter. This result complements the results of papers showing that equity volatility affects investment decisions, over and above the level of equity valuations. Leahy and Whited (1996), Bloom, Bond, and Van Reenen (2007), and Stein and Stone (2012) find a negative effect on a firm's investment of the volatility of its own stock. Our focus, instead, is on the volatility of banks' and not of firms' valuations.

3.5 Employment

Do bank valuations affect other firms' real decisions such as those regarding employment? The model in Table 11 uses the change in the logarithm of the number of employees as the dependent variable. The covariates are the same as in the basic investment specification of Table 4, with the addition of the logarithm of the lagged number of employees. In Figure 6, we plot the effects of the CDS spread and its volatility on employment growth. Again, worse banks' financial market conditions impact negatively young and small firms. For instance, for a firm of five years of age, a one-standard-deviation increase in the CDS spread leads to a reduction of the growth rate in employment of 0.169 standard deviations (significant at the 5% level). The main difference, relative to the results on investment, is that there is no significant positive effect for older/larger firms.

As in the case of the investment function, we implement several robustness checks: we modify our choice of instruments; we control for industry-specific, region-specific, firm-age specific, firm-size specific, and bank-size specific time fixed effects; and we control for measures of the firm's creditworthiness. Again, our main results hold.

3.6 Bank debt

The effect of fluctuations in the banks' cost of funding is likely to be transmitted to firms' real decision through the impact they have on the cost and access to bank debt. We do not have information about the interest rate charged to firms or other aspects of debt contracts, such as collateral requirements. However, we have balance-sheet information on the stock of bank debt, which reflects the interaction between the credit *supply* decisions on the part of the bank and the credit *demand* decisions on the part of the firm.

Table 12 models the growth rate of firms' bank debt. In addition to the effects of banks' cost-of-funding measures in levels and interacted with age and size, we also control for the lagged logarithm of bank debt, sales growth, the ratio of tangible assets to total assets, sales and cash flow over total assets, and the logs of age and size. As in the case of investment and employment, worse banks' financial market conditions result in a slowdown in the growth rate of bank debt for small and young firms. For a new firm, a one-standard-deviation increase in the CDS spread leads to a reduction of the growth rate of bank debt of 0.1 standard deviations.[38]

In Figure 7, we plot the effects of the different bank financial variables on the growth of bank debt. Again, the effects are qualitatively analogous to those documented for the investment and employment functions.

[38] We performed the same robustness checks as in the case of the employment function and our main results are largely unchanged.

3.7 Implied aggregate effects and allocative efficiency

While our empirical analysis is performed at the *firm* level, it is also interesting to assess the quantitative effect of changes in banks' cost of funding on *aggregate* capital accumulation. We thus perform a *ceteris paribus* exercise, whereby we compute the difference between actual investment and the counterfactual investment that would have resulted had the bank cost of funding stayed at the previous year's level, while all the other covariates (year dummies included) remained at their actual values.[39] In fact, our exercise is likely to underestimate the impact of changes in banks' financial valuations as we ignore their effect on firms' cash flows and sales.[40] Specifically, using equation (3), we can compute

$$I_{it} - \hat{I}_{it} = K_{it-1}\left[\frac{I_{it}}{K_{i,t-1}} - \widehat{\left(\frac{I_{it}}{K_{i,t-1}}\right)}\right] = K_{it-1}\alpha_{it}(\text{FINVAR}_{it} - \text{FINVAR}_{it-1}). \tag{4}$$

which measures the difference between the firm's actual investment and its counterfactual investment had FINVAR_{it}—the CDS spread, in this analysis—stayed at the previous year's level.

We can then aggregate the difference between actual and counterfactual investment across firms for which $I_{it} - \hat{I}_{it}$ is *negative* and relate it to the aggregate average capital stock over years t and $t-1$, to obtain

$$\text{NEG}_t = \frac{\sum_{i, I_{it}-\hat{I}_{it}<0} w_i |I_{i,t} - \hat{I}_{it}|}{\sum_{i=1}^{N_t} w_i (K_{it} + K_{it-1})/2}, \tag{5}$$

where w_i is the firm-specific sampling weight employed to reproduce the population aggregates. NEG measures the aggregate percentage reduction in the capital stock as a result of the change in

[39] Our exercise is similar in spirit to the analysis of Chodorow-Reich (2013), who computes a counterfactual measure of firm-level employment based on the assumption that the health of the firm's loan syndicate, as measured by the syndicate's lending to other firms, was the same as that of the healthiest syndicate.

[40] Moreover, we are keeping constant the year dummies that contain the effects of the *common* component of the CDS spreads together with other macro factors. This may lead to further underestimate the total impact of CDS spreads on investment activity.

banks' financial valuations. Similarly, we can aggregate the difference between actual and hypothetical investment across firms for which $I_{it} - \hat{I}_{it}$ is *positive*, to obtain:

$$\text{POS}_t = \frac{\sum_{i, I_{it}-\hat{I}_{it} \geq 0} w_i (I_{i,t} - \hat{I}_{it})}{\sum_{i=1}^{N_t} w_i (K_{it} + K_{it-1})/2}. \tag{6}$$

The *net* effect of changes in FINVAR_{it} on the aggregate rate of capital accumulation at time t equals $\text{NET}_t = \text{POS}_t - \text{NEG}_t$. In addition, it is interesting to measure the *total* reallocation of investment due to changes in FINVAR_{it}.[41] The total amount of investment reallocation is measured as $\text{SUM}_t = \text{POS}_t + \text{NEG}_t$, whereas the amount of investment reallocation in *excess* of the minimum amount needed to accommodate the net investment change is $\text{EXC}_t = \text{SUM}_t - |\text{NET}_t|$.

We are also interested to measure how the reallocation of investment has impacted the efficiency of resource allocation. To do so, we compare the aggregate marginal value product of capital generated by actual investment, relative to that generated by counterfactual investment. We use the sales-to-capital ratio as the indicator firms' marginal-value product and compute the index:[42]

$$\text{EFF}_t = \frac{\sum_{i=1}^{N_t} (S_{i,t}/K_{i,t-1}) w_i I_{i,t}}{\sum_{i=1}^{N_t} (S_{i,t}/K_{i,t-1}) w_i \hat{I}_{i,t}}. \tag{7}$$

The index is less than one one if in year t actual investment was allocated less efficiently than counterfactual investment. The basic idea is to see whether or not resources are allocated to more profitable firms, relative to the counterfactual benchmark.

We can perform a similar analysis for the net change in employment. Let $\widehat{\Delta E_{it}}$ denote the

[41]See Herrera, Kolar, and Minetti (2013) for an analysis of credit reallocation across firms in U.S. states following deregulation of the credit markets. Their calculations and ours are in the spirit of Davis and Haltinwanger (1992).

[42]This is strictly speaking correct if firms share a common log-linear demand function and a Cobb-Douglas production function; see Galindo, Schiantarelli, and Weiss (2007).

counterfactual change in the number of employees. We have

$$\text{NEG}_t = \frac{\sum_{i,\Delta E_{it}-\widehat{\Delta E_{it}}<0} w_i|\Delta E_{it} - \widehat{\Delta E_{it}}|}{\sum_{i=1}^{N_t} w_i(E_{it} + E_{it-1})/2} \quad (8)$$

$$\text{POS}_t = \frac{\sum_{i,\Delta E_{it}-\widehat{\Delta E_{it}}>0} w_i|\Delta E_{it} - \widehat{\Delta E_{it}}|}{\sum_{i=1}^{N_t} w_i(E_{it} + E_{it-1})/2} \quad (9)$$

and

$$\text{EFF}_t = \frac{\sum_{i=1}^{N_t}(S_{i,t}/E_{i,t})w_i\widehat{\Delta E_{i,t}}}{\sum_{i=1}^{N_t}(S_{i,t}/E_{i,t})w_i\Delta E_{i,t}}. \quad (10)$$

Note that in the index above the counterfactual quantity appears at the numerator, rather than at the denominator as in equation (7). The index is defined in this way because, in all years, both numerator and denominator are negative—they are both positive in the case of investment. As a result, as in the case of investment, the index is less than one one if in year t the actual net change in employment was allocated less efficiently than the counterfactual employment change.

Results for aggregate investment are presented in Table 13, where we focus on the CDS spread as the cost-of-funding measure. With the only exception of 2009, the net effect of the change in banks' cost of funding on aggregate investment (NET_t) is negative, and sizable in 2011: -0.68%. In 2011 we also have the largest investment reallocation (SUM_t), 5.56% and the largest excess investment reallocation (EXC_t), 4.88%. These numbers are substantial, given that in 2011 the aggregate investment rate ($\sum_{i=1}^{N_t} w_{it}I_{it}/[\sum_{i=1}^{N_t} w_i(K_{it} + K_{it-1})/2]$) was only 0.33%. Turning now to the efficiency index (EFF_t), it is always less than one, as low as 0.90 and 0.91 in 2008 and 2011, respectively, indicating a 10% and 9% loss of allocative efficiency relative to the previous year. Hence, the 2011 sovereign debt crisis, through its effect on banks' cost of funding, lead to a significant reduction in the aggregate investment rate. In addition, both crises brought about a substantial reduction in the efficiency of capital allocation.

Results for the net aggregate change in employment are reported in Table 14. In the case of employment, the vast majority of the differentials relative to the counterfactual employment change are negative. Hence, the aggregate positive differential, POS_t, is essentially zero in all years, and the aggregate net differential, NET_t, is always negative and equal to $-\text{NEG}_t$. Moreover, the total amount of employment reallocation, SUM_t, equals NET_t, and, hence, the excess reallocation, EXC_t, equals zero. The aggregate net employment change is substantial in 2008 and 2011, representing reductions of 1.76% and 1.92%, respectively. As to the efficiency index, it is always less than one, reaching a minimum value of 0.89 in 2011, and the second lowest value, 0.97, in 2008, confirming that the two crises have led to a reduction in efficiency, with resources allocated away from the more profitable firms. This loss of allocative efficiency is noteworthy and consistent with the notion that at least some Italian banks engaged in the practice of "evergreening:" the delayed recognition of losses in a bank's loan portfolio, through the roll over of loans to high-risk and less profitable borrowers, in order not to further impair reported capital and earnings (Peek and Rosengren, 2005). Moreover, the previously-discussed insignificant interaction of banks' CDS with the firms' measures of creditworthiness is also consistent with the allocation of credit to Italian firms being driven by factors other than credit quality.[43]

4 Conclusions

This is the first paper to empirically investigate the link between market-based measures of banks' cost of funding and the decisions of client firms. Our analysis focuses on the Italian experience during the financial and sovereign debt crises. These two crises generate heterogeneous time-series variation in banks' financial valuations, depending upon their U.S. or sovereign debt exposure, and

[43] Albertazzi and Marchetti (2010) provide evidence consistent with evergreening on the part of Italian banks in the aftermath of the Lehman Brothers collapse.

this variation is crucial for our identification strategy. The Italian experience is especially interesting, as Italian firms are heavily dependent on bank lending. In our analysis, we take advantage of a unique data set, covering a large number of small, privately held firms, with information on firm-bank relationships.

We find robust evidence that higher banks' cost of funding leads young and small client firms to invest less, hire fewer workers, and reduce the growth of bank borrowing. Importantly, the effects that we document go over and beyond the effects of banks' balance-sheet variables and analyst earnings expectations. Among the financial variables used in our empirical work, CDS spreads are more informative than Tobin's Q for firm's decisions, indicating that the cost of debt matters more than the cost of equity. Moreover, both the level of CDS spreads and their (orthogonalized) volatility seem to matter. We conclude that financial volatility has real consequences, even for *privately held* firms, and that a key transmission channel is the banking system.

While our econometric analysis is performed at the firm level, it also has important aggregate implications. We find that, through their impact on banks' cost of funding, the 2008 and, especially, the 2011 crisis, lead to sizable reductions in the aggregate level and the allocative efficiency of capital accumulation and employment growth.

Appendix

A.1 Banks in the sample

CDS spreads are available for ten banking groups (covering a total of 96 individual banks; see numbers by group reported in parenthesis): Unicredit (9), Intesa Sanpaolo (32), Monte dei Paschi di Siena (4), Banca Nazionale del Lavoro, Banca Popolare di Milano (5), Banca Popolare dell'Emilia Romagna (14), Unione di Banche Italiane (14), Banco Popolare (12), Crédit Agricole (4), Deutsche Bank.

Equity valuations are available for 21 banking groups (covering a total of 123 individual banks; see numbers by group in parenthesis) including, in addition to the groups listed above, also: Tercas (3), Credito Emiliano, Cassa di Risparmio di Genova (4), Banca Popolare di Vicenza (3), Banca Popolare di Sondrio, Banca Sella, Veneto Banca (3), Credito Valtellinese (6), Banca Popolare dell'Etruria e del Lazio (3), Banco di Desio e della Brianza, Cassa di Risparmio di San Miniato.

A.2 Variable definitions

A.2.1 Firm-level variables

- I_{it}: gross investment—the change in gross capital over the year. Gross capital is defined as the sum of net capital (tangible fixed assets) and the accumulated depreciation on tangible assets.
- K_{it}: end-of-year net capital (tangible fixed assets).
- Sales_{it}: firm total sales over the year.
- Cash flow_{it}: cash flow over the year. Cash flow is defined as operating income before depreciation net of taxes payable, interest payments, non-operating income, and extraordinary items.
- Age_{it}: end-of-year age.
- Assets_{it}: end-of-year total assets.
- Altman score_{it}: Altman Z-score as computed in Altman, Hartzell, and Peck (1995): $Z''_{it} = 6.56X_{1,it} + 3.26X_{2,it} + 6.72X_{3,it} + 1.05X_{4,it}$ where $X_{1,it}$ to $X_{4,it}$ are (in order): working capital to total assets, retained earnings to total assets, EBIT to total assets, and book value of equity to total liabilities.

- PC of bal. sheet charact. is the first principal component of the following balance-sheet variables: sales to total assets, cash flow to total assets, floating capital to total assets, liquid assets to total assets, ROA, ROE, working capital to sales, equity and long term debt to fixed assets, long term debt to total debt, total debt to total assets, liquidity to short term debt, labor costs to value added, value added to sales. The first principal component explains the 35% of the total variance.
- Employees_{it}: end-of-year employees.
- Bank Debt_{it}: end-of-year stock of bank debt.
- Sales growth_{it}: rate of growth of sales between years $t-1$ and t.
- $\text{Tangible assets}_{it}$: end-of-year tangible assets.

A.2.2 Bank-level variables

- CDS_{it}: average of daily CDS spreads over the year.
- CDS vol_{it}: standard deviation of daily changes in the CDS spread over the year.
- Tobin's Q_{it}: average bank Tobin's Q over the year. Tobin's Q is defined as the ratio between the market value of the bank and the replacement cost of its assets, i.e., equity-market capitalization, plus liabilities, preferred equity, and minority interest, over total assets.
- Equity vol_{it}: standard deviation of daily continuously-compounded equity returns over the year.
- PC_{it}: first principal component extracted from CDS_{it}, CDS vol_{it}, Tobin's Q_{it}, and Equity vol_{it}.
- $\text{Sovereign debt held}_{it}$: end-of-year amount of Euro-denominated sovereign bonds held by the bank.
- $\text{\$ Assets}_{it}$: end-of-year amount of dollar-denominated assets held by the bank.
- $\text{CDS}_{ITA,t}$: average of daily five-year CDS spreads on Italian Treasury bonds over the year.
- $\text{CDS}_{US,t}$: average of daily five-year CDS spreads for the U.S. banking sector over the year.
- Exposure to U.S. banks: $\frac{\text{\$ Assets}_{i,2006}}{\text{Total assets}_{i,2006}} \times \text{CDS}_{US,t}$.
- Exposure to Italian sovereign debt: $\frac{\text{Sovereign debt held}_{i,2006}}{\text{Total assets}_{i,2006}} \times \text{CDS}_{ITA,t}$.

- Liquid assets$_{it}$: end-of-year liquid assets, defined as the sum of cash and equivalents, deposits with banks, loans to banks, deposits with central banks and government authorities, and other securities.
- Short-term funding$_{it}$: end-of-year short-term funding, defined as the sum of deposits and other short-term borrowing (loans with maturity less than one year).
- Tier 1 capital ratio$_{it}$: end-of-year Tier 1 capital ratio, defined as the ratio between Tier 1 regulatory capital and risk-weighted assets. Regulatory Tier 1 capital, is the sum of common equity—including equity injections from the government—and retained earnings.
- Deposits$_{it}$: end-of-year total deposits—the sum of customer deposits (current, savings, and term), bank deposits, and other deposits (those deposits that do not belong to the previous categories).
- Total funding$_{it}$: end-of-year total funding, defined as the sum of short- and long-term funding.
- Charge-offs$_{it}$: end-of-year total charge-offs, defined as those non-performing loans the bank recognizes to be no longer collectable.
- ROE$_{it}$: return on equity over the year, defined as the ratio between net income and total equity.
- Earnings forecasts$_{it-1:t+1}$ discounted sum of analyst earnings forecasts for years $t-1$, t and $t+1$. We compute the discounted sum of expected earnings at different horizons, with a discount rate of 0.967.
- PC (CDS, CDS vol)$_{it}$: first principal component of CDS spread and CDS-spread volatility. The factor loading are 0.71 and 0.70, respectively. The overall explained variance is 98%.
- PC (Tobin's Q, Equity vol)$_{it}$: first principal component of Tobin's Q and Equity vol. The factor loadings are -0.71 and 0.70, respectively. The overall explained variance is 70%.
- CDS vol. residual$_{it}$: residual of a pooled OLS regression of CDS vol$_{it}$ on CDS$_{it}$, with $\hat{\beta}_{\text{CDS}} = 0.88$ and $R^2 = 0.92$.
- Equity vol residual$_{it}$: residual of a pooled OLS regression of Equity vol$_{it}$ on Tobin's Q$_{it}$ with $\hat{\beta}_{\text{Tobin's Q}} = -.39$ and $R^2 = 0.16$.

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Table 1: Summary Statistics: Banks

	2006	**2007**	**2008**	**2009**	**2010**	**2011**
CDS_t	0.12%	0.18%	0.81%	1.02%	1.37%	2.83%
CDS vol_t	0.00%	0.02%	0.06%	0.05%	0.08%	0.15%
Tobin's Q_t	103%	100%	97.1%	97.1%	95.9%	95.7%
Equity vol_t	1.26%	1.37%	3.75%	3.21%	2.67%	4.15%
$\frac{\text{\$ assets}_t}{\text{Total assets}_t}$	6.32%	3.81%	2.84%	2.91%	2.96%	1.37%
$\frac{\text{Sovereign debt held}_t}{\text{Total assets}_t}$	1.85%	1.85%	2.68%	4.91%	7.09%	4.81%
$\frac{\text{Liquid assets}_t}{\text{Short-term funding}_t}$	6.97%	5.89%	4.41%	8.17%	8.67%	6.40%
$\text{Tier–1 capital ratio}_t$	6.93%	6.76%	6.68%	7.72%	8.90%	9.39%
$\frac{\text{Deposits}_t}{\text{Total funding}_t}$	45.0%	46.9%	46.6%	47.0%	46.5%	43.2%
$\frac{\text{Charge-offs}_t}{\text{Total assets}_t}$	1.75%	1.68%	1.94%	3.41%	4.06%	4.42%
$\frac{\text{Earnings forecasts}_{t-1:t+1}}{\text{Total assets}_{t-1}}$	0.76%	1.09%	0.91%	0.54%	0.39%	0.42%
ROE_t	11.7%	13.5%	6.67%	3.36%	5.12%	-15.2%

Notes: Median values of bank variables.

Table 2: Summary Statistics: Firms

	2006	**2007**	**2008**	**2009**	**2010**	**2011**
$\frac{I_t}{K_{t-1}}$	8.73%	7.86%	11.8%	3.53%	3.48%	3.12%
$\frac{\text{Cash flow}_t}{\text{K}_{t-1}}$	25.4%	26.9%	23.6%	15.8%	18.1%	17.5%
$\frac{\text{Sales}_t}{\text{K}_{t-1}}$	797%	805%	771%	573%	599%	599%
Sales growth_t	7.14%	5.88%	0.61%	-11.1%	3.29%	2.01%
$\Delta \ln(\text{Bank Debt})_t$	2.63%	5.66%	0.92%	-6.92%	0.00%	-0.49%
$\frac{\text{Bank debt}_t}{\text{Total assets}_t}$	26.1%	24.8%	26.8%	26.1%	26.3%	26.9%
$\frac{\text{Tangible assets}_t}{\text{Total assets}_t}$	14.7%	14.4%	13.8%	18.0%	16.9%	17.3%
Total assets_t (1m euro)	1.15	1.21	1.30	1.29	1.37	1.43
# Employees_t	12	12	14	13	13	13
Age_t	14	15	16	17	18	19

Notes: Median values of firm variables.

Table 3: Banking Relationships

	Type of banking relationship		
	Single	**Double**	**Multiple**
Age - Q1	87.5%	10.7%	1.79%
Age - Q2	84.3%	12.5%	3.13%
Age - Q3	83.6%	12.4%	4.03%
Age - Q4	80.5%	15.1%	4.46%
Size - Q1	86.4%	11.4%	2.27%
Size - Q2	87.2%	11.0%	1.75%
Size - Q3	82.2%	13.4%	4.49%
Size - Q4	76.7%	17.0%	6.32%
Total	83.0%	13.3%	3.77%

Notes: Percentage of firms with one, two, or multiple banking relationships, for different age and size quartiles.

Table 4: Firms' Investment and Banks' Valuations.

Dependent variable $\frac{I_t}{K_{t-1}}$

	(1)	(2)	(3)	(4)	(5)
FINVAR:	CDS	CDS vol	Tobin's Q	Equity vol	PC
FINVAR_t	-1.053***	-1.023***	2.021***	-0.901***	-1.380***
	(0.298)	(0.284)	(0.745)	(0.325)	(0.314)
$\text{FINVAR}_t \times \ln(1+\text{age}_t)$	0.297***	0.293***	-0.624***	0.268***	0.408***
	(0.0897)	(0.0838)	(0.222)	(0.0980)	(0.0953)
$\frac{\text{Sales}_t}{\text{K}_{t-1}}$	0.122***	0.128***	0.121***	0.135***	0.138***
	(0.0365)	(0.0381)	(0.0353)	(0.0418)	(0.0401)
$\frac{\text{Cash flow}_t}{\text{K}_{t-1}}$	0.132***	0.143***	0.126***	0.136***	0.141***
	(0.0279)	(0.0296)	(0.0312)	(0.0333)	(0.0291)
N	17085	16999	18349	17487	15590
Hansen p-value	0.736	0.718	0.420	0.442	0.868
AR(1) p-value	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.901	0.901	0.760	0.699	0.695
FINVAR:	CDS	CDS vol	Tobin's Q	Equity vol	PC
FINVAR_t	-2.487***	-2.991***	0.950***	-2.137**	-2.523***
	(0.833)	(0.951)	(0.342)	(0.835)	(0.633)
$\text{FINVAR}_t \times \ln(\text{Total assets}_{t-1})$	0.256***	0.311***	-0.106***	0.226**	0.262***
	(0.0886)	(0.101)	(0.0367)	(0.0883)	(0.0675)
$\frac{\text{Sales}_t}{\text{K}_{t-1}}$	0.102***	0.127***	0.125***	0.0978***	0.107***
	(0.0389)	(0.0414)	(0.0409)	(0.0373)	(0.0394)
$\frac{\text{Cash flow}_t}{\text{K}_{t-1}}$	0.151***	0.160***	0.138***	0.142***	0.138***
	(0.0303)	(0.0334)	(0.0367)	(0.0329)	(0.0315)
N	17113	17027	18380	17519	15616
Hansen p-value	0.508	0.579	0.182	0.184	0.344
AR(1) p-value	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.820	0.623	0.856	0.889	0.656

Notes: System GMM with firm- and year-specific effects. Additional controls (omitting the i subscript): $\ln(1+\text{age}_t)$ or $\ln(\text{assets}_{t-1})$. "CDS" is the average of daily bank CDS spreads over the year, "CDS vol" is the standard deviation of daily changes in the bank CDS spreads over the year, "Tobin's Q" is the average bank Tobin's Q over the year, "Equity vol" is the standard deviation of daily returns over the year, and "PC" is the first principal component of the previous four variables. Variables normalized by their standard deviation. Set of instruments: $\frac{\text{Sales}_t}{K_{t-1}}$, $\frac{\text{Cash flow}_t}{K_{t-1}}$, and exposure to Italian sovereign debt and U.S. banks (and their interactions), all lagged two or three periods. Robust standard errors in parentheses. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$. "Hansen" denotes the test of over-identifying restrictions; "AR(q)" denotes the Arellano and Bond (1991) test of q^{th} order serial correlation.

Table 5: Firms' Investment and Banks' Valuations: Robustness.

		CDS_t	$CDS_t \times \ln(1+age_t)$	Hansen p
Subsample	Single bank relationships	-1.265***	0.351***	0.550
		(0.352)	(0.105)	
Instruments for CDS_t	Exogenous	-1.443***	0.416***	0.206
		(0.425)	(0.122)	
	Internal	-0.946***	0.262***	0.368
		(0.337)	(0.097)	
	External (t)	-1.343***	0.394***	0.284
		(0.407)	(0.121)	
Additional controls	Altman score	-0.712***	0.196***	0.456
		(0.184)	(0.055)	
	PC of bal. sheet charact.	-0.658***	0.177**	0.182
		(0.250)	(0.741)	
Alternative year effects	Common	-1.053***	0.297***	0.736
		(0.298)	(0.089)	
	Industry	-0.978***	0.272***	0.636
		(0.333)	(0.099)	
	Region	-0.996***	0.279***	0.675
		(0.327)	(0.098)	
	Firm age	-1.258***	0.358***	0.479
		(0.411)	(0.121)	
	Firm size	-0.978***	0.274***	0.460
		(0.324)	(0.097)	
	Bank size	-1.011***	0.281***	0.499
		(0.311)	(0.091)	
Estimation	Difference GMM	-1.511***	0.440***	0.482
		(0.453)	(0.131)	

Notes: System GMM with firm- and year-specific effects. Additional controls (omitting the i subscript): $\frac{Sales_t}{K_{t-1}}$, $\frac{Cash\ flow_t}{K_{t-1}}$, $\ln(1 + age_t)$, $\ln(assets_{t-1})$. Column 1, 2, and 3 report, respectively, the coefficients of CDS_t and $CDS_t \times \ln(1 + age_t)$, and the Hansen p-value of each specification. The top panel report the baseline estimation on the subset of firms with single bank relationship. The second panel presents three different set of instruments for CDS_t: not instrumented (Exogenous), instrumented with lagged values of included variables (Internal instruments) or with contemporaneous exposures to Italian sovereign debt and U.S. banks. The third panel augments the baseline specification with two alternative measures of firms' creditworthiness: the Altman Z-score as in Altman, Hartzell, and Peck (1995) (Altman score) or the principal component of several measures of financial solidity (PC of bal. sheet charact.). The fourth panel presents alternative specifications of the year effects. Time fixed effects are either common across all firms (Common), or vary by 12 industries (Industry), by 20 geographical regions (Region), by old and young firms (Firm age), by small and large firms (Firm size) or by small and large banks (Bank size). The threshold to identify small and large or young and old is the median of the respective distribution. The last panel presents the baseline specification estimated with difference GMM (Difference GMM). "CDS" is the average of daily bank CDS spreads over the year. Variables are normalized by their standard deviation. Robust standard errors in parentheses. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table 6: Firms' Investment and Banks' Valuations, Controlling for Banks' Balance-sheet Variables.

Dependent variable $\frac{I_t}{K_{t-1}}$

FINVAR:	(1) CDS	(2) CDS vol	(3) Tobin's Q	(4) Equity vol	(5) PC
FINVAR_t	-0.906***	-1.711***	2.612**	-1.131**	-1.645***
	(0.345)	(0.615)	(1.282)	(0.485)	(0.602)
$\text{FINVAR}_t \times \ln(1+\text{age}_t)$	0.263***	0.472***	-0.793**	0.339**	0.465**
	(0.0993)	(0.178)	(0.379)	(0.147)	(0.183)
$\frac{\text{\$ assets}_{t-1}}{\text{Total assets}_{t-1}}$	0.186	0.888	1.129	-0.175	0.120
	(0.583)	(0.642)	(0.836)	(0.716)	(0.759)
$\frac{\text{\$ assets}_{t-1}}{\text{Total assets}_{t-1}} \times \ln(1+\text{age}_t)$	-0.0486	-0.259	-0.360	0.0431	-0.0358
	(0.171)	(0.185)	(0.252)	(0.212)	(0.220)
$\frac{\text{Sovereign debt held}_{t-1}}{\text{Total assets}_{t-1}}$	-0.192	0.0786	-0.299	0.297	0.950
	(0.360)	(0.723)	(0.465)	(0.386)	(0.758)
$\frac{\text{Sovereign debt held}_{t-1}}{\text{Total assets}_{t-1}} \times \ln(1+\text{age}_t)$	0.0545	-0.0294	0.0817	-0.0891	-0.284
	(0.107)	(0.212)	(0.134)	(0.111)	(0.223)
$\frac{\text{Liquid assets}_{t-1}}{\text{Short-term funding}_{t-1}}$	0.141	0.0720	0.642	-0.370	-0.392
	(0.240)	(0.377)	(0.468)	(0.351)	(0.396)
$\frac{\text{Liquid assets}_{t-1}}{\text{Short-term funding}_{t-1}} \times \ln(1+\text{age}_t)$	-0.0417	-0.0187	-0.186	0.110	0.116
	(0.0702)	(0.110)	(0.137)	(0.102)	(0.115)
Tier–1 capital ratio_{t-1}	0.0421	0.0754	-0.0262	-0.0431	0.0675
	(0.0336)	(0.0529)	(0.0310)	(0.0325)	(0.0578)
Tier–1 capital $\text{ratio}_{t-1} \times \ln(1+\text{age}_t)$	-0.0143	-0.0192	0.00849	0.0135	-0.0113
	(0.0105)	(0.0133)	(0.00878)	(0.00881)	(0.0143)
$\frac{\text{Deposits}_{t-1}}{\text{Total funding}_{t-1}}$	-0.251	-0.0713	0.0754	0.376	-0.116
	(0.288)	(0.438)	(0.389)	(0.467)	(0.485)
$\frac{\text{Deposits}_{t-1}}{\text{Total funding}_{t-1}} \times \ln(1+\text{age}_t)$	0.0738	0.0361	-0.0199	-0.112	0.0464
	(0.0843)	(0.127)	(0.113)	(0.135)	(0.141)
$\frac{\text{Charge-offs}_{t-1}}{\text{Total assets}_{t-1}}$	0.512	-0.188	-0.295	-1.106*	-0.778
	(0.354)	(0.808)	(0.804)	(0.581)	(0.707)
$\frac{\text{Charge-offs}_{t-1}}{\text{Total assets}_{t-1}} \times \ln(1+\text{age}_t)$	-0.149	0.0764	0.0775	0.330**	0.242
	(0.104)	(0.239)	(0.233)	(0.166)	(0.209)
N	14947	14940	16207	15427	13809
Hansen p-value	0.252	0.462	0.151	0.374	0.436
AR(1) p-value	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.848	0.300	0.549	0.913	0.570

Notes: System GMM with firm- and year-specific effects. Additional controls (omitting the i subscript): $\ln(1+\text{age}_t)$. "CDS" is the average of daily bank CDS spreads over the year, "CDS vol" is the standard deviation of daily changes in the bank CDS spreads over the year, "Tobin's Q" is the average bank Tobin's Q over the year, "Equity vol" is the standard deviation of daily returns over the year, and "PC" is the first principal component of the previous four variables. Variables normalized by their standard deviation. Set of instruments: $\frac{\text{Sales}_t}{K_{t-1}}$, $\frac{\text{Cash flow}_t}{K_{t-1}}$, bank balance sheet variables, and exposure to Italian sovereign debt and U.S. banks (and their interactions), all lagged two or three periods. Robust standard errors in parentheses. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$. "Hansen" denotes the test of over-identifying restrictions; "AR(q)" denotes the Arellano and Bond (1991) test of q^{th} order serial correlation.

Table 7: Firms' Investment and Banks' Valuations, Controlling for Bank Losses due to the Lehman and Sovereign Debt Crises and Earnings.

Dependent variable $\frac{I_t}{K_{t-1}}$

FINVAR:	(1) CDS	(2) CDS vol	(3) Tobin's Q	(4) Equity vol	(5) PC
FINVAR_t	-1.811***	-1.430***	1.418*	-0.764**	-1.518**
	(0.605)	(0.551)	(0.826)	(0.364)	(0.687)
$\text{FINVAR}_t \times \ln(1+\text{age}_t)$	0.522***	0.399**	-0.411*	0.219**	0.434**
	(0.178)	(0.164)	(0.243)	(0.107)	(0.207)
$\frac{\$\text{ assets}_{t-1}}{\text{Total assets}_{t-1}} \times \Delta\text{CDS}_{US,t}$	-0.314	0.117	0.963	-0.0456	-0.0562
	(0.655)	(0.700)	(0.753)	(0.680)	(0.791)
$\frac{\$\text{ assets}_{t-1}}{\text{Total assets}_{t-1}} \times \Delta\text{CDS}_{US,t} \times \ln(1+\text{age}_t)$	0.0825	-0.0331	-0.291	0.0147	0.0119
	(0.198)	(0.213)	(0.222)	(0.202)	(0.238)
$\frac{\text{Sovereign debt held}_{t-1}}{\text{Total assets}_{t-1}} \times \Delta\text{CDS}_{ITA,t}$	0.0989	0.0125	0.0202	-0.776**	-0.108
	(0.392)	(0.383)	(0.361)	(0.310)	(0.413)
$\frac{\text{Sovereign debt held}_{t-1}}{\text{Total assets}_{t-1}} \times \Delta\text{CDS}_{ITA,t} \times \ln(1+\text{age}_t)$	-0.0334	-0.00375	-0.0149	0.208**	0.0172
	(0.114)	(0.111)	(0.100)	(0.0897)	(0.119)
ROE_t	-0.617	-0.128	0.487	0.308	-0.196
	(0.578)	(0.472)	(0.448)	(0.445)	(0.611)
$\text{ROE}_t \times \ln(1+\text{age}_t)$	0.179	0.0326	-0.146	-0.0979	0.0475
	(0.172)	(0.138)	(0.128)	(0.127)	(0.184)
$\frac{\text{Sales}_t}{\text{K}_{t-1}}$	0.129***	0.122***	0.123***	0.116***	0.119***
	(0.0320)	(0.0322)	(0.0330)	(0.0316)	(0.0366)
$\frac{\text{Cash flow}_t}{\text{K}_{t-1}}$	0.144***	0.146***	0.109***	0.141***	0.154***
	(0.0317)	(0.0302)	(0.0333)	(0.0275)	(0.0331)
N	16145	16381	17605	16752	15099
Hansen p-value	0.724	0.599	0.264	0.688	0.590
AR(1) p-value	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.857	0.912	0.756	0.811	0.840

Notes: System GMM with firm- and year-specific effects. Additional controls (omitting the i subscript): $\ln(1+\text{age}_t)$. "CDS" is the average of daily bank CDS spreads over the year, "CDS vol" is the standard deviation of daily changes in the bank CDS spreads over the year, "Tobin's Q" is the average bank Tobin's Q over the year, "Equity vol" is the standard deviation of daily returns over the year, and "PC" is the first principal component of the previous four variables. Variables normalized by their standard deviation. Set of instruments: $\frac{\text{Sales}_t}{K_{t-1}}$, $\frac{\text{Cash flow}_t}{K_{t-1}}$, bank profitability variables, and exposure to Italian sovereign debt and U.S. banks (and their interactions), all lagged two or three periods. Robust standard errors in parentheses. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$. "Hansen" denotes the test of over-identifying restrictions; "AR(q)" denotes the Arellano and Bond (1991) test of q^{th} order serial correlation.

Table 8: Firms' Investment and Banks' Valuations, Controlling for Analyst Earnings Forecasts.

Dependent variable $\frac{I_t}{K_{t-1}}$

	(1)	(2)	(3)	(4)	(5)
FINVAR:	CDS	CDS vol	Tobin's Q	Equity vol	PC
FINVAR_t	-0.957***	-1.220***	1.826***	-1.039***	-1.002***
	(0.352)	(0.404)	(0.609)	(0.342)	(0.380)
$\text{FINVAR}_t \times \ln(1+\text{age}_t)$	0.266**	0.331***	-0.530***	0.312***	0.284**
	(0.103)	(0.120)	(0.179)	(0.105)	(0.113)
$\frac{\text{Earnings forecasts}_{t-1:t+1}}{\text{Total assets}_{t-1}}$	0.634**	0.679**	0.403**	0.541**	0.567**
	(0.308)	(0.314)	(0.185)	(0.232)	(0.278)
$\frac{\text{Earnings forecasts}_{t-1:t+1}}{\text{Total assets}_{t-1}} \times \ln(1+\text{age}_t)$	-0.194**	-0.206**	-0.121**	-0.164**	-0.173**
	(0.0949)	(0.0974)	(0.0560)	(0.0707)	(0.0856)
$\frac{\text{Sales}_t}{\text{K}_{t-1}}$	0.158**	0.183***	0.222***	0.125***	0.149**
	(0.0676)	(0.0682)	(0.0617)	(0.0414)	(0.0734)
$\frac{\text{Cash flow}_t}{\text{K}_{t-1}}$	0.128***	0.103***	0.0664*	0.119***	0.111***
	(0.0349)	(0.0359)	(0.0348)	(0.0321)	(0.0363)
N	16596	16832	18056	17243	15590
Hansen p-value	0.582	0.765	0.176	0.193	0.500
AR(1) p-value	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.530	0.303	0.998	0.603	0.442

Notes: System GMM with firm- and year-specific effects. Additional controls (omitting the i subscript): $\ln(1+\text{age}_t)$. "CDS" is the average of daily bank CDS spreads over the year, "CDS vol" is the standard deviation of daily changes in the bank CDS spreads over the year, "Tobin's Q" is the average bank Tobin's Q over the year, "Equity vol" is the standard deviation of daily returns over the year, and "PC" is the first principal component of the previous four variables. Earnings forecasts_t denotes the discounted sum of analyst earnings forecasts for years $t-1$, t and $t+1$. Variables normalized by their standard deviation. Set of instruments: $\frac{\text{Sales}_t}{K_{t-1}}$, $\frac{\text{Cash flow}_t}{K_{t-1}}$, Earnings forecasts_t, and exposure to Italian sovereign debt and U.S. banks (and their interactions), all lagged two or three periods. Robust standard errors in parentheses. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$. "Hansen" denotes the test of over-identifying restrictions; "AR(q)" denotes the Arellano and Bond (1991) test of q^{th} order serial correlation.

Table 9: Firms' Investment and Banks' Valuations, CDS v. Tobin's Q.

Dependent variable $\frac{I_t}{K_{t-1}}$

	(1)	(2)	(3)
CDS_t	-1.159***		
	(0.417)		
$\text{CDS}_t \times \ln(1+\text{age}_t)$	0.325***		
	(0.124)		
Tobin's Q_t	0.00526		
	(0.840)		
Tobin's $\text{Q}_t \times \ln(1+\text{age}_t)$	0.0126		
	(0.248)		
CDS vol_t		-1.642***	
		(0.550)	
CDS $\text{vol}_t \times \ln(1+\text{age}_t)$		0.460***	
		(0.154)	
Equity vol_t		0.531	
		(0.430)	
Equity $\text{vol}_t \times \ln(1+\text{age}_t)$		-0.157	
		(0.127)	
PC (CDS, CDS $\text{vol})_t$			-1.460***
			(0.542)
PC (CDS, CDS $\text{vol})_t \times \ln(1+\text{age}_t)$			0.419***
			(0.156)
PC (Q, Equity $\text{vol})_t$			0.716
			(0.640)
PC (Q, Equity $\text{vol})_t \times \ln(1+\text{age}_t)$			-0.220
			(0.193)
$\frac{\text{Sales}_t}{\text{K}_{t-1}}$	0.125***	0.120***	0.122***
	(0.0380)	(0.0360)	(0.0365)
$\frac{\text{Cash flow}_t}{\text{K}_{t-1}}$	0.141***	0.149***	0.136***
	(0.0290)	(0.0316)	(0.0287)
N	16762	16028	15590
Hansen p-value	0.577	0.720	0.531
AR(1) p-value	0.000	0.000	0.000
AR(2) p-value	0.792	0.600	0.703

Notes: System GMM with firm- and year-specific effects. Additional controls (omitting the i subscript): $\ln(1+\text{age}_t)$. "CDS" is the average of daily bank CDS spreads over the year, "CDS vol" is the standard deviation of daily changes in the bank CDS spreads over the year, "Tobin's Q" is the average bank Tobin's Q over the year, "Equity vol" is the standard deviation of daily returns over the year, and "PC" is the first principal component of the previous four variables. Variables normalized by their standard deviation. Set of instruments: $\frac{\text{Sales}_t}{K_{t-1}}$, $\frac{\text{Cash flow}_t}{K_{t-1}}$, and exposure to Italian sovereign debt and U.S. banks (and their interactions), all lagged two or three periods. Robust standard errors in parentheses. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$. "Hansen" denotes the test of over-identifying restrictions; "AR(q)" denotes the Arellano and Bond (1991) test of q^{th} order serial correlation.

Table 10: Firms' Investment and Banks' Valuations, Levels v. Volatilities.

Dependent variable $\frac{I_t}{K_{t-1}}$

	(1)	(2)
CDS_t	-0.150***	
	(0.0549)	
$\text{CDS}_t \times \ln(1+\text{age}_t)$	0.0320***	
	(0.00973)	
CDS vol residual_t	-0.416***	
	(0.0509)	
CDS vol $\text{residual}_t \times \ln(1+\text{age}_t)$	0.117***	
	(0.0140)	
Tobin's Q_t		1.596**
		(0.720)
Tobin's $\text{Q}_t \times \ln(1+\text{age}_t)$		-0.475**
		(0.209)
Equity vol residual_t		-0.935***
		(0.350)
Equity vol $\text{residual}_t \times \ln(1+\text{age}_t)$		0.281***
		(0.105)
$\frac{\text{Sales}_t}{\text{K}_{t-1}}$	0.114***	0.115***
	(0.0334)	(0.0372)
$\frac{\text{Cash flow}_t}{\text{K}_{t-1}}$	0.148***	0.133***
	(0.0299)	(0.0314)
N	16560	17271
Hansen p-value	0.282	0.290
AR(1) p-value	0.000	0.000
AR(2) p-value	0.620	0.945

Notes: System GMM with firm- and year-specific effects. Additional controls (omitting the i subscript): $\ln(1+\text{age}_t)$. "CDS" is the average of daily bank CDS spreads over the year, "CDS vol" is the standard deviation of daily changes in the bank CDS spreads over the year, "Tobin's Q" is the average bank Tobin's Q over the year, "Equity vol" is the standard deviation of daily returns over the year, and "PC" is the first principal component of the previous four variables. Variables normalized by their standard deviation. Set of instruments: $\frac{\text{Sales}_t}{K_{t-1}}$, $\frac{\text{Cash flow}_t}{K_{t-1}}$, and exposure to Italian sovereign debt and U.S. banks (and their interactions), all lagged two or three periods. Robust standard errors in parentheses. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$. "Hansen" denotes the test of over-identifying restrictions; "AR(q)" denotes the Arellano and Bond (1991) test of q^{th} order serial correlation.

Table 11: Firms' Employment and Banks' Valuations.

Dependent variable: $\Delta \ln(\text{Employees})_t$

FINVAR:	(1) CDS	(2) CDS vol	(3) Tobin's Q	(4) Equity vol	(5) PC
FINVAR_t	-0.261***	-0.428**	0.769***	-0.00564	-0.376**
	(0.0812)	(0.184)	(0.235)	(0.0974)	(0.178)
$\text{FINVAR}_t \times \ln(1+\text{age}_t)$	0.0492***	0.0535***	-0.231***	0.0296	0.0458**
	(0.0139)	(0.0175)	(0.0587)	(0.0200)	(0.0218)
$\ln(\text{Employees}_{t-1})$	-0.00984	0.000291	0.0167	-0.111*	-0.139**
	(0.0442)	(0.0521)	(0.0330)	(0.0619)	(0.0699)
$\frac{\text{Sales}_t}{\text{Total assets}_{t-1}}$	0.0226	0.0256	0.174*	-0.0803	0.0208
	(0.108)	(0.135)	(0.0984)	(0.133)	(0.138)
$\frac{\text{Cash flow}_t}{\text{Total assets}_{t-1}}$	0.305***	0.346***	0.329***	0.340***	0.354***
	(0.0836)	(0.0944)	(0.0877)	(0.0938)	(0.104)
N	15466	15433	16262	15301	14082
Hansen p-value	0.184	0.177	0.334	0.375	0.558
AR(1) p-value	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.170	0.303	0.352	0.558	0.367
FINVAR:	CDS	CDS vol	Tobin's Q	Equity vol	PC
FINVAR_t	-0.515***	-0.643**	2.868**	-0.226	-0.592**
	(0.178)	(0.265)	(1.115)	(0.256)	(0.276)
$\text{FINVAR}_t \times \ln(\text{Total assets}_{t-1})$	0.0438***	0.0586***	-0.289***	0.0293	0.0598***
	(0.0154)	(0.0195)	(0.109)	(0.0235)	(0.0232)
$\ln(\text{Employees}_{t-1})$	0.0304	0.181	0.386*	0.0428	0.0466
	(0.111)	(0.167)	(0.220)	(0.161)	(0.166)
$\frac{\text{Sales}_t}{\text{Total assets}_{t-1}}$	0.236**	0.166	0.104	0.00702	0.00625
	(0.105)	(0.155)	(0.161)	(0.117)	(0.124)
$\frac{\text{Cash flow}_t}{\text{Total assets}_{t-1}}$	0.316***	0.369***	0.501***	0.317***	0.381***
	(0.0835)	(0.112)	(0.125)	(0.0813)	(0.0880)
N	15513	15481	16311	15340	14119
Hansen p-value	0.376	0.312	0.684	0.461	0.532
AR(1) p-value	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.177	0.301	0.358	0.567	0.349

Notes: System GMM with firm- and year-specific effects. Additional controls (omitting the i subscript): $\ln(1+\text{age}_t)$ or $\ln(\text{assets}_{t-1})$. "CDS" is the average of daily bank CDS spreads over the year, "CDS vol" is the standard deviation of daily changes in the bank CDS spreads over the year, "Tobin's Q" is the average bank Tobin's Q over the year, "Equity vol" is the standard deviation of daily returns over the year, and "PC" is the first principal component of the previous four variables. Variables normalized by their standard deviation. Set of instruments: $\frac{\text{Sales}_t}{\text{Total assets}_{t-1}}$, $\frac{\text{Cash flow}_t}{\text{Total assets}_{t-1}}$, $\ln(\text{Employees}_t)$, and exposure to Italian sovereign debt and U.S. banks (and their interactions), all lagged two or three periods. Robust standard errors in parentheses. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$. "Hansen" denotes the test of over-identifying restrictions; "AR(q)" denotes the Arellano and Bond (1991) test of q^{th} order serial correlation.

Table 12: Firms' Bank Borrowing and Banks' Valuations.

Dependent variable: $\Delta \ln(\text{Bank Debt})_t$

	(1)	(2)	(3)	(4)	(5)
FINVAR:	CDS	CDS vol	Tobin's Q	Equity vol	PC
FINVAR_t	-0.111***	-0.122***	0.182**	-0.0719**	-0.132***
	(0.0429)	(0.0463)	(0.0816)	(0.0295)	(0.0508)
$\text{FINVAR}_t \times \ln(1+\text{age}_t)$	0.0181***	0.0121**	-0.0560***	0.0149**	0.0216***
	(0.00534)	(0.00566)	(0.0183)	(0.00660)	(0.00601)
$\ln(\text{Bank debt}_{t-1})$	-0.0288***	-0.0285**	-0.0287**	-0.0329**	-0.0285**
	(0.00955)	(0.0114)	(0.0128)	(0.0140)	(0.0124)
N	10574	10520	11015	10499	9761
Hansen p-value	0.969	0.743	0.999	0.977	0.998
AR(1) p-value	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.233	0.227	0.477	0.436	0.192
FINVAR:	CDS	CDS vol	Tobin's Q	Equity vol	PC
FINVAR_t	-0.355***	-0.442**	1.032**	-0.602***	-0.710***
	(0.137)	(0.175)	(0.460)	(0.190)	(0.201)
$\text{FINVAR}_t \times \ln(\text{assets}_{t-1})$	0.0274**	0.0338**	-0.0992**	0.0559***	0.0600***
	(0.0123)	(0.0159)	(0.0434)	(0.0176)	(0.0185)
$\ln(\text{Bank debt}_{t-1})$	-0.0284***	-0.0200**	-0.0270**	-0.0113	-0.0145
	(0.00975)	(0.0102)	(0.0120)	(0.00983)	(0.0102)
N	10574	10572	11015	10541	9802
Hansen p-value	0.986	0.851	0.658	0.879	0.982
AR(1) p-value	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.230	0.228	0.482	0.464	0.206

Notes: System GMM with firm- and year-specific effects. Additional controls (omitting the i subscript): Sales growth_{t-1}, $\frac{\text{Tangible assets}_{t-1}}{\text{Total assets}_{t-1}}$, $\frac{\text{Sales}_t}{\text{Total assets}_{t-1}}$, $\frac{\text{Cash flow}_t}{\text{Total assets}_{t-1}}$, $\ln(1+\text{age}_t)$ or $\ln(\text{assets}_{t-1})$. "CDS" is the average of daily bank CDS spreads over the year, "CDS vol" is the standard deviation of daily changes in the bank CDS spreads over the year, "Tobin's Q" is the average bank Tobin's Q over the year, "Equity vol" is the standard deviation of daily returns over the year, and "PC" is the first principal component of the previous four variables. Variables normalized by their standard deviation. Set of instruments: $\frac{\text{Sales}_t}{\text{Total assets}_{t-1}}$, $\frac{\text{Cash flow}_t}{\text{Total assets}_{t-1}}$, Sales growth_t, $\frac{\text{Tangible assets}_{t-1}}{\text{Total assets}_{t-1}}$, and exposure to Italian sovereign debt and U.S. banks (and their interactions), all lagged two or three periods. Robust standard errors in parentheses. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$. "Hansen" denotes the test of over-identifying restrictions; "AR(q)" denotes the Arellano and Bond (1991) test of q^{th} order serial correlation.

Table 13: Aggregate effects and allocative efficiency: investment.

	(1) NEG	(2) POS	(3) NET	(4) SUM	(5) EXC	(6) EFF
$(\text{CDS}_{it} - \text{CDS}_{it-1})$						
2007	0.08%	0.04%	-0.04%	0.12%	0.08%	0.98
2008	0.54%	0.43%	-0.11%	0.97%	0.86%	0.90
2009	0.22%	0.38%	0.16%	0.60%	0.44%	0.93
2010	0.70%	0.60%	-0.10%	1.30%	1.20%	0.97
2011	3.12%	2.44%	-0.68%	5.56%	4.88%	0.91
Average	0.93%	0.77%	-0.16%	1.71%	1.49%	0.94

Notes: Aggregate effects of ΔCDS_{it} on firms' capital accumulation. The table refers to the difference between the actual investment and the counterfactual investment if banks' CDS spreads had stayed at the previous year's level. NEG_t is the ratio between the aggregate negative difference and the aggregate average capital over the current and previous year (see equation (5)). POS_t is the ratio between the aggregate positive difference and the previous year's total capital (see equation (6)). NET_t is defined as $\text{NET}_t = \text{POS}_t - \text{NEG}_t$; SUM_t is defined as $\text{SUM}_t = \text{POS}_t + \text{NEG}_t$. EXC_t is defined as $\text{EXC}_t = \text{SUM}_t - |\text{NET}_t|$. EFF_t is the measure of allocative efficiency defined in equation (7).

Table 14: Aggregate effects and allocative efficiency: employment.

	(1) NEG	(2) POS	(3) NET	(4) SUM	(5) EXC	(6) EFF
$(\text{CDS}_{it} - \text{CDS}_{it-1})$						
2007	0.14%	0.00%	-0.14%	0.14%	0.00%	0.99
2008	1.76%	0.00%	-1.76%	1.76%	0.00%	0.97
2009	0.34%	0.00%	-0.34%	0.34%	0.00%	0.99
2010	0.38%	0.00%	-0.38%	0.38%	0.00%	0.99
2011	1.92%	0.00%	-1.92%	1.92%	0.00%	0.89
Average	0.91%	0.00%	-0.91%	0.91%	0.00%	0.96

Notes: Aggregate effects of ΔCDS_{it} on firms' employment. The table refers to the difference between the actual employment and the counterfactual employment if banks' CDS spreads had stayed at the previous year's level. NEG_t is the ratio between the aggregate negative difference and the aggregate average employment over the current and the previous year's total employment (see equation (8)). POS_t is the ratio between the aggregate positive difference and the aggregate average employment over the current and previous year total employment (see equation (9)). NET_t is defined as $\text{NET}_t = \text{POS}_t - \text{NEG}_t$; SUM_t is defined as $\text{SUM}_t = \text{POS}_t + \text{NEG}_t$. EXC_t is defined as $\text{EXC}_t = \text{SUM}_t - |\text{NET}_t|$. EFF_t is the measure of allocative efficiency defined in equation (10).

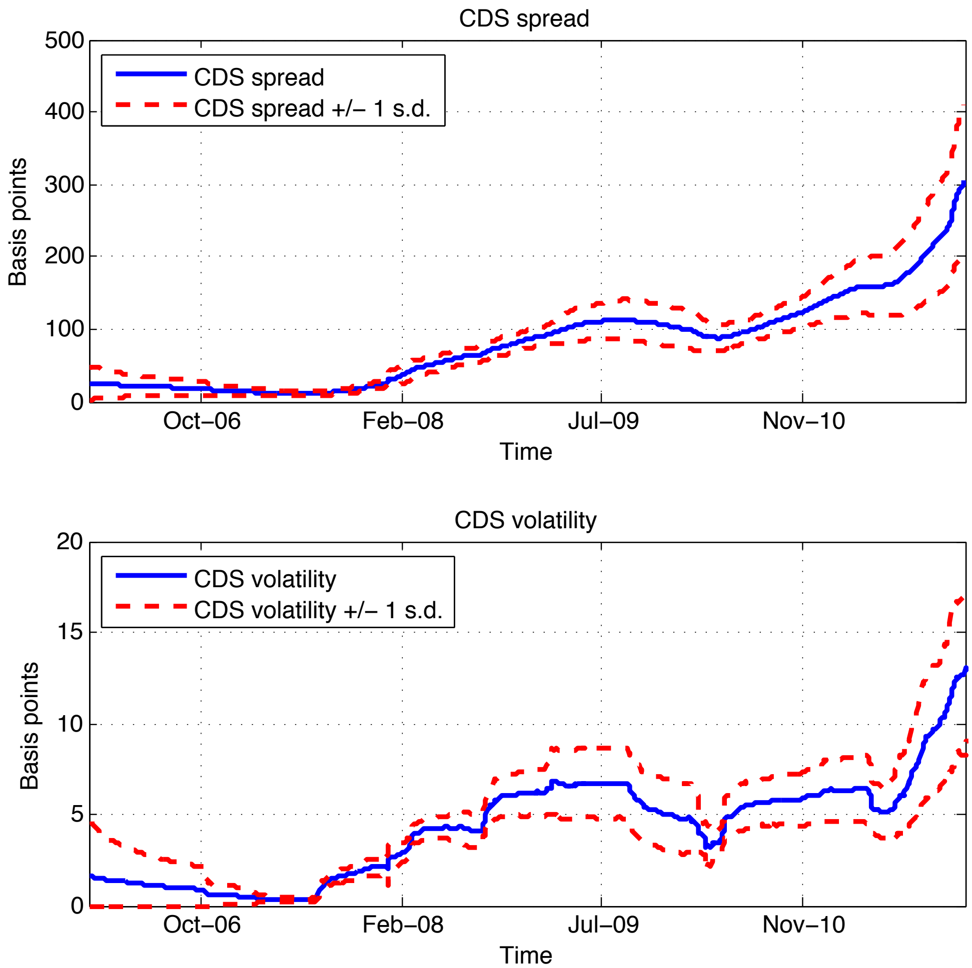

Figure 1: Level and volatility of the CDS spreads for Italian banks (2006–2011).

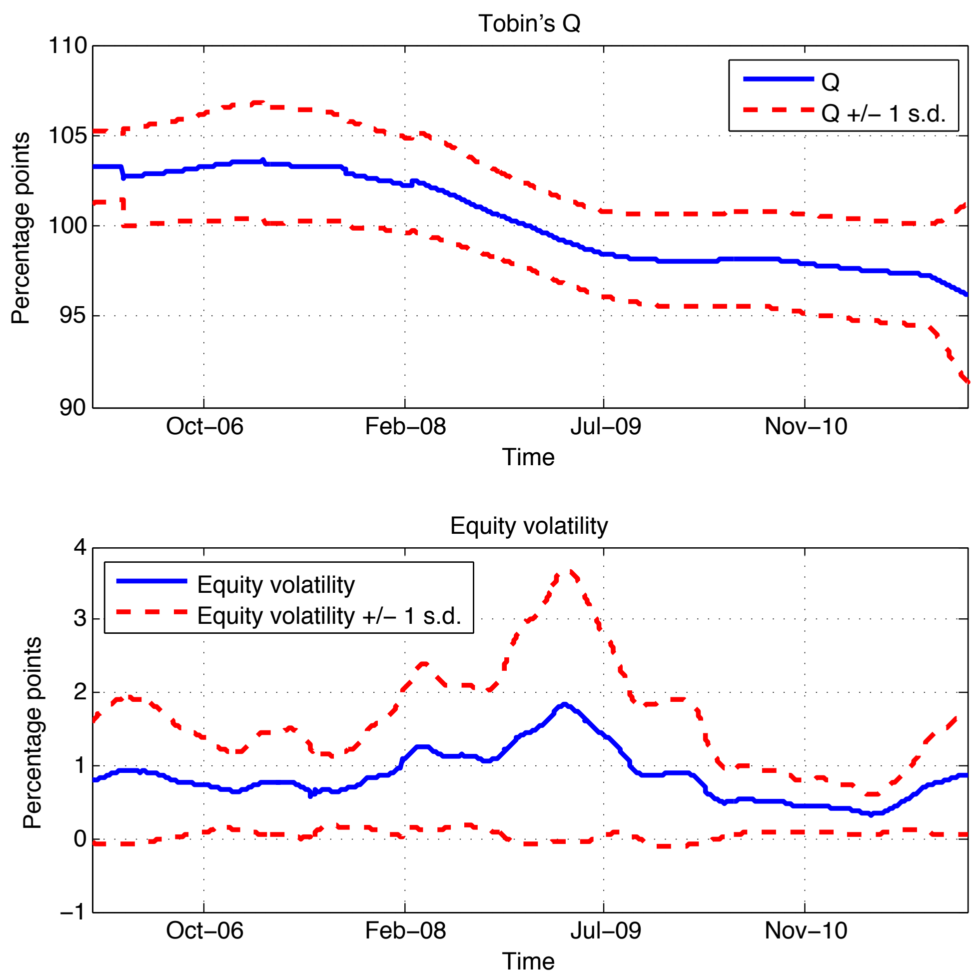

Figure 2: Level and volatility of the stock market valuations for Italian banks (2006–2011).

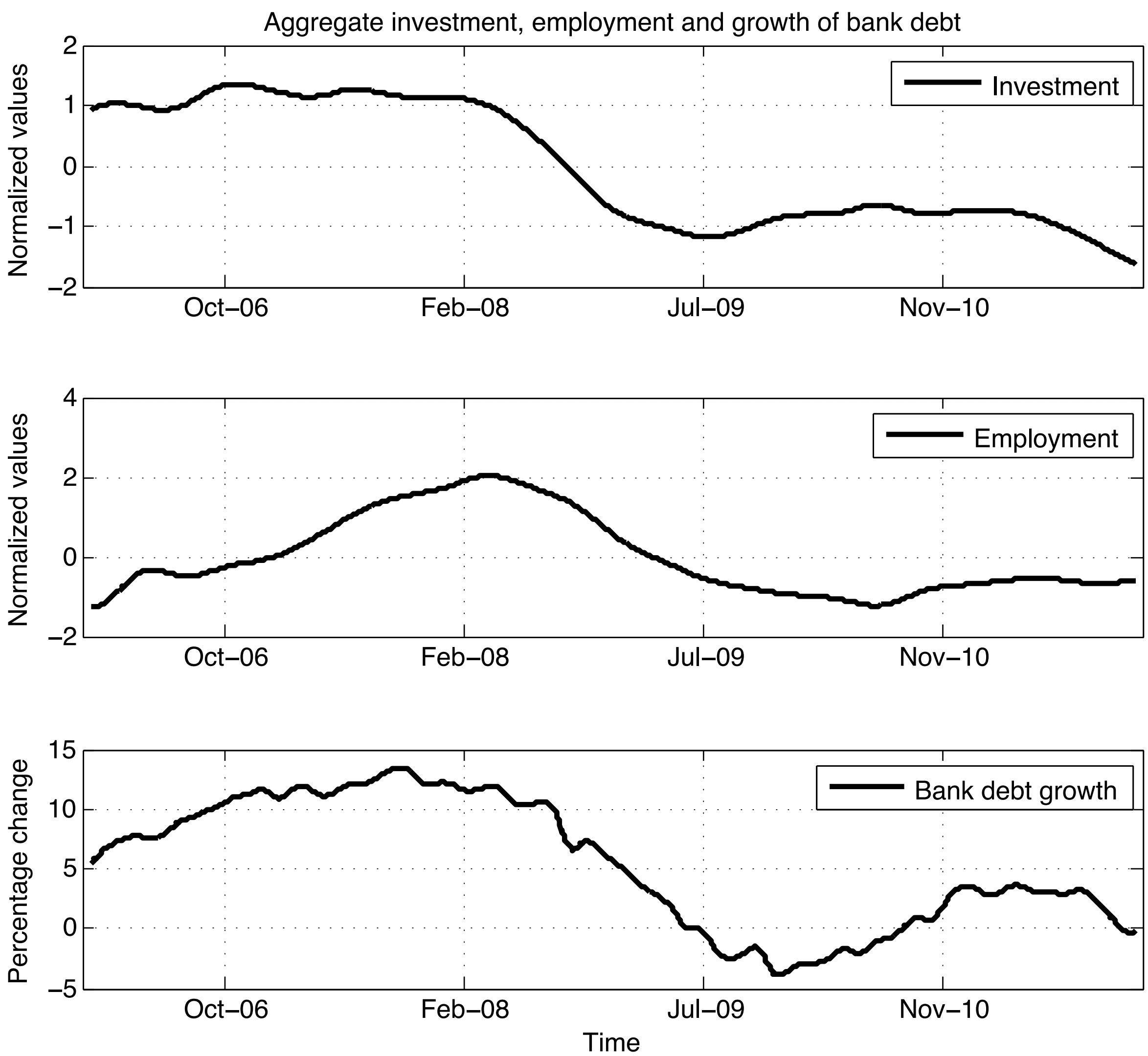

Figure 3: Aggregate investment, employment and bank debt growth for Italian firms (2006–2011).

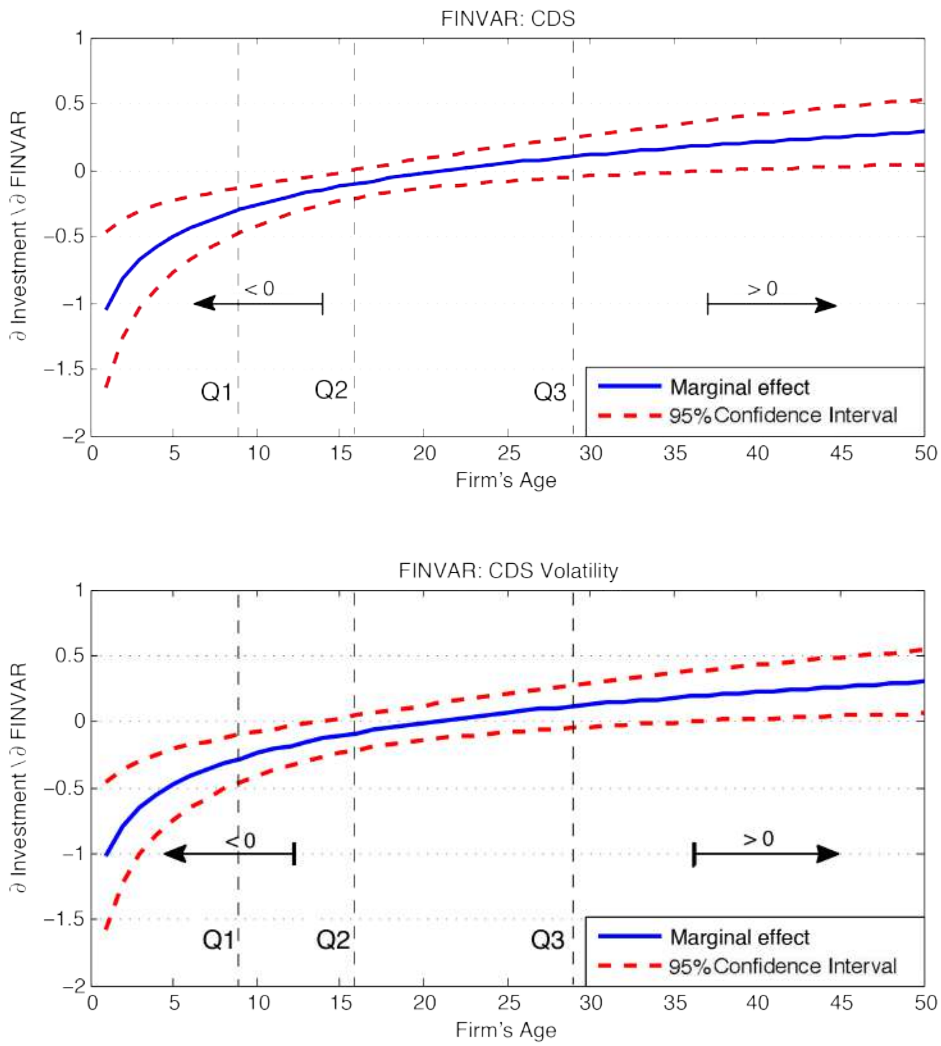

Figure 4: Marginal effect of a unitary increase in FINVARit on firm investment for different values of firm age. The black arrows highlight the regions of significance. Investment is expressed in units of standard deviations. FINVAR: CDS and CDS volatility.

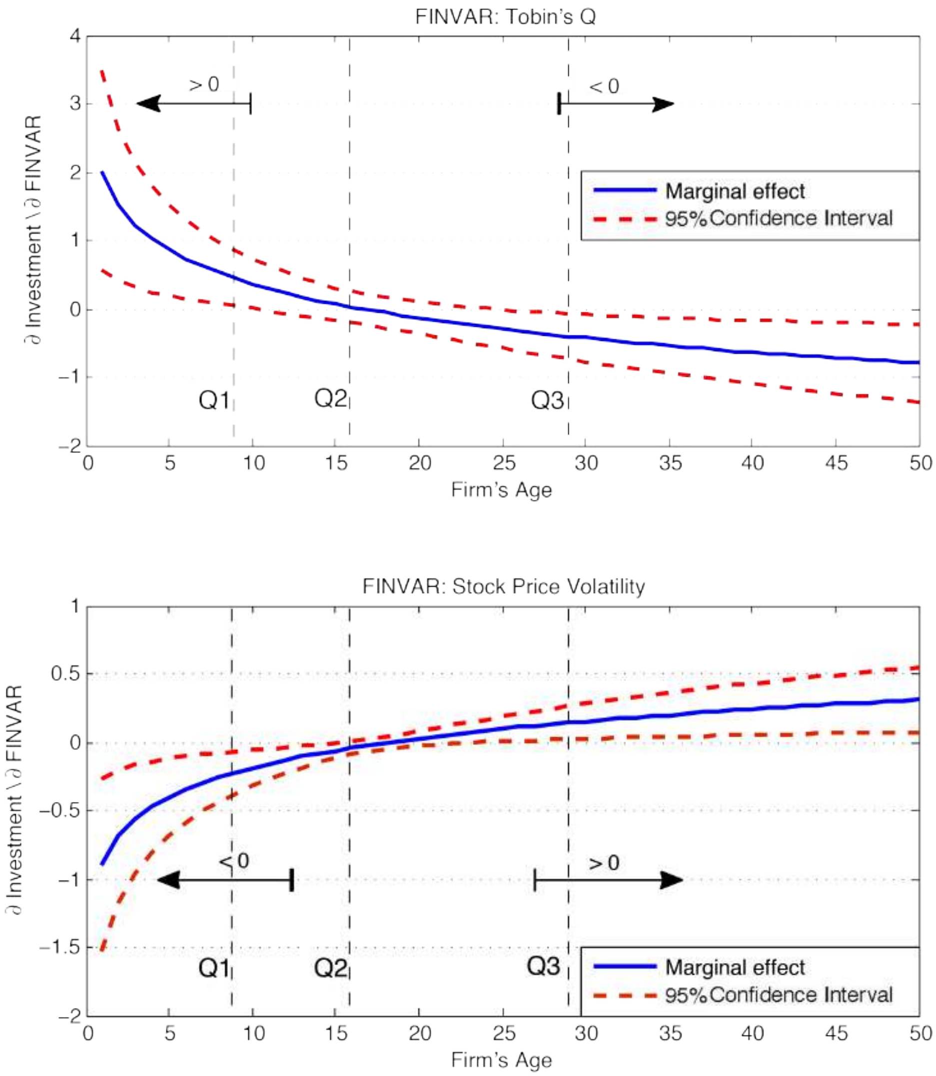

Figure 5: Marginal effect of a unitary increase in FINVAR_{it} on firm investment for different values of firm age. The black arrows highlight the regions of significance. Investment is expressed in units of standard deviations. FINVAR: Tobin's Q and equity volatility.

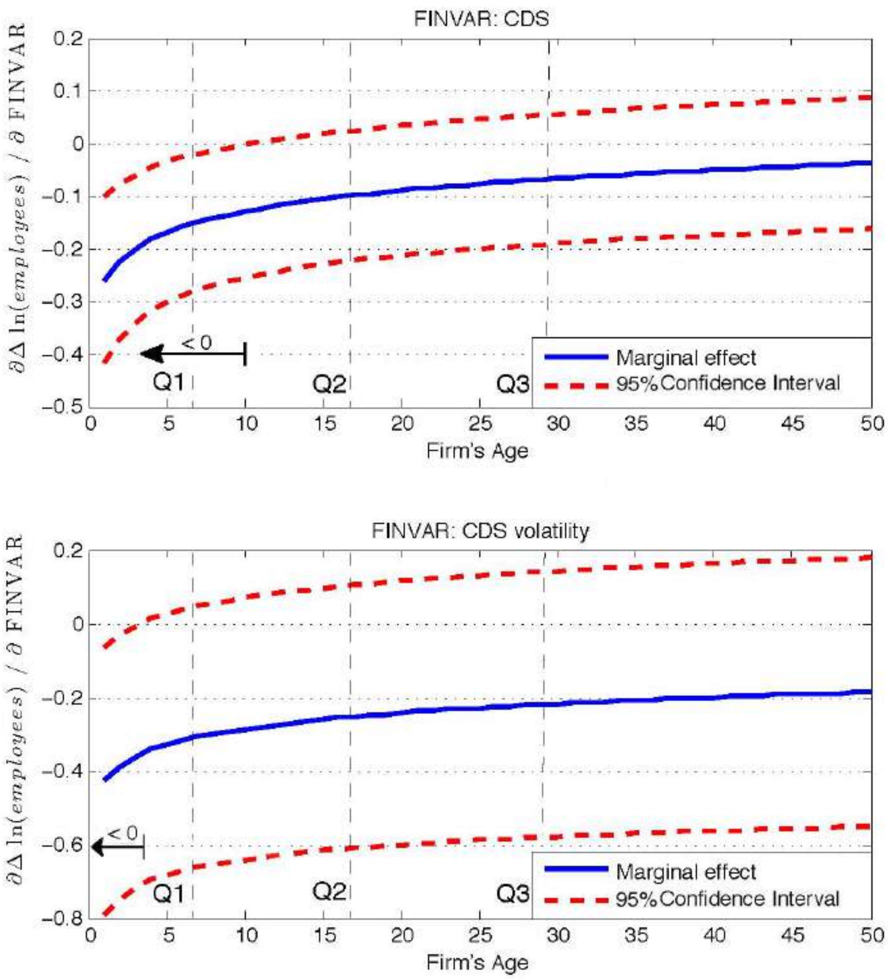

Figure 6: Marginal effect of a unitary increase in FINVAR*it* on firm employment growth for different values of firm age. The black arrows highlight the regions of significance. Employment growth is expressed in units of standard deviations. FINVAR: CDS and CDS volatility.

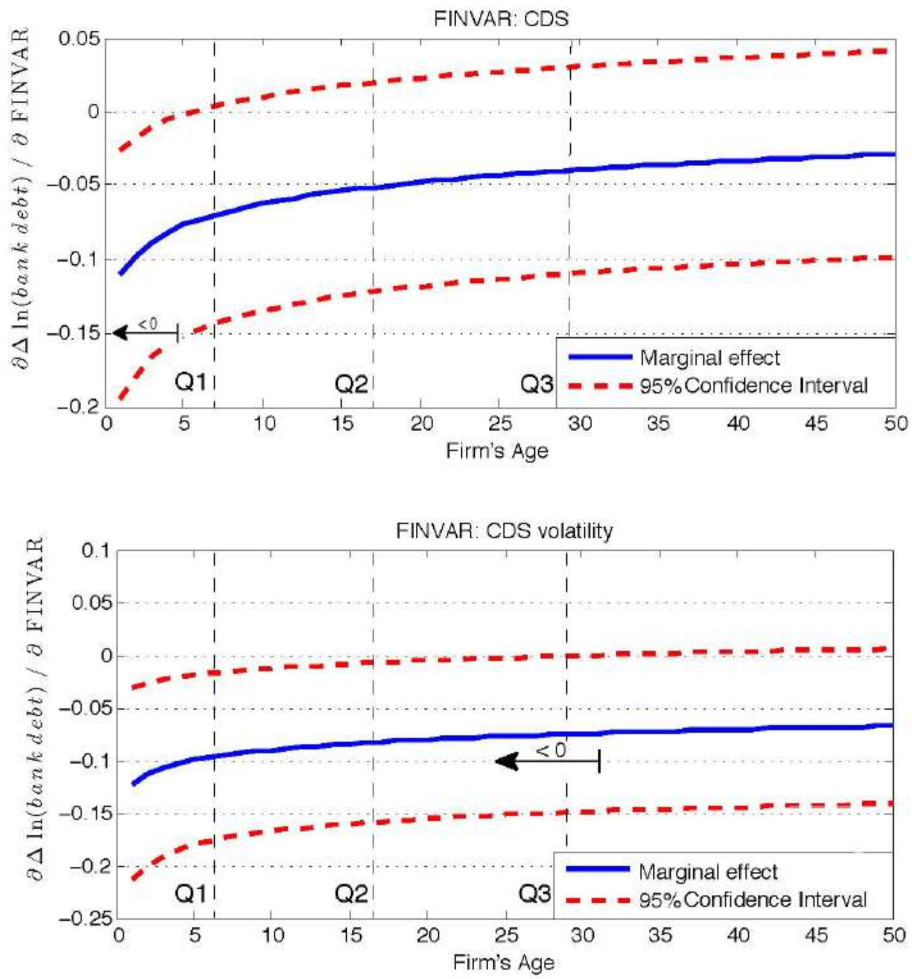

Figure 7: Marginal effect of a unitary increase in FINVARit on firm bank-debt growth for different values of firm age. The black arrows highlight the regions of significance. Bank-debt growth is expressed in units of standard deviations. FINVAR: CDS and CDS volatility.