Family Firms, Bank Relationships and Financial Constraints: A Comprehensive Score Card[1]

Alexander Karaivanov, Simon Fraser University
Jesús Saurina, Bank of Spain
Robert M. Townsend, MIT

December 2016

Abstract

We examine the effect of financial constraints on firm investment and cash flow. We combine data from the Spanish Mercantile Registry and the Bank of Spain Credit Registry to classify firms according to their number of banking relations (with none, one, or several banks) and according to whether they are family-owned, not family-owned, or belong to a family-based network of firms. Our empirical strategy is structural, based on a dynamic model solved numerically to generate the joint distribution of firm capital (size), investment and cash flow, both in cross-sections and in panel data. We consider three alternative financial market settings: financial autarky, borrowing/lending in a single asset, and moral hazard constrained state-contingent credit; estimate each via maximum likelihood; and compare across these financial regimes. We validate the structural approach by showing that it performs well in traditional categories by stratifying firms by size and age and finding that smaller and younger firms are more constrained. Formal financial arrangements through banks do help, but the evidence is mixed. For family firms, especially those belonging to networks based on ownership, we find that they are almost always associated with a more flexible market/contract environment and hence are less financially constrained than non-family firms. This result survives stratifications of family and non-family firms by bank status. Family firms are better able to allocate funds and smooth investment over states of the world and time, arguably done informally or through the cash flow generated at the level of the network.

JEL classification: C61, D82, D92, G21, G30
Keywords: financial constraints, family firms, bank lending, structural estimation and testing.

[1]Research support from The US National Science Foundation, The National Institute of Health, The John Templeton Foundation, The Gates Foundation through the University of Chicago Consortium on Financial Systems and Poverty and The Social Sciences and Humanities Research Council of Canada is gratefully acknowledged. This paper is the sole responsibility of its authors and the views presented here do not necessarily reflect those of Banco de Espana or the Eurosystem. We thank V. Salas and K. Ueda for comments and suggestions on earlier versions. We also appreciate the excellent comments from participants in the Far East Meeting of the Econometric Society, the European Economic Association conference, the Society of Economic Dynamics meeting, and the Econometric Society World Congress. Any remaining errors are our own. We are grateful to S. Ruano for her superb research assistance to an earlier significantly different version of the paper as well as to J. Galan for his research assistance with the current version.

1 Introduction

Over the past two decades a large part of the literature on firms' investment at the micro level has focused on the influence of financial constraints.[2] Some authors have used models of information or incentive problems in capital markets to motivate the role and origin of endogenous financial constraints. Both moral hazard, due to the costly monitoring of outcomes or of the managers' allocation of resources, and adverse selection, due to asymmetric information about the quality of investment projects, can introduce a wedge between the cost of internal and external finance.[3] Other authors assume exogenously incomplete credit markets, for example borrowing or saving in a single risk-free asset. In all cases the ultimate result is limited access to external finance – firms have to restrict investment when internal cash is insufficient to invest at the first-best level.[4]

In this paper we analyze what type of firms are financially constrained in their investment when facing cash flow fluctuations – both within a single period and over time. We adopt a fully structural modeling approach so as to be specific about (some of) the mechanisms determining the financial constraints, through the lens of theory. In doing so, we try to avoid some of the back and forth in the debates concerning the mapping between reduced form empirical work, on the one hand, and theory on the other, though in our view these debates have been productive (e.g., Kaplan and Zingales,1997 and 2000 vs. Fazzari et al., 1988 and 2000).[5] Our results contribute to this research by integrating theory and data, given that we analyze jointly the firms' investment sensitivity to cash flow and estimate the underlying financial regime, among a variety of alternatives, for groups of firms stratified by age, size, family ownership status and number of banking relations. To our knowledge, this comprehensive, score-card approach combining a variety of structural models with a number of key stratifications of the data is unique to the literature. Another strength of the paper is that the theories of financial constraints that we test are dynamic; that is, we explicitly model and pay attention to the firms' intertemporal incentives to save and invest, for example, constrained now versus constrained in the future. However, we also offer an important caveat about our structural approach at the outset: no model or set of models is sufficiently comprehensive to incorporate all possible factors affecting firms' investment decisions and constraints. We do our best to be clear about the limitations of our approach, including the important issue of selection on unobservables, though heterogeneity in unobservables is admitted in two of the three models we consider.

Our main definition of financial constraints is about how damaging, or alternatively how flexible, is the financing/information regime cell in which a firm resides, based on the estimation of alternative dynamic models. The regimes range from financial autarky to unrestricted borrowing/lending with an institution or market to moral

[2]Schiantarelli (1996) and Hubbard (1998) provide extensive reviews.

[3]On adverse selection see Jaffee and Russell (1976) or Stiglitz and Weis (1981). Myers and Majluf (1984) focus on information problems affecting equity financing. The effects of moral hazard are treated in Jensen and Meckling (1976) among others. Williamson (1987) derives the possibility of credit rationing in the context of optimally designed contracts when profit outcomes can only be observed at a cost. On costly state verification see also Townsend (1979) and Diamond (1984).

[4]The cost gap between external debt and internal funds could be explained by information costs but it could also be due to taxes or other transaction costs.

[5]As argued by Kaplan and Zingales (1997, 2000), a firm is either constrained or unconstrained, a binary variable, and thus the degree of cash flow sensitivity does not necessarily indicate the exact nature or severity of financial constraints. Gomes (2001), Cooper and Ejarque (2003) and others have challenged further the Fazzari et al. (1988) interpretation by demonstrating that financing constraints are neither necessary nor sufficient for cash flow effects. Papers that reject the monotonic relationship between cash flow sensitivity and financial constraints include Fohlin (1998), Cleary (1999), Houston and James (2001), and Fuss and Vermeulen (2006). On the other hand, Schmid (2009) shows that, in a model with incomplete markets due to limited commitment, the cash flow effect is significant and therefore suitably modelled financial frictions could rationalize the evidence on cash flow sensitivity.

hazard constrained insurance and credit arrangement with a bank or conglomerate. We tabulate the placement of firms into these cells based on key characteristics emphasized in the literature: size and age, bank finance (no, single, or multiple bank lenders), and family status (non-family, family-owned, or in a family-linked network determined by ownership). We disaggregate the data into multiple firm categories, for example, small and young single-banked firms that are family connected vs. small and young single-banked with no family connections, etc. The bottom line is a score card or indicator for which group of firms is more severely financially constrained and which less so.

We use data from two large comprehensive databases on Spanish non-financial firms. First, we rely on the Spanish Mercantile Registry to obtain balance sheets, profit and loss accounts, information on financial/real flows (capital, investment, cash flow) and firm characteristics (ownership, age, etc.) Second, we use the Bank of Spain Credit Registry (CIR) to classify firms according to whether they have borrowed from a single Spanish credit institution, from several institutions, or from none.[6] Since the minimum reporting threshold was low (6,000 Euros per loan) over our sample period, the CIR data are essentially a census of all banking loans granted to non-financial firms in Spain. In the estimation we focus on firms that continuously maintain the same banking status (unbanked, single-banked or multi-banked) in all years of data. We also construct an indicator of whether a firm is family owned, not family owned or part of a family network defined by ownership shares. Essentially, we analyze the investment behavior of Spanish firms taking into account their age, size, bank relationships and ownership structure. We are doing this for a country where funding for firms is overwhelmingly dominated by banks and for a period of time (1997-2007) that corresponds to the longest continuous expansion of the Spanish economy under a lending boom that fuelled firms' investment expansion. We look at three sub-periods in a balanced manner: 1997-2000, which corresponds to the investment expansion after the 1993 recession in the wake of entering the Eurozone; 2001-2003, an economic slowdown as a result of recession in core Euro zone countries; and finally 2004-2007, the years right before the financial crisis erupted and investment collapsed and also a time when lending and liquidity was at its peak.

Compared to previous approaches relying on more reduced form analysis, including panel data GMM,[7] the main advantage of our structural approach is that we can assess not only whether financing constraints affecting firm investment are absent or present (perfect vs. imperfect credit markets), but determine the most likely nature of these financial constraints within the taxonomy of the structural models we compute, estimate and statistically test. Here we feature three prototypical models (autarky, exogenously incomplete markets, and endogenously incomplete markets due to moral hazard) but, as shown in Karaivanov and Townsend (2014), other models of financial constraints can be easily added. For example, a complete markets setting was considered in earlier drafts but rejected by the data. We explicitly model the dynamics and interaction of present vs. future constraints as firm size and credit conditions (proxied by state variables in the models), evolve endogenously over time within each financial regime. For example, a firm could have high cash flow in the current period but anticipate constraints in future periods and so its current investment may not respond much to current cash flow. Alternatively, the firm may carry past debt (in the borrowing/lending model), or have low promised utility due to having been net transfer recipient in the past (in the moral hazard model), which would affect its current investment. Our approach very

[6] For instance, Jiménez et al. (2012, 2014, 2016) have used extensively both databases to analyze monetary policy and financial stability issues. Here, we focus on the real side of the economy by investigating non-financial firms' investment.

[7] See, among others, Bond and Meghir (1994) and Bond et al (2003).

much takes these dynamic interactions into account, both with respect to their implications in the cross-section and more obviously for panel data.

The empirical literature has documented that, in addition to the fundamentals determining investment dynamics such as expected future profitability and the user cost of capital, firms' internal funds influence in a positive and significant manner their investment decisions, with more intensity for firms affected by capital market imperfections. Since the seminal paper of Fazzari et al. (1988), an extensively used empirical strategy consists of separating 'constrained' and 'unconstrained' firms according to a priori assumptions on the likelihood that they are subject to information or incentive problems, then testing whether the neoclassical investment equation derived under the assumption of perfect capital markets with adjustment costs describes the behaviour of unconstrained firms but not that of constrained firms.[8] Typical firm characteristics used as a priori proxies for the importance of capital market imperfections are firm's size, age, and dividend policy.[9] A few papers stratify by relationship with industrial or financial groups, and this turns out to be related to our findings.

We first follow the literature and stratify our sample by firm age and size. This is indeed the approach of Fazzari et al. (1988), with the idea that the smaller and/or younger is a firm, the more likely it is to be constrained. There are also life-cycle firm finance models in the theoretical literature which reach the same conclusion (Clementi and Hopenhayn, 2006 and Albuquerque and Hopenhayn, 2004, featuring either moral hazard or limited enforcement). A large literature on models with financing constraints makes current net worth a constraint on credit (Banerjee and Duflo, 2005; Gine and Townsend, 2004; Jeong and Townsend, 2007) and part of this literature focuses on persistence and how businesses save over time to overcome constraints (Buera and Shin, 2013; Moll, 2014; Banerjee and Moll, 2010; Mestieri, Schauer and Townsend, 2016).

We find a clear pattern by firm age and size – estimating using data from large and old firms results in a smoother best-fitting financial regime compared to using corresponding data for small and young firms (for example, moral hazard over borrowing or autarky; or alternatively, borrowing over autarky). These results suggesting less constrained financial environment for large and old firms are consistent with the previous findings from the empirical literature that such firms tend to feature smoother investment / cash flow relationship compared to smaller and younger firms. In some respects, this validates the structural method we employ.

Related but not identical is the large literature on bank finance. Banks are thought to have a comparative advantage in producing information about borrowing firms (Diamond, 1984; Bond, 2004). To the extent that bank relationships mitigate asymmetric information problems between savers and borrowers and facilitate monitoring, the incidence of financial constraints on firms' investment and its sensitivity to cash flow could differ across firms stratified by the strength of their bank relationships.[10] The empirical research evaluating the costs and benefits of bank relationships is extensive, including papers studying differences in firms' investment behavior. In most cases, closer bank relationships are associated with lower sensitivity of investment to cash flow (Elston, 1996 for

[8]There are two main empirical approaches, pioneered by Fazzari et al. (1988) and Bond and Meghir (1994) respectively. The former is based on estimating the Q-model of investment, extended by a proxy for the availability of internal funds and testing for differences in the sensitivity of investment to cash flow between constrained and unconstrained firms. The latter approach estimates an investment Euler equation which should hold for unconstrained firms but be mis-specified for constrained firms. Both approaches assume perfect competition, constant returns to scale and quadratic adjustment costs.

[9]Schiantarelli (1996) provides an exhaustive list and discussion.

[10]The strength of bank relationships has been defined in the literature as: the relationship's length (Petersen and Rajan, 1994; Berger and Udell, 1995 and Degryse and Van Cayseele, 2000); scope, that is, type and number of financial services (Petersen and Rajan, 1994 and Degryse and van Cayseele, 2000), bank's ownership (Elston, 1996; García-Marco and Ocaña, 1999; Fohlin, 1998 and Chirinko and Elston, 2006;) or the number of banks (Petersen and Rajan, 1994; Houston and James, 2001 and Fuss and Vermeulen, 2006).

Germany; García-Marco and Ocaña, 1999 for Spain; and Houston and James, 2001 for the USA). However, some authors find no significant effect of bank relationships on cash flow sensitivity (Fuss and Vermeulen, 2006 for Belgium) or a positive effect (Fohlin, 1998, for Germany).[11] For Spain, Carbo-Valverde et al. (2008) find that the investment of SMEs is sensitive to bank loans for unconstrained firms but not for constrained firms (defined as firms with desired borrowing larger than the amount of credit provided by banks) and that trade credit predicts investment but only for constrained firms.[12] In addition, unconstrained firms use bank loans to finance trade credit provided to other firms.[13]

We use data on the firms' banking relationships from the Bank of Spain CIR and categorize non-financial Spanish firms into continuously unbanked, single-banked and multi-banked.[14] At one extreme is the literature on financial access which finds that, without formal credit access (unbanked), businesses can be quite constrained, hence with high marginal returns although not always accounting for risk premia (De Mel et al., 2008; Evenson and Gollin, 2003; Udry and Anagol, 2006; Samphantharak and Townsend, 2016). Having access to a single bank can be thought a priori to be helpful – there is a large literature on relationship banking based on the premise that information about borrowers is extremely important in the lending process, especially for small firms which are often considered informationally opaque.[15] The literature on multiple bank access draws mixed conclusions. On the one hand, financial access from two or more lenders could mean more available credit and hence less binding financial constraints. On the other hand, allowing borrowing from multiple sources may lead to enforcement or adverse selection problems which relates to the literature on coordination failures without credit registries and contingencies in loan contracts (Bizer and DeMarzo, 1992; Green and Liu, 2015). More generally, there is both theoretical and empirical research which finds that competition among banks can be either good or bad depending on the setting (Petersen and Rajan, 1995; Cetorelli, 2001; Alessandrini et al., 2009; Degryse and Ongena, 2005; Zhorin and Townsend, 2014).

Stratifying by firms' banking status, our findings are mixed. In the whole sample, we find that the best-fitting financial regime for unbanked firms is, in the majority of cases, more constrained than the best-fitting regime for single- and multi-banked firms but there are also specifications in which the same regime is best-fitting regardless of banking status. Focusing on small and young firms, we do find that unbanked firms are best fit by a (weakly) less smooth regime than single- or multi-banked firms, that is, evidence that small and young unbanked firms are more financially constrained. However, looking at large and old firms stratified by banking status we see a different pattern – in the 2004-2007 and 2001-2003 data large and old unbanked firms exhibit the same degree

[11] Other papers investigate differences in the role of bank relationships in alleviating financial constraints at different stages of the credit cycle. For example, Vickery (2005) shows that the benefits of bank relationships are higher when credit conditions are poor or deteriorating. Direct evidence from matched data suggests that borrowers are unable to smooth bank liquidity shocks completely (Khwaja and Mian, 2008; Jiménez, et al, 2012; Schnabl, 2010). Some authors also find that bank capital shocks have real consequences in the form of decreased investment by borrowers (Gibson, 1995; Kang and Stulz, 2000; Gan, 2007; Chava and Purnanandam, 2009).

[12] Although not focusing on bank relationships, the influence of financial constraints on the investment decisions of Spanish firms is also analysed in Alonso-Borrego (1994), Estrada and Vallés (1998) and Hernando and Tiorno (2002).

[13] Fohlin and Iturriaga (2010) study the relationship between investment-cash flow sensitivity (ICFS), bank relationships and firm ownership structure. They find that bank relationships via equity or debt have little effect on Spanish firms' ICFS. In contrast, firms with high ownership concentration exhibit significantly lower sensitivity. D'Espallier et al. (2011) use a Bayesian approach to study ICFS among 90 listed Spanish firms and provide evidence that high-ICFS firms have higher financing needs while faced with fewer available external financing sources.

[14] We implicityly assume that multi-bank lending delivers an outcome as if a firm were dealing with a unified sector, as when banks can coordinate, but this is a limitation of the model.

[15] For comprehensive reviews on relationship banking see Boot (2000) or Elyasiani and Goldberg (2004).

of financial constraints and are sometimes less constrained than single-banked or multi-banked firms of the same type. Of course, these firms may have saved or financed their way out of constraints.

We also study the importance of family ownership, on its own and in conjunction with age, size and banking status, for the degree and nature of financial constraints faced by firms. For example, there is a literature on the positive and negative attributes of family-owned firms (Caspar et al., 2010). Bertrand and Schoar (2006) review world-wide evidence on family controlled businesses, contrasting theoretical arguments for the higher efficiency of family firms vs. cultural theories claiming the contrary. Khanna an Yafeh (2007) characterize business groups, with particular attention to family groups, as 'paragons' or 'parasites'. Specific instances include risk sharing in family networks, as in Kinnan and Townsend (2012) for Thai SME's and Samphantharak (2003) for larger conglomerates versus the literature on 'tunnelling' as in Bertrand et al. (2002) and others. Papers on family-tied firms in Europe include Cronqvist and Nilsson (2003) for Sweden, Sraer and Thesmar (2004) for France or Maury (2006) for a sample of Western European countries (see also Morck (2005) for an exhaustive historical review).

We hypothesize that ownership connections between family firms and the resulting network they form may increase these firms' financing possibilities outside of the banking system and may allow such networked firms, including unbanked, to behave as if they face less strict financial constraints compared to family firms that are not part of a network or compared to non-family firms. Indeed, our structural estimation results using both cross-sectional and panel-data joint distributions of capital, investment and cash flow show that the data from family firms are better fit by less constrained financial regimes than the corresponding data for non-family firms. More interestingly, we find strong evidence that family-networked firms (firms in a family-based network constructed by ownership shares) face less strict financing constraints compared to non-networked family firms ('pure family' firms which are individually or family owned but not owners of other firms). This result is robust across firm age and size strata and across banking status. It points towards an advantage of family networks in accommodating investment needs to cash flows obtained in different firms which are parts of the network. By shifting funds from firms with less investment opportunities and more cash flow to others where the opposite holds, family networks may surmount financial constraints that otherwise could put downward pressure on firms' investment levels and smoothing capabilities. About 'pure family' firms, we find that, still in terms of their ability to smooth investment,they tend to fall in between the non-family and family-networked firms and seem more similar to non-family firms than to family-networked firms.

Finally, while the 1997–2007 data we use corresponds to different growth periods of the Spanish economy, we do not find a strong or obvious pattern in terms of the best-fitting models of financial constraints over time although we do see more instances of the least constrained (moral hazard) regime appearing as best-fitting in the 2004-07 data, the period of the credit ramp-up before the financial crisis.

Our results on family and family-networked firms are in line with the literature reviewed above that shows the importance, both from a theoretical and an empirical point of view, of internal financial markets in allocating resources while competing with external funding sources. In Spain higher levels of finance beyond bank borrowing come not from bonds but from trade credit and the Spanish analogue to chaebols or zaibatsu business groups (Hoshi et al., 1990). Pindado and De La Torre (2011) consider whether family control alleviates or exacerbates investment cash flow sensitivity (ICFS) in the Euro zone. They find that family-controlled firms have lower sensitivities and this is mainly attributable to family firms with no deviations between cash flow and voting rights and to family firms in which family members hold managerial positions. Consistent with our results here obtained using a completely different structural methodology, the authors argue that family control seems to mitigate investment inefficiencies that derive from capital market imperfections. Andres (2011) finds a similar result using German data – when compared to firms of similar size and dividend payout ratio, the investment outlays of founding family owned firms are consistently less sensitive to internal cash flow (see also Anderson et al., 2003 for related evidence on US founding family owned firms having lower cost of debt financing). Crespi and Martin-Oliver (2015) further document that during crisis periods, family firms are less subject to credit constraints than non-family firms and thus the impact of lack of credit on their capital structure is less severe. In Spain, Lopez-Gracia and Andujar-Sanchez (2015) find that growth opportunities, financial distress costs, and internal resources are the main factors that differentiate family vs. non-family businesses.

The computational and empirical methods we use are based on Karaivanov and Townsend (2014) where we estimate and statistically test dynamic models of consumption and investment with data on households running small businesses in rural and (semi-)urban Thailand. We find that in the rural sample a saving only or borrowing in a single asset regime provide best fit using joint data on consumption, assets, investment, and income. In contrast, a moral hazard model fits best the business and consumption data in the urban sample. In addition to the different setting, here we focus on firm investment and cash flow and the role of bank relationships and firm ownership. In Karaivanov and Townsend we also found that family or other networks help households achieve better consumption smoothing; similarly here, but using completely different data, we find that family-networked firms exhibit investment/cash flow patterns corresponding to less severe financial constraints both in the cross-section and over time. Our approach also relates to other papers that use data to try to tell apart different models of financial constraints from one another, although not necessarily in a fully structural way (Ligon, 1998; Paulson and Townsend, 2004; Paulson et al., 2006; Ahlin and Townsend, 2007; Dubois et al., 2008; Karaivanov, 2012; Kinnan, 2014).

A limitation of our approach, but not exclusive to it, concerns the role of selection on unobservables. First, to be consistent with the theory and control for the possible endogeneity of bank relationships, in constructing the sample used in the structural estimation, we focus only on firms that remain continuously in the same bank status category for all years in the data. The firms' ownership status (family or non-family) is also treated as time invariant as we have only one measure for it in the data. The underlying assumption is that constant banking and ownership status proxy for the firms staying in the same financial regime over time – the dynamic programming problem implies that the firms would behave approximately as if they were set to be in that category forever, as if at the end of the sample they are still not near making a transition. We discuss this approximation in the theory section. This assumption, however, cannot be directly tested. Moreover, when we estimate using panel data for our constructed categories, we need a balanced panel in order to compute the joint likelihood of investment and cash flow over time. Nonetheless, we also perform robustness checks using all available data.

Firms within a given banking status or family category could be substantially different from those in another category for other reasons too. We do incorporate endogenous, unobserved-to-the-econometrician variables within the models – unobserved 'promised utility' (present discounted value of profits) in the moral hazard model and unobserved debt/savings in the borrowing model. But any other remaining heterogeneity is not yet fully incorporated into the models. We did try estimation runs in which we removed firm fixed effects from the capital stock, investment and cash flow data. Doing so, however, removed a substantial part of the data variation and the Vuong comparison test was unable to pick up statistically significant differences in the financial constraints between the firm categories – for example in all stratifications by bank or family status that we tried we obtained the borrowing and lending model as best-fitting.

2 Model

2.1 Setting

We model a firm's payoff function as $u(c, z) = c - \nu(z)$ where c is dividends to the owner, analogous to 'consumption', and z is 'effort' in management and production, as if the firm is run by a single agent or is a conglomerate with perfect internal markets so we have Gorman aggregation. The cost of effort $\nu(z)$ is strictly increasing. Preserving the separability in c and z, the function $u(c, z)$ can be generalized to accommodate risk aversion (see the robustness section).

Following the literature on firm investment (e.g., Bond and Meghir, 1994), the firm's production function maps current, costlessly adjustable input, z and capital, k into total revenue, y. The general notation is

$$y = F(k, z, \theta)$$

where θ is a firm-specific shock. The firm's net profits or cash flow, $q(k, z, \theta)$ equal revenue net of expenses for hired labor and other material input costs which we do not write explicitly. The firm's capital, k and its cash flow, q are observables in our empirical implementation, while the effort z is an unobservable choice variable. The general setting allows the revenue shocks θ to be auto-correlated, which is important in the cash flow versus productivity debate in the literature, but here we focus on the case in which, conditional on k and z, the shocks θ are i.i.d. over time and across firms. Since capital k does not depreciate fully, we do allow for autocorrelation in cash flow q.

Suppose the shock θ can take on a finite number of values, $\{\theta_1, ..., \theta_m\}$ and let q_i be net profits (cash flow) in the state of the world θ_i. Call $Q \equiv \{q_i\}_{i=1}^m$ the set of all possible cash flow levels. The probability of realizing a particular net profit level q_i depends on the firm's capital stock k and effort z used in production. To capture the stochasticity of $q(k, z, \theta)$ and their dependence on capital and effort, we denote by $P(\tilde{q}|k, z)$, for any $\tilde{q} \in Q$, the probability of the firm having net profits equal to $\tilde{q}$ conditional on its capital stock, k and effort level, z.

Firm capital depreciates at rate $\delta \in (0, 1)$ and follows the law of motion,

$$k_t = (1 - \delta)k_{t-1} + I_t,$$

where I_t denotes period-t investment. As in Bond and Meghir (1994), we assume that investment I_t adds immediately to the capital stock k_t used in the current period t production.[16] Investment I_t is observable in the empirical implementation. There also could be a cost, $g(k, I) \geq 0$ of adjusting the firm's capital stock. This cost is convex in investment I and is subtracted from the firm's current net profits q. We estimate the model both with and without such adjustment costs.

The firm discounts future profits with the factor $\beta \in (0, 1)$. For most of what follows we set β equal to the

[16] In Bond and Meghir (1994) investment is subtracted as cost in the net profit function. Note also that in our paper cash flow, q is already net of wages and other costs. In Bond and Meghir (1994) these non-capital input decisions are explicit.

inverse of the borrowing and lending market rate, $\beta = 1/R$, where $R = 1 + r$ is the gross interest rate, but more generally, we allow β and $1/R$ to differ, for example, $R \geq 1/\beta$, so that the firm can achieve higher payoff in the future by saving at the market rate. We could also easily incorporate two interest rates, R^B for borrowing and R^S for saving, with $R^B \geq R^S$.

2.2 Financial Regimes

We consider three alternative financial regimes under which a firm may operate. The regimes can be thought of representing financial markets environments which differ by their level of market sophistication or financial constraints. First, a firm could be in what we call financial *autarky* (regime A). In this regime the firm is assumed to have no access to financial markets. It must finance all investment and dividends from its net profits q. Second, a firm could be in what we call a *saving or borrowing* regime (B). This regime can be interpreted as the firm only having access to a financial market allowing it to borrow or lend in a single non-contingent asset with fixed gross interest rate R. Third, a firm could operate in a more complex financial regime with contingent financial assets but subject to endogenous financial constraints because of an information problem stemming from unobservability of effort z – a *moral hazard* (MH) regime.

Financial autarky (A)

We can write a firm's problem under autarky (no access to financial markets) as the following dynamic program:

$$\begin{aligned} \Pi^A(k) &= \max_{\{k',c(q),z\}} \sum_{q \in Q} P(q|k',z)[u(c(q),z) + \beta \Pi^A(k')] \\ &\quad \text{s.t. } c(q) + k' - (1-\delta)k = q - g(k, k' - (1-\delta)k) \text{ for all } q \in Q \end{aligned}$$

where, conforming with Bond and Meghir's (1994) timing, the state variable k denotes the beginning-of-period capital stock while k' denotes the (post-investment) capital stock used in current period production. Current period investment, I equals $k' - (1-\delta)k$. The budget/feasibility constraint holds for each possible realization of net profits, q. Dividends $c(q)$ are contingent on the q realization.

Saving and borrowing (B)

In this financial regime a firm can borrow or save at an exogenously given gross market interest rate R. This can be thought of the firm trading in a single non-contingent asset with fixed return, similarly to the permanent income hypothesis setting (Bewley, 1977). There is no possibility of default or contingencies of any kind. Given beginning-of-period capital stock k and debt b, the firm's problem in this exogenously incomplete financial market setting can be written as:

$$\begin{aligned} \Pi^B(k,b) &= \max_{\{k',b'(q),c(q),z\}} \sum_{q \in Q} P(q|k',z)[u(c(q),z) + \beta \Pi^B(k', b'(q))] \\ &\quad \text{s.t. } c(q) + k' - (1-\delta)k + Rb - b'(q) = q - g(k, k' - (1-\delta)k) \text{ for all } q \in Q \end{aligned}$$

where $b'(q)$ denotes next period's debt or savings.[17] The assumption of no default implies an endogenous upper

[17] Positive values of b are interpreted as debt, negative values are interpreted as savings.

bound on debt, $\bar{b}$ (if debt exceeds $\bar{b}$ the problem has no solution). In the empirical analysis firms' debt or savings, b is treated as source of unobservable heterogeneity with a parameterized and estimated initial distribution (see Appendix A).

Moral hazard constrained credit (MH)

To model more complex financial regimes which allow for risk-contingent premia, transfers, and debt, we write the firm owners' payoff as $u(c, z) + \beta w'$, where

$$c = \tau + (1 - \delta)k - k' - g(k, I)$$

is current dividends, k is the beginning-of-period capital stock and k' is the post-investment capital used in production. The variable w' is next period's "promised utility", that is, discounted expected future payoff. In the risk-neutrality case it equals the discounted value of all expected dividends from next period onward. The firm is assumed to have access to a risk-neutral lender with discount factor $1/R$. The lender, or collection of lenders, is modelled as a principal maximizing discounted expected returns when facing a long-term contract with a firm with current promised utility w and initial capital k. Both the lender and the firm have full commitment.

In this formulation, it is as if all net profits q go to the lender but some part is then returned to the firm via the transfer $\tau(q)$ contingent on the realization of net profits q. The firm bears the costs of changes to its capital stock, that is, it pays for investment (and adjustment costs) but, assuming full observability, its capital stock and investment are effectively under the control of the lender. In contrast, the effort z is unobserved by the lender and so the firm must be given incentives to perform – a moral hazard problem arises.

To write the contracting problem in this setting, call $V^{MH}(k, w)$ the risk-neutral lender's (or collection of lenders) profits from facing a firm with beginning-of-period capital, k and current promised utility, w belonging to the set W (to be determined below). The lender solves:

$$V^{MH}(k, w) = \max_{\{k', w'(q), \tau(q), z\}} \sum_{q \in Q} P(q|k', z)[q - \tau(q) + (1/R)V^{MH}(k', w'(q))] \tag{1}$$

subject to two constraints. First, the contract must satisfy the "promise keeping" constraint stating that, in expectation, the firm must receive discounted payoff (the l.h.s.) equal to the promise w,

$$\sum_{q \in Q} P(q|k', z)[u(c(q), z) + \beta w'(q)] = w \quad \text{(PK)}$$

where $c(q) \equiv \tau(q) + (1 - \delta)k - k' - g(k, k' - (1 - \delta)k)$.

Second, due to the moral hazard problem, the lender faces, for all k, the following incentive compatibility constraint,

$$z = \arg\max_{\tilde{z}} \sum_{q \in Q} P(q|k', \tilde{z})[u(c(q), \tilde{z}) + \beta w'(q)] \quad \text{(ICC)}$$

The setting of perfect credit markets or full information, in which the borrower's effort z is observable/contractible is easily modeled and can be computed too, in the tradition of the literature, by maximizing (1) only subject to the participation constraint (PK) without imposing the incentive constraint (ICC).

Similarly to debt/savings in the B model, promised utility, w is treated as a source of unobserved heterogeneity in the MH model, with its initial distribution parameterized and estimated (see Appendix A).

The dynamic models of firm financial constraints presented above assume that the firms' financial access status does not change over time, only their state variables k and b or w evolve. Theoretically, this is meant to approximate firms that are in a "steady state" with regards to the financial environment and the constraints they face, that is they are (possibly infinitely) far away in time from a potential future regime transition. In principle, our model can be extended along the lines of Townsend and Ueda (2010) to allow transitions between financial regimes over time but we abstract from this here. Townsend and Ueda consider financial autarky (agents exposed to idiosyncratic risk) and a financial sector providing full insurance to idiosyncratic risk as two extreme settings, with costly entry into the financial sector. They find that the optimal saving behavior of agents in autarky is approximated the better the more distant is entry into the financial sector.

In sum, we model three dynamic financial regimes ranging from most constrained (autarky) to least constrained (moral hazard) in terms of availability of credit and ability to smooth investment both over time and across states. We estimate and test these three regimes based on their implications for firms' investment and its sensitivity to cash flow using maximum likelihood, as explained in Section 4.

2.3 Example

We solve a one-period version of the model to illustrate the differences between the three financial regimes in their implications for firm assets, k investment, I and dividend policy, c for any given realized net profits /cash flow, q. To keep the example as simple and tractable as possible, assume that there are only two possible net profits levels, q_L and q_H with $q_H > q_L > 0$. The probability of q_H being realized is $p(k', z)$ where the function p is strictly increasing in both arguments and has strictly decreasing partial derivatives satisfying Inada conditions. The firms are risk neutral with payoff function $u(c, z) = c - \nu(z)$ where v is strictly increasing and convex. There are no capital adjustment costs.

Financial autarky / Saving and borrowing (A / B)

In a one-period setting, the firm cannot save or borrow and hence the autarky (A) and the borrowing/lending in a single asset (B) regimes coincide. Given initial capital k_0, the firm's problem is to choose capital, k (equivalently, choose investment, $I = k - (1-\delta)k_0$) and effort, z to use in production, as well as dividends in each state.

$$\begin{gathered}\max_{c_L, c_H, z, k} p(z,k)c_H + (1-p(z,k))c_L - v(z) \\ \text{s.t. } c_i = q_i + (1-\delta)k_0 - k \quad \text{for } i = L, H \\ \text{and } c_i \geq 0 \quad \text{for } i = L, H\end{gathered} \tag{2}$$

The FOCs with respect to k and z at an interior solution are:

$$\frac{\partial p(z,k)}{\partial k}(q_H - q_L) = 1$$

$$\frac{\partial p(z,k)}{\partial z}(q_H - q_L) = v'(z),$$

after substituting for c_i from the budget constraint. Call k^* and z^* the values solving the above two equations. Note that k^* and z^* are the same as the "first-best" capital and effort levels that an unconstrained firm would choose (risk neutrality is key for this).[18]

Assume that given the Inada conditions and the assumed $v(z)$, the FOC with respect to z always has an interior solution. Then, the solution to problem (2), call it (c_i^B, z^B, k^B), looks as follows. If q_L and k_0 are sufficiently large so that the non-negativity constraint on dividends in the low state c_L does not bind at k^*, that is, $q_L + (1-\delta)k_0 - k^* > 0$ then the firm chooses k^B and z^B at the unconstrained values k^* and z^* which implies $c_i^B = q_i + (1-\delta)k_0 - k^*$. If, however, q_L and k_0 are such that the non-negativity constraint on c_L binds (corner solution), then the solution to problem (2) has instead $c_L^B = 0$, $k^B = q_L + (1-\delta)k_0$, $c_H^B = q_H - q_L$ and z^B solving the effort FOC evaluated at $k = k^B$. The firm would like to invest more but it is constrained.

Moral hazard (MH)

The one-period version of the firm's problem in the moral hazard regime can be written as follows, assuming initial promise w_0 that delivers zero profits to the lender,

$$\max_{c_L, c_H, z, k} \; p(z,k)c_H + (1-p(z,k))c_L - v(z)$$

$$\text{s.t. } p(z,k)c_H + (1-p(z,k))c_L + k = p(z,k)q_H + (1-p(z,k))q_L + (1-\delta)k_0 \quad \text{(ZP)}$$

$$\frac{\partial p(z,k)}{\partial z}(c_H - c_L) = v'(z) \quad \text{(ICC)}$$

where we used the "first-order approach" to replace the firm's incentive constraint with respect to the action z with its first order condition (ICC). It can be shown that, with two output levels and $p(z,k)$ strictly concave in z, the first order approach is valid (see Karaivanov, 2012 for a proof).

Substituting from the zero-profits constraint (ZP) into the objective, the problem simplifies to

$$\max_{c_H, c_L, k, z} \; p(z,k)\Delta q - k - v(z) \qquad (3)$$
$$\text{s.t. (ICC)}$$

Note first that, if we ignore (ICC) for the moment and assume interior solution, we would obtain the exact same FOCs with respect to k, z as in the A/B regime. Therefore, choosing $k^{MH} = k^*$ and $z^{MH} = z^*$ and setting $c_H^{MH} - c_L^{MH} = q_H - q_L$ would also satisfy constraint (ICC) and hence solve problem (3). From (ZP) we then obtain that $c_i^{MH} = c_i^B$. Intuitively, at an interior solution, when the first-best effort and capital stock z^* and k^* are feasible, a *risk neutral* firm would choose them and the incentive constraint would be automatically satisfied (there is no trade-off between insurance and efficiency).

[18] To see this, write the problem of an unconstrained firm,

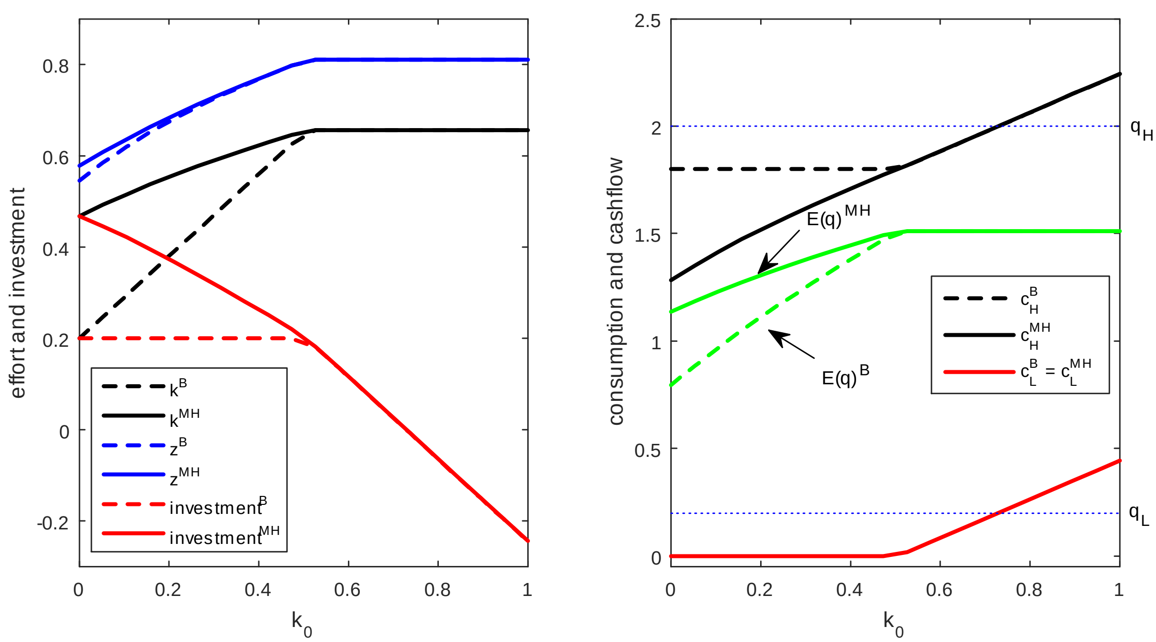
$$\max_{k, z, c_H, c_L} \; p(z,k)c_H + (1-p(z,k))c_L - v(z)$$
$$\text{s.t. } p(z,k)c_H + (1-p(z,k))c_L + k = p(z,k)q_H + (1-p(z,k))q_L + (1-\delta)k_0$$

and notice that, after substituting for $p(z,k)c_H + (1-p(z,k))c_L$ from the resource constraint, the FOCs with respect to k and z are the same.

However, suppose that q_L and k_0 are such that the non-negativity constraint on c_L binds at k^*. In the A/B setting above, this required a constrained choice for capital $k^B = q_L + (1-\delta)k_0 < k^*$. In the moral hazard regime, the firm can do better and choose a higher level of investment, $k^{MH} \in (k^B, k^*)$ by "borrowing" from the high state at the expense of reducing c_H. The reason is that, unlike in the A or B regimes, only the cross-state constraint (ZP) must be satisfied. The downside of the reduction in c_H is (all else equal) reduced effort relative to the first best. The exact outcome can be worked out numerically from this trade-off.

Figure 1 illustrates the solutions for capital, effort, investment ($I = k - (1+\delta)k_0$) and dividends, c_i in each state, as we vary initial capital k_0. The computed example uses the functional forms $p(z,k) = \sqrt{kz}$ and $u(c,z) = c - \frac{z^2}{2}$ and the parameters $q_H = 2$, $q_L = .2$, $\delta = .1$. We see that for high k_0 (above approximately 0.5) the B/A and MH solutions coincide. For these parameters the first-best input choices, k^* and z^* are feasible and incentive compatible. In contrast, for low values of k_0 the B/A and MH model solutions differ in their implied investment, effort, expected cash flow, and dividends. Specifically, in the moral hazard constrained setting firms invest more on average and achieve higher expected cash flow.

Figure 1: Computed Solutions – Autarky / Borrowing vs. Moral Hazard



Multiple periods

The one-period illustrative example demonstrated that the implications of the moral hazard (MH) and borrowing (B) models regarding firms' investment and cash flow differ when the moral hazard problem has a "bite", that is when the first-best input levels k^* and z^* cannot be implemented without violating the non-negativity constraints on dividends, c. The reason for the difference is that the one-period borrowing setting is essentially one of financial autarky – the firm bears the full extent of the cash flow shocks while, in contrast, in the MH regime it is partially insured against those shocks as it can use the financial intermediary to transfer resources across states of the world.

In a multi-period setting the basic intuition is similar, however, differences between all three financial regimes (A, B and MH) arise when the first-best is unattainable because of binding non-negativity constraints. Compared to the one-period example, in a multi-period borrowing (B) regime the firm gains the additional ability to smooth investment (use the first-best input levels) by being able to borrow against future periods. However, the firm's borrowing is ex-post non-contingent (the same repayment must be made independent of cash flow) and hence, since we do not allow default, the firm faces an endogenous borrowing limit imposed by the non-negativity of consumption in the worst possible history of cash flow realizations. In contrast, in the moral hazard (MH) regime the firm faces a single $t = 0$ budget constraint (the intermediary's zero profits constraint) in terms of expected inflows vs. outflows *both across time and across states of the world*. That is, through the financial intermediary, the firm can not only borrow against future cash flows (as it could do in the B regime) but also against other states of the world (unlike in the B regime). In sum, in a multi-period setting, when the first-best is unattainable, the key difference between the B and MH regimes is enhanced in the direction already illustrated in our one-period example – namely, the firms' ability to carry resources across states of the world in the MH regime softens the debt repayment constraint.

To illustrate this argument more formally, consider a two-period example. The saving and borrowing regime (B) has six separate resource constraints indexed by time period and cash flow state history:

$$\begin{aligned} c_1^i + k_1 &= q_i + (1-\delta)k_0 + b^i \text{ for } i = \{L, H\} \\ c_2^{ij} + k_2^i &= q_j + (1-\delta)k_1 - Rb^i \text{ for } ij = \{LL, LH, HL, HH\}, \end{aligned}$$

where the subscripts on k, c and b indicate time period and the superscripts indicate state. Resources are movable across time via saving or borrowing (the b^i's) but not across states. The autarky regime (A) has the same constraints but with $b^i = 0$ for all i – there is no way to transfer resources neither across periods nor across states. In contrast, the moral hazard (MH) regime has a single ex-ante resource constraint – resources are movable both across states and across time periods,

$$\sum_{i=L,H} \pi_1^i(k_1, z_1)(c_1^i + k_1 - q_i) + \sum_{ij=\{LL,LH,HL,HH\}} \pi_2^{ij}(k_2^i, z_2)(c_2^{ij} + k_2^i - q_j) = (1-\delta)(k_0 + (1/R)k_1)$$

These findings have implications for the models' predictions about the joint distribution of the observables – capital (k), investment (I) and cash flow (q), both in a cross-section as seen in Figure 1 for the one-period model, and over time and states as discussed above.

3 Data and descriptive analysis

3.1 Data sources

We use two unique and very detailed data sources. The first is the SABI-INFORMA database which provides annual economic and financial information at the firm level. The database collects annual public financial statements deposited by firms at the Spanish Mercantile Registry. Therefore, we have annual balance sheets and profit and loss statements for each firm. In addition, and crucial for our study, SABI- INFORMA provides static information on firm characteristics such as location, age, industry and, in particular, ownership.[19] The database allows us to obtain direct information about firms' total assets (A), fixed assets (k), sales revenue (S) and age. Using balance sheet data, we obtain information about firm investment (I), defined as fixed assets at time t minus fixed assets at $t-1$ plus depreciation, that is, $I_t = k_t - (1-\delta)k_{t-1}$; firm cash flow ($q$), defined as operating profit plus depreciation; firm debt (D), defined as short-term creditors plus long-term creditors, firm liquidity ratio (LR), defined as cash / short-term creditors. Last but not least, we have access to information about firm shareholders (ownership). Therefore, we are able to classify firms as family or non-family owned. Using ownership shares data, we are also able to identify whether family firms are part of a larger network of firms.

The second data source we use is the Credit Register (CIR) of Banco de España (the Spanish central bank). This database is unique because it is a census of loans granted to Spanish firms by Spanish credit institutions (mainly commercial banks, savings banks and credit cooperatives) or by the subsidiaries and branches of foreign banks operating in Spain.[20] The Bank of Spain Credit Registry (CIR) contains monthly information on the stock of all credits over a minimum threshold granted by credit institutions operating in Spain to Spanish firms. Since the minimum threshold has been very low over the sample period (6,000 Euros), this database contains essentially all banking loans granted to non-financial firms in Spain (i.e., it is a census of bank lending to non-financial firms). CIR provides information about the banking status of the firm (no relationship, one, or several bank relationships) as well as the amounts each bank is lending to the firm.

The combination of these two data sets provides annual information on various economic and financial characteristics, ownership, and the banking relationships for a large sample of Spanish non-financial firms during the period 1997-2007. In the rest of the paper, we refer to this merged database as SABI-CIR.[21] By its nature, this is an unbalanced panel as a consequence of entry and exit of firms; because of changes in the composition of the firms' portfolio for which SABI-INFORMA collects information from the Spanish Mercantile Registry; or due to the filtering we did on the raw data that may lead to dropping some, but not necessarily all, observations on a given firm.[22] Additionally, we exclude publicly listed firms (around 165) since their access to funds from capital equity markets as an alternative to bank loans would show as a different financing mechanism and could blur the overall findings. The resulting unbalanced dataset contains 4,749,653 observations, corresponding to 972,639 firms observed over the period 1997-2007. Moreover, we use information of firm ownership to focus on family firms and networks of family firms (see below), so that we can analyze not only the impact of bank relationships on real investment by firms but also the role played by family ties.

A priori, the properties of the data, characterized by wide coverage in terms of firm age, size and industry categories, make it attractive for studying the existence of financing constraints influencing investment patterns and cash flow sensitivity. Of particular interest for us are the roles of family status and banking relationships in alleviating, or not, financial constraints on Spanish non-financial firms which, as non-listed companies, tend to be

[19] Information is static in the sense that it reflects the status of the firm at the moment the information was first supplied, which does not necessarily coincide with the actual status of the firm over the years.

[20] For detailed analysis of the database see Jiménez et al (2006), (2009), (2012), (2014) and (2016).

[21] The list of all variables we use and their definitions is provided in Appendix B.

[22] We dropped, for any given year, observations corresponding to firms declaring interest payments equal or higher than total debt or negative equity. Moreover, we dropped the value of a variable if the variable is, by definition, non-negative, but the firm reports a negative value. We applied this filter to: sales, total assets, tangible assets, financial income, financial expenses, short term debt, long term debt, commercial debt, and cash.

informationally opaque.

3.2 Firm Characteristics

3.2.1 Bank relationships

We investigate the association of banking relations with firm's investment decisions. For this purpose, we define and distinguish three groups of firms depending on the number of banking relations maintained by the firm. The number of banking relations is defined as the number of banks reporting at least one loan to the Bank of Spain Credit Registry (CIR) for this particular firm and time period. According to this definition, in each year a firm in our sample can be classified into two categories: "unbanked firms", those with no banking loans registered in CIR (that is, no bank loan granted), and "banked firms", those with at least one loan registered (granted) in CIR. Additionally, within the category of banked firms, we distinguish between firms with loans from a single bank only ("single-banked firms") and firms funded by two or more banks ("multiple-banked firms").

3.2.2 Family and network status

In order to investigate the role of family firms, either directly or indirectly owned, we construct an indicator variable for each firm in our data, called 'family status', f_j which indicates whether each firm j is directly family owned or is part of family-based business network. The family status classification is done based on the date this information was requested from SABI-INFORMA (March 2014) and it is not possible to track any changes in this condition over the sample period. The identification of family firms is done through the algorithm described below.

Algorithm for defining family firms

1. We start by creating a list of all non-financial firms in which 50% or larger share is held by an individual person or family (reported shareholder type is "*Una o más personas físicas o familias*"). For all firms in this list (280,534) we record their name and fiscal ID number. These firms are considered directly family owned.

2. To the list of directly family-owned firms constructed in Step 1 we add, using a recursive procedure, all other firms owned (with 50% or larger share) by firms in the family firm list. That is, we enlarge the initial set of family firms with all firms for which the major shareholders are family firms as defined in Step 1. To do so we use information on the holdings (names and percentage of direct shares) of non-financial firms in other firms.

3. In the first iteration of the recursive procedure used to obtain the set of family firms we combine the 280,534 family firms from Step 1 with the ownership share data from Step 2. We find 19,079 firms held (direct holding $\geq$ 50%) by family firms from the Step 1 list. We check and drop any duplicate firms which have already been included in that list (212 firms). As a result, at the end of this first iteration we add 18,867 firms to the list of family firms (it now contains 280,534 + 18,867 = 299,401 firms) held by individuals or families or by 9,839 firms from the Step 1 list.

4. We repeat the process with the 18,867 firms added in Step 3, essentially proceeding along a tree and following the branches of ownership. The result is 3,497 additional family firms in the second iteration; 868 in the third iteration; 846 in the fourth; 8 in the fifth, 35 in the sixth and 0 in subsequent iterations. In the final list we drop duplicate observations (140) that correspond to firms held with equal percentage (exactly 50%) by two different firms. In these cases only one observation is recorded. The overall outcome from the recursive process is 304,515 family firms, either directly family-owned or indirectly owned by a family or individual via an ownership chain consisting of other firms.

In sum, we call family firms those firms that are controlled by an individual or family directly or through subsequent control stakes.

Pure family firms vs. family-networked firms

We further identify two sub-groups of interest within the set of family firms. Specifically, we call pure family firms all family firms which are directly owned by individuals or families and do not own other firms. In contrast, we call family-networked firms all family firms that are part of a network of firms constructed by ownership. This category consists of (i) all family firms that are directly owned by an individual/family and own other firms and (ii) all family firms that are owned by other family firms. The reason we distinguish these sub-groups of family firms is that they can look quite different in practice (e.g., a 'mom-and-pop' store vs. a firm which is part of a large business group).

In Figure 2 we present several examples of family-based networks among the firms in our data. The simplest example of a network is case A, where firm B is a subsidiary of firm A which is owned by family X. We are able to identify such direct relationships between firms as long as a firm such as A owns more than 50% of the shares of a subsidiary (firm B in the example). We do this up to the seventh level of ownership hierarchy (e.g., if firm B owns more than 50% of a third firm, and so on, up to a seventh firm).

More complex family networks in which a firm is owned by two or more family firms are also illustrated on Figure 2. We distinguish two possibilities: case B, in which a single family firm (firm A) owns more than 50% of the shares of another firm (firm C); and case C, in which two firms (A and B) jointly hold more than 50% of the shares of a third firm (firm C), but A and B individually hold less than 50% of firm C each. Case C is not considered in the current analysis given the identification complexity of such ownership structures.

To understand more clearly the structure of family networks in the data, we present a case study in Figure 3. It was selected because of the multiple interactions it features including both banked and unbanked firms. In this case, a person (Mr. X) is the sole owner of two firms (A, unbanked and B, banked), which are accordingly classified as pure family firms. Mr. X also holds 47% of a third firm (C, unbanked). If we only accounted for Mr. X's participation, firm C would not be considered as a family firm given our definition; however, when the shares of other firms owned by Mr. X's family are taken into account, there is an additional 17% share, so the total adds up to 64% and hence firm C is classified as a family firm. Observe also that there exist two more firms (D, unbanked and E, banked), which are not directly owned by Mr. X but instead are owned by firm C. This interaction describes the second tier of the family network in this case study and consequently we also classify firms D and E as family firms. All three of firms C, D and E are family-networked family firms. It is possible that those indirectly family owned firms hold further shares in other firms. Indeed, this is the case for firm E which holds more than 50% of another firm (F, banked). This relationship represents a third tier of the family network and firm F is also classified as family (-networked) firm. Finally, there are two more network tiers in the studied case. Firm F is the sole holder of the unbanked firms G and H, while firm H owns 100% of firm K. Accordingly, firms G, H and K are also classified as family (-networked) firms, completing a five-tier family network.

In the Figure 3 case study there are further, more complex, ownership interactions involving firms I (banked) and J (unbanked). Both Mr. X and other family firms in the network own shares in I and J. However, only adjacent nodes with the criterion of $\geq$ 50% of ownership were considered in constructing the family networks from the whole data sample. Hence, we are not identifying cases such as firm J as a family-networked firm. In a sense, we are being conservative in our definition of family networks by counting only the cases in which we are completely certain that a given firm is fully controlled by a family. For example, firm C in case C on Figure 2 is also not included in the set of family firms because there is no guarantee that it is controlled more than 50% by family representatives. There are also data limitations regarding such cases because identification numbers or exact shares are missing for minor shareholders.

Notice that within the same family network, we can have coexistence of unbanked and banked firms. As mentioned earlier, this can help us understand financing connections within the network. For example, unbanked family firms may benefit from funding from other firms in the family network which are either single or multi-banked. In the case study depicted on Figure 3, unbanked firms such as G, H, J and K may benefit from direct connections with banked firms such as B, E, and F. Banked firms could also receive additional financing through the network. Such family network interactions may therefore explain our finding that family firms seem to be facing less strict financing constraints compared to non-family firms. But we will find that bank relationships per se do not always offer a strict monotonic improvement and so being indirectly connected to banks should not either.

To get a clearer idea of the various kinds of firms defined by direct or indirect family ownership, consider the 2004-2007 balanced panel sample, one of the three that we use in the structural estimation. Out of 100,745 firms in total, 42,012 (41.7%) are family firms as defined above. Within the set of family firms, 39,620 (94.3%) are directly owned by a person or family and 39,715 (94.5%) do not own other firms. Taking the intersection of these two sets yields 38,950 (92.7%) pure family firms. Also within the set of family firms, 2,297 firms (5.5%) are owners of other firms, out of which 670 are directly owned, via 50% or higher share**,** by a person or family**.** The latter, together with the 2,392 firms (5.7%) that are owned by family firms comprise the total of 3,062 (7.3%) family-networked firms. The relatively large fractions of firms owning or owned by other firms within the family-networked category suggest that many family networks are relatively complex**.** We report overall statistics for the entire data we use below, stratified by key categories.

3.3 Data used in the structural estimation – sample construction and summary statistics

We use a subset of the full dataset described earlier to structurally estimate and compare the three alternative models of dynamic financial constraints presented in Section 2. To estimate each model we use data on firm's tangible fixed assets, k_{jt} which we interpret as 'firm size'; investment I_{jt}; and net profits, q_{it}, where j indexes firms and t indexes time. We therefore keep in our sample only the firms j for which data on all three variables (k_{jt}, I_{jt}, q_{jt}) are available for at least one year. This reduces the sample from 4,749,653 observations on 972,639 firms to 3,718,286 observations on 805,118 firms, a drop of approximately 20%. The reason is data availability in the (non-mandatory, unlike CIR) SABI-INFORMA database as we need information on the three variables per firm in a given year and moreover computing firm investment requires two observations on fixed assets from consecutive years.

Table 1, panel A, column (1) reports summary statistics for these firms. Mean age is 11 years. A large fraction (48%) have credits from multiple banks, 31% are single-banked and a significant fraction (21%) are unbanked. We classify 32% of the firms as family firms, of which the majority are pure family firms. The summary statistics for firm assets, investment and cash flow reveal substantial heterogeneity in all three variables – the standard deviations are much larger than the mean values and there are long right tails (the means are substantially larger than medians). For example, median investment is approximately 10 thousand Euros, which is nearly 20 times lower than mean investment (196 thousand) and nearly 1500 times lower than the standard deviation in investment across firms.

To reflect the model assumption that firms are approximated as in a steady state with regards to their financial environment and constraints, in the structural estimation we restrict attention only to firms which maintain a *continuing banking status*, that is, firms which are continuously unbanked, continuously single-banked, or continuously multi-banked over all years in which they are present in the full dataset (not only the specific years in the balanced panels defined below). This reduces the sample to 1,493,181 observations on 385,539 continuing banking status firms – see column (2) in part A of Table 1. Comparing columns (1) and (2), we see that continuing banking status firms are on average larger (with higher mean and median fixed assets k, investment I and cash flow q values), and with a larger fraction of multi-banked and smaller fraction of single-banked firms. Mean firm age and the fraction of family firms are approximately the same as in the full sample.

In the maximum likelihood estimation (see the next section for details), in order to test fully the implications of our dynamic models, we perform runs which emphasize the dynamic nature of the data as in time series or panel. In addition we also do runs with cross-sectional data. To accommodate this, we construct two four-year balanced panels of capital, investment and cash flow, $\{k_{jt}, I_{jt}, q_{jt}\}$ data – a panel covering 1997-2000 (the first four years in the data) and a panel covering years 2004-2007 (the latest years for which we have data). We also construct one three-year balanced panel spanning the intermediate period, 2001-2003. Each of the three panels consists of all firms with non-missing data on all of $\{k_{jt}, I_{jt}, q_{jt}\}$ for *all* of the chosen years and which maintain a continuing banking status as defined above. In choosing the time length of the panels we aim to strike a balance between (i) having multiple observations of the same firm over time (these are used in the estimation runs with panel or time series data), (ii) potential attrition concerns, and (iii) preserving a sufficiently large sample size to be able to further stratify by firm size, age, banking, and family status. We also perform robustness estimation runs with data on continuing banking status firms without requiring a balanced panel (the firms featured in column (2) in Table 1), and show that our results remain robust, see Section 4.3.

The three balanced panels we feature contain in total 880,727 observations for 135,451 distinct firms. These firms represent 13.9% of all firms in the SABI-CIR database and cover approximately 43% of aggregate total assets, 46% of aggregate debt, and 55% of aggregate banking debt in SABI-CIR. With respect to the entire population of Spanish non-financial firms, the coverage of the balanced panels is around 44% of the aggregate total assets and 59% of the total amount of loans given by Spanish credit institutions to Spanish non-financial firms.

Columns (1) and (2) in part B of Table 1 report data summary statistics corresponding to columns (1)-(2) in

Table 1, part A but focusing on the most recent balanced panel, 2004-07, as an example.[23] Column (3) in Table 1, part B reports summary statistics for the 2004-07 balanced panel of continuing bank status firms described above. Comparing column (3) with columns (1) and (2) in Table 1, part B, we see that among the firms in the balanced panel there are more multi-banked firms and hence they are larger. There are also more family firms and less unbanked and single-banked. The mean firm age in column (3) is larger too but part of this is by construction, since the reported mean age is computed at the observation (not the firm) level, and since we require each firm in the balanced panel to have observations for at least four consecutive years.

Looking across banking status, Table 2 shows that unbanked firms tend to be the smallest in terms of all three of assets (k), cash flow (q) and investment (I), as we compare the reported means and medians. The difference between unbanked and single-banked firms in those dimensions is much smaller than the difference between those two categories and multi-banked firms. Looking at the standard deviation values we see that there is more heterogeneity among multi-banked firms. Multi-banked firms also have significantly higher mean and median total assets and sales compared to unbanked and single-banked. They also have higher debt to assets ratio, lower liquidity ratio and are older.

Tables 2 and 2B provide summary statistics, including on various financial ratios and indicators, for the pooled sample of firms from the three balanced panels (1997-00, 2001-03 and 2004-07) described above. In Table 2, we break down the data by firm banking status (unbanked, single-banked or multi-banked) and by firm family status (family, non-family). Looking across the Table 2 columns, comparing family vs. non family firms we see that the largest fraction of family firms is among multi-banked firms (around 50% of all) while the lowest fraction is among unbanked firms (17%). Another robust pattern in Table 2 is that, comparing the median assets, cash flow and investment k, q and I, family firms tend to be larger than non-family firms, although the difference for multi-banked firms is small. The financials section of Table 2 (these data are not used in the estimation) in addition suggest that family firms have larger median sales and cashflow-to-assets ratio, q/k compared to non-family firms.

Table 2B breaks down family firms into pure family vs. family-networked, as defined earlier, and compares them to non-family firms. We see that pure family firms look more similar to non-family firms on most dimensions. Family-networked firms tend to have larger median and mean assets, cash flow and investment. There is larger variability (comparing the coefficient of variation, std. deviation / mean) in assets and investment among non-family firms compared to pure family and family-networked.

Last but not least, we can see some symptoms of the financial situation of family-networked firms that will be consistent with our findings below. Relative to pure family and non-family firms, family-networked firms have lower median liquidity ratios, especially among unbanked, that is, seem to need less liquidity. Family-networked firms also have consistently lower debt-to-assets ratios, that is, seem less reliant on formal funding sources.

[23] Corresponding summaries for the 1997-00 and 2001-03 panels are presented in Table A1 in the Appendix. The reported data in Table A1, column (2) for the 2001-03 period are very similar to those in 2004-07 while in 1997-00 we observe slightly larger median values of k, I, q which could be explained by the larger fraction of multi-banked firms (72%) vs. 51% in Table 1.

4 Results

4.1 Computation and empirical method

To solve and structurally estimate the three dynamic models of firms' investment behavior under alternative financial constraints, we re-write each of the dynamic programming problems from the previous section as linear programs (Prescott and Townsend, 1984; Phelan and Townsend, 1991; Karaivanov and Townsend, 2014). To do so, we first discretize the programs from Section 2.2 by assuming that all state and choice variables belong to finite grids (that is, each variable takes a finite number of values). Second, we use the discretized problems to define the joint probability distribution over the choice variables such as effort, z, capital k', etc. and net profits q, conditional on the current state (e.g., beginning-of-period capital k) as new choice variables in a linear program. Details are available in Appendix A.

The rationale for using a linear programming (LP) approach is two-pronged. First, it is well-known from the mechanism design and contract theory literatures (e.g., Rogerson, 1985; Phelan and Townsend, 1991) that the incentive compatibility constraints (ICC) in the moral hazard problem can introduce non-convexities. One possible way the literature has dealt with this issue is to make specific assumptions on the preferences, the production technology and the distribution of shocks which allow using the so-called "first-order approach" whereby the incentive constraint is replaced by its first order condition which under the assumptions made becomes necessary and sufficient for maximum (Rogerson, 1985). Alternatively, Abraham and Pavoni (2008) propose a numerical verification algorithm whereby a solution is obtained using the first-order approach (assuming it is valid) and then a global maximization routine is invoked to verify whether an optimum is achieved.

In contrast, by re-writing the contracting problem as a linear program in terms of joint probabilities (lotteries) over the choice variables we obtain a convex problem by construction and thus we can use arbitrary (including non-convex and non-separable) preferences or technology to compute the model. Even though the autarky (A) and borrowing (B) regimes can be solved using standard non-linear methods, we use the LP method to ensure consistency with the solutions to the moral hazard (MH) regime. This consistency is important for the model comparison tests we perform in the empirical part. In addition, our linear programming solution method has the advantage of offering a direct and intuitive mapping from the dynamic LP solutions, π (which are probability distributions) to the *likelihood* of the observed data – capital k, investment I, and net profits q, under the null hypothesis of each model regime.

To structurally estimate and statistically test across the dynamic models of firm credit access described in Section 2: autarky (A), non-contingent saving/borrowing (B) and moral hazard (MH), we use the general approach developed in Karaivanov and Townsend (2014) adapted to the specific models here. In brief, our empirical strategy is as follows. We use the probabilistic form of the solutions to the dynamic linear programs exhibited in Appendix B, together with assumed parametric distribution for measurement error and parameteric distribution of the initial unobserved state variables and write down a likelihood function measuring the goodness-of-fit between the data and each of the three alternative dynamic models of financial access. A basic description of the method is provided in Appendix C; interested readers are referred to Karaivanov and Townsend (2014) for the full details.

We then use the maximized likelihood value for each model (at the MLE parameter estimates) and perform a formal model comparison test (Vuong, 1989) about whether we can statistically distinguish, pairwise, between the models relative to the data. We thus approach the data as if we are agnostic about which theoretical model fits best and let the data determine this. The Vuong test does not require that either of the compared models be correctly specified. If, as in our setting, two compared models are statistically non-nested (see Vuong, 1989 for formal definition), the test-statistic is normally distributed under the null hypothesis that the two models are equally close to the data in the KLIC sense (a tie). If the null is rejected (the Vuong Z-statistic is large enough in absolute value), we conclude that the model with higher likelihood is closer to the data than the alternative. Due to the Vuong test's pairwise comparison nature, its outcomes are not always fully transitive (for example, models X and Y can be each tied with model Z but X can 'win' over Y). When reporting results we handle this issue by listing as 'best fitting' the highest-likelihood financial regime and all other regimes statistically tied with it, in order of decreasing likelihood. The results of the Vuong test, a 'horse race' among the three models, inform us which model(s) fits the data best and also which models can be rejected as likely to have generated the data.

4.2 Baseline results

Tables 3 and 4 report the baseline model comparison results obtained using the Vuong test. The results are displayed in reverse chronological order, starting from the most recent data and going back in time. Each column contains the Vuong test statistics comparing the three financial regimes pairwise (three possible pairs in total). A statistically significant test statistic (in the Table we report 1%, 5%, and 10% significance levels, denoted by ***, ** and * respectively) indicates that we are able to reject the null hypothesis that both compared models are equally close to the data in the KLIC sense. That is, the model regime whose abbreviation (MH, B or A) is listed in the table entries fits the data better than the alternative model to which it is compared, at the top of the column. The last column of each section in Tables 3 and 4 reports the best-fitting model overall for that particular estimation run. All results in Tables 3 and 4 assume risk neutrality ($\sigma = 0$). We perform a robustness test allowing for risk aversion in Section 4.3.

We report results for the whole sample of firms and also when the sample is stratified by firm age and size. For a given panel (e.g., 2004-07), we define "small and young" firms to be all firms which have assets k below the median and are less than 10 years old in the first year of the panel (2004). Similarly, we call "large and old" all firms which have assets k equal or above the median and are 10 years or older in year 1 of the panel.

4.2.1 Age, size and banking status

In Table 3, we study how the best-fitting financial regime varies when we compare all vs. small and young vs. large and old firms. We use both panel data (on investment alone, rows 1.1-1.3; or investment and cash flow, rows 2.1-2.6) and assets, investment, cash flow cross-sections (parts 3-5 of the Table).

We see a very clear pattern by age and size – estimating using data from large and old firms results in a smoother best-fitting financial regime compared to using corresponding data for small and young firms. This is especially evident in the 2004-2007 pre-crisis period when the lending boom and activity was at its peak – the MH regime is best-fitting (including ties) among large and old firms in 11 out of the 15 estimated specifications. As one example, MH, MH and B fit the 2004 data for large and old respectively unbanked, single-banked and mutli-banked firms while the corresponding result for small and young firms is A,A,A (see Table 3, rows 3.4–3.6). In the (I, q) two-year panel runs (rows 2.1-2.6) all six specifications yield MH as best-fitting among large and old firms while A (and B on two occasions) are best-fitting for small and young.

More generally, comparing the best-fitting regime for large and old firms with those for small and young firms we count 13 instances of strict dominance in terms of smoothing (MH over B or A, or B over A), 2 instances of weak dominance (rows 3.2 and 5.4), and 6 instances in which the estimated best-fitting financial regime is the same. In the three remaining cases (rows 1.2, 1.3 and 5.6) a less smooth regime does appear for large and old firms but it is tied with another regime (row 1.3) or matches/dominates one of two tied regimes for small and young firms (rows 1.2 and 5.6). For example, in the estimation with 1997 data on multi-banked firms, regime B is best-fitting for large and old firms while MH and B are tied for best fit for small and young firms. Our results suggesting a less constrained financial environment for large and old firms are consistent with previous findings from the empirical literature that older and larger firms are able to achieve smoother investment / cash flow relationship compared to small and young firms.

Regarding firms' banking status, our findings are mixed. In the whole sample, consisting of the large/old, small/young and more firms, (Table 3, columns A, reading down the rows), the best-fitting financial regime for unbanked firms tends to be less smooth than the best-fitting regime for single- and multi-banked firms, for example, A for unbanked vs. B for single- and B for multi-banked firms in rows 3.1–3.3, 3.4–3.6 and 5.4-5.6; or A for unbanked, B for single-banked and MH for multi-banked firms in rows 2.1-2.3 and 2.4-2.6. However, in other specifications we obtain B as best-fitting throughout (rows 4.1-4.3 and 5.1-5.3). Focusing on small and young firms (Table 3, columns B) the data on unbanked firms are best fit by a (weakly) less smooth regime than single- or multi-banked firms from the corresponding year and category – compare rows i.1 and i.4 in each section with rows i.2 and i.3 or i.5 and i.6 for $i = 1, ..., 5$. In this sense we find evidence that small and young unbanked firms are more financially constrained. Looking at large and old firms categorized by banking status, however, (Table 3, columns C) we see a different pattern – in the 2004-07 and 2001-03 data unbanked firms do at least as well if not better than single-banked and multi-banked firms of the same type.

4.2.2 Family vs. non-family firms

In Tables 4A and 4B we stratify the sample by family status, that is, whether a firm is owned or not by a person/family either directly or via a network of subsidiaries, in addition to stratifying by the firms' size/age and banking status. We look first at Table 4A which uses data for all firms stratified by family status. Comparing the corresponding lines for family vs. non-family firms, we see that the best fitting financial regime for family firms is never more constrained compared to the best fitting regime for non-family firms from the same year of the data and not infrequently is strictly less constrained. There are 13 instances of the same regime, 2 instances of weak dominance, and 12 instances of strictly significantly smoother financial regime for family firms. This pattern holds both when we use investment and cash flow or investment panel data (sections 1, 2 and 4 in Table 4A), and also with cross-sectional (k, I, q) data from any of the three balanced panels.

For example, using a two-year (I, q) panel data from 2004 and 2007 (Table 4A, rows 2.4-2.6) we see that the borrowing and lending (B) regime fits the data best for unbanked family firms while the more restrictive financial autarky (A) regime is best-fitting for non-family firms. The MH and B regimes are tied for best fit using data from single-banked family firms while again A is best fitting for non-family firms. MH is best-fitting for both multi-banked family and non-family firms. Similarly, with the 2004 (k, I, q) cross-sectional data (rows 3.4-3.6) regime B fits best for unbanked firms both with and without family status. For single-banked firms we see that MH fits best for family/networked firms while B fits best for the same-year non-family firms. For multi-banked firms (row 3.6) the MH and B regimes are tied for family firms while B alone is best fitting for non-family firms.

The same pattern holds when we control for firm size and age in the continuation Table 4B (see the sections labeled “IV. Small and young” and “V. Large and old”). For example, in 1997 (rows 9.4–9.6) for small and young firms we obtain B,A; B; and MH as the best fitting financial regimes for unbanked, single-banked and mutli-banked family firms respectively, while A; B and B are the best fitting financial regimes for the corresponding non-family firm categories. The same pattern also holds for large and old firms (Table 4B, section V) – for example, MH, MH and B fit best for unbanked, single-banked and mutli-banked family/network firms in 2007 (rows 10.1–10.3) while MH, B and B fit best for the corresponding categories by bank status for non-family firms. The exact same result holds in the 2004 data. In fact, looking over all estimation runs (that is, *all rows* in Tables 4A and 4B) there is no exception from the pattern that the best-fitting financial regime (allowing for Vuong test ties) for family firms (columns A) is weakly less constrained than the best fitting regime for non-family firms of the same bank status, age and size in the same year (columns B).[24]

4.2.3 Pure family vs. family-networked firms

In Table 5 we further divide family firms into two categories, as defined in Section 3.2.2 – “pure family” firms, that is, family firms directly owned by individuals or families and “family-networked” firms, that is, firms that are part of a network of family firms constructed by ownership. Columns A of Table 5 report the Vuong model comparison test results for pure family firms, columns B report the Vuong test results for the family-networked firms and finally columns C report the Vuong test results for non-family firms. Columns C simply repeat the corresponding results from Table 4A to make comparisons easier. In sections 4 and 5 of Table 5, we also show estimation results (cross-sections only) with the 1997-00 and 2001-03 data.

There are two main takeaways from Table 5. First, comparing the corresponding lines in columns A and B, we see that the data from the family-networked firms indicate that they seem to be able to smooth better their capital stock and/or investment given cash flow fluctuations. The best-fitting financial regimes for family-networked firms, when allowing for Vuong test ties, are weakly less constrained than those for pure-family firms. There are 5 instances of the same best-fitting regime, 7 instances of weak dominance, and 6 instances of strictly significantly smoother financial regime for family firms. There are five cases in which a more constrained regime is statistically tied for best-fitting for family-networked firms (rows 2.3, 2.6, 3.2, 3.4 and 4.2) but in all such instances a (weakly) less constrained regime is also best-fitting. Columns B of Table 5 also exhibit more regime ties compared to columns A, which is caused by small sample size (there are only 231 single-banked and 359 unbanked family-networked firms). For example, in row 2.1, the autarky regime (A) fits best the 2004-06 (I, q) panel data for pure family firms while the borrowing and lending (B) regime fits best the corresponding data from family-networked firms. Similarly, in row 2.2, regime B fits best for pure family while moral hazard (MH) fits best for family-networked firms.

The second takeaway from Table 5 is that pure family firms tend to fall in between the non-family and family-networked firms and, in many cases, seem more similar to non-family firms than to family-networked firms. For instance, see rows 2.2 and 2.5 using (I, q) panel data, where the B regime fits best for pure family firms, the A regime for non-family and the MH regime for family-networked firms. More generally, comparing pure family

[24] All three regimes are statistically tied in row 12.4 for family firms.

to non-family firms in columns A and C in Table 5, we see that the best-fitting regime in rows 1.3, 2.1, 2.3, 2.6 and all rows in sections 3–6 (in total, 18 specifications) is the same for pure family and non-family firms. In the remaining 5 cases, pure family firms exhibit more investment cash flow smoothing than non-family firms.

Unfortunately, due to data limitations we cannot complement or replace Table 4B with another table which looks at family-networked firms alone vs. all other firms stratified by size and age as well as by banking status. The reason is sample size – when broken down by banking status and/or size and age, the samples of family-networked firms become very small (as low as 200 firms) which renders the Vuong test inconclusive. One can see evidence of this in Table 5, columns B (observe the large number of regime ties, relative to columns A and C). We are able, however, in Table 5, Section 6, to stratify and compare pure family vs. family-networked vs. non-family firms by age and size alone, for any continuing banking status. The results match what we found in the other rows of Table 5 – family-networked firms are able to smooth investment weakly better than non-family firms while pure family firms look the same as non-family firms. We also confirm the results from Table 3 that large and old firms do weakly or strictly better than small and young firms in all family status categories.

Regarding the underlying mechanism through which family-networked firms seem able to smooth investment more than pure family and non-family firms, a potentially important caveat is that, given the data we have, we are unable to directly analyze possible peer effects or spillovers within family networks. In our data, we look at each individual firm to determine its banking status, age and size. In a network, however, family firms are linked and another firm in the network could have an alternative (better) financial access that benefits all members. We do control however, for firm characteristics for which we have available data (firm size, age, banking status) and our results remain robust. Moreover, when banks decide whether to grant a loan to a firm, they screen not only the firm but also the whole economic group to which it belongs, to avoid any painful surprise in future. Therefore, our results are robust to credit risk management by banks that takes into account potential leakages of funding among family-networked firms.

4.3 Robustness

Table 6 contains the Vuong test model comparison results from various robustness runs. Unless otherwise mentioned, these robustness runs use 2004 (k, I, q) data from the 2004-07 balanced panel.

We first re-run the estimation on cross-sectional (k, I, q) data from 2004 but, unlike in the baseline estimation runs in Table 4A, rows 3.1-3.3, we *do not use* the 2004-07 balanced panel. That is, the samples used in Table 6, rows 1.1-1.3 consist of all firms with continuing banking status and without missing data for 2004 only. This results in a significantly larger sample size (for instance, there are 6,337 unbanked family firms in Table 6, row 1.1 vs. 3,221 unbanked family firms in the 2004-07 balanced panel used in Table 4A, row 3.1). We see from Table 6, rows 1.1-1.3 that our main results from Table 4A are not a feature of requiring a balanced panel and remain robust – family firms are characterized by a financial regime that is less constrained than that characterizing non-family firms (the best-fitting regimes for unbanked, single-banked and multi-banked family firms are B, MH and B vs. A, A and B for the corresponding non family firms). Similar results obtain using 2000 (k, I, q) data (see Table 6, rows 1.4-1.6). Once again, the data from family firms is better fit by less constrained financial regime than that from non-family firms.

The next robustness check (Table 6, rows 2.1-2.3) pools all firms with any continuing banking status in the 2004-07 panel and shows that the main baseline results from Tables 3 (on firm size and age) and Table 4A (on family status) remain valid. As in Table 3, the data from small and young firms is fit best by a more constrained financial regime (autarky, A) than the data from large and older firms (borrowing, B). This is true for both family and non-family firms. The results in Table 6, rows 2.1-2.3 also suggest that family firms are (weakly) less financially constrained than non-family firms, as in Table 4A. This is true for the whole sample of continuing banking status firms and also when stratified by age and size.

In Table 6, rows 3.1-3.3 we perform a placebo test by assigning "family status" *at random* to the firms in our sample, using 2004 (k, I, q) cross-sectional data. We see that, as expected, the bilateral Vuong test results and the best-fit financial regimes are identical across columns A (pseudo 'family' firms) and columns B (pseudo 'non-family' firms) in Table 6, rows 3.1-3.3. In fact (not shown in the Table) the maximized likelihoods of all models are numerically very close between the two placebo test samples.

In Table 6, rows 4.1-4.3 we allow for a small degree of risk aversion by setting the relative risk aversion parameter to $\sigma = 0.1$. We see that the main result regarding family vs. non family firms is preserved – the best-fitting financial regime for family firms is weakly less constrained than that for non-family firms, most clearly for unbanked firms. In rows 5.1-5.3 we allow for quadratic capital stock adjustment costs in the model of the form $g(k_t, I_t) = \frac{1}{2} b k_t \left[\frac{I_t}{k_t}\right]^2$ and estimate the additional parameter b. We see that adding such ad hoc adjustment costs blurs the statistical distinction between the financial regimes both across banking status and family status. Notice that, unlike most of the literature, we are not comparing a complete markets model vs. a model with adjustment costs proxying for financial frictions. Instead, we model the source of financial frictions explicitly, as either arising from an exogenously incomplete markets model (in the A and B financial regimes) or an endogenously incomplete markets model (the MH financial regime). Adding identical ad hoc adjustment costs to those models clearly diminishes, in an exogenous and perhaps artificial manner, the differences across the financial constraints we have intended to model.

So far in all estimation runs we have used firms which maintain continuing banking status through time. In Table 6, part 6 we look at firms that switch banking status using 2004 and 2007 (k, I, q) cross-sectional data. That is, we do not require continuing banking status. The previous results about family vs. non-family firms is preserved albeit in a weak form. Note, however, that this robustness check stretches the interpretation and connection with the theory as we do not allow transitions in banking status and financial regime when we compute the models.

Finally, in part 7 of Table 6 we do a robustness check on the model timing and use the joint distribution of next-period assets, investment and cash flow, that is (k', I, q) rather than (k, I, q). The data on family firms is again best-fit by a less constrained financial regime (including ties), confirming the earlier findings.

5 Conclusions

We study the role of financial constraints on the investment decisions of non-financial firms. We investigate whether firms' size and age, together with bank-firm relationships (with no, single or multiple banks) shape those constraints in such a way as to end up with different investment and cash flow cross-sectional distributions and dynamics. We pay particular attention to the interaction of those factors with firm ownership, that is, whether financial constraints may differ among family-controlled firms, family-networked firms or non-family firms.

We use firm investment and cash flow data from the Spanish Mercantile Registry and combine it with data from the Bank of Spain Credit Registry which provides a census of all bank loans above 6,000 Euro granted to Spanish firms. The data cover the 1997-2007 period in Spain when firms' output, investment and credit access grew at high and persistent rates. The wide heterogeneity in firms' size, age, bank relationships and ownership in the data allows us to estimate the impact of financial constraints on firms' investment and statistically distinguish between types of credit constraints across different firm strata. Firm investment is a key variable for economic growth, so this interaction of real and financial considerations is both important and timely.

We estimate using maximum likelihood three non-nested dynamic models of financial constraints ranging from autarky, to exogenously incomplete markets (borrowing/saving in a single asset), to endogenously incomplete markets with state-contingent borrowing/transfers (moral hazard) for firms differing in their number of bank relations, age and size, or family ownership status. In line with our dynamic models of firm investment subject to a persistent source of financial constraints, we focus attention to firms that maintain the same banking and family ownership status continuously. We then determine the type of financial constraints for each firm category using a statistical model comparison test. The unique matching of our two data sources allows us to disentangle the roles that firm characteristics such as age or size play together with bank/non-bank relationships and family/non-family ownership and to ultimately obtain a score card for which firm categories are more severely financially constrained and which less so.

Our baseline findings are in line with the previous literature on investment constraints which uses different empirical method, but we also provide several new insights, especially on the role that family firm structures and networks may play in overcoming constraints to investment which result from shocks to cash flow when also taking into account bank-firm relationships. We find a clear pattern by firm age and size, with results suggesting a less constrained financial environment for large and old firms relative to smaller and younger firms. This is consistent with the previous findings in the empirical literature showing that larger and older firms tend to feature smoother investment / cash flow relationship. We also interpret these results as an important validation for our structural maximum likelihood approach.

Regarding firms' ownership structure, we find strong evidence that family firms are less financially constrained than non-family firms. Moreover, we also find clear evidence that firms which are part of family-based networks constructed using ownership shares face less strict credit constraints compared to non-networked ('pure family') firms that are family-owned but do not own other firms. These results are robust across firm age and size stratifications as well as across banking status. We interpret these findings as showing that family-based firm networks seem able to reduce or surmount financial constraints that otherwise may hamper firms' investment and growth and their capability to smooth out cash flow shocks.

When stratifying by firms' banking status we obtain mixed results. In the whole sample, unbanked firms are, in most cases, estimated to be more constrained than single- or multi-banked firms; however there are also specifications in which we cannot distinguish between the financial regimes. Interacting banking status with firm age and size, we find evidence that small and young unbanked firms are more financially constrained. However, among large and old firms we see a different pattern: large and old unbanked firms are equally or sometimes even less constrained than single-banked and multi- banked firms of the same type.

Contrary to a significant part of the literature, we apply a structural model of firm investment, capital and cash flow decisions to a rich and heterogeneous dataset, as described before. Compared to previous work relying on reduced form analysis, the main advantage of our structural approach is that we can assess not only whether financing constraints affecting firm investment are absent or present, but also determine the most likely nature of these financial constraints within a list of prototypical theoretical models. A second important advantage of our structural approach is the explicit modeling of the dynamic interaction of present vs. future constraints as firm size and credit conditions captured in the model state variables evolve endogenously over time.

All in all, using our robust structural approach with multiple data samples, we find several important patterns regarding the investment constraints faced by non-financial firms. Some of these patterns are in line with the existing literature (e.g., the results on firm age and size) while others are new (e.g., the results on firm ownership and bank relationship interactions). Our results also suggest that key structural characteristics of firm organization (family networks) or behaviour (bank funding) may be an optimal response to overcome or reduce financial constraints. Further research is needed on this crucial selection issue, ultimately linking to a better understanding of the micro underpinnings of firm finance and investment.

References

[1] Abraham, A. and N. Pavoni (2008), "Efficient Allocations with Moral Hazard and Hidden Borrowing and Lending: A Recursive Formulation," *Review of Economic Dynamics* 11(4), p.781-803.

[2] Ahlin, C. and R. Townsend (2007), "Using repayment data to test across models of joint liability lending", *Economic Journal* 117, p.F11-F51.

[3] Albuquerque, R. and H. Hopenhayn (2004), "Optimal Lending Contracts and Firm Dynamics", *Review of Economic Studies*, 71(2), p.285-315.

[4] Alessandrini, P., F. Presbitero and A. Zazzaro (2009), "Banks, Distances and Firms' Financing Constraints", *Review of Finance* 13, p.261-307.

[5] Alonso-Borrego, C. (1994), "Estimating dynamic investment models with financial constraints", Working paper 9418, CEMFI.

[6] Anderson, R., S. Mansi and D. Reeb (2003), "Founding family ownership and the agency cost of debt", *Journal of Financial Economics* 68(2), p.263–85.

[7] Andrés, C., (2011), "Family ownership, financing constraints and investment decisions", *Applied Financial Economics* 21, p.1641-59.

[8] Banerjee, A. and E. Duflo (2005), "Growth Theory through the Lens of Development Economics", *Handbook of Economic Growth*, vol. 1(A), P. Aghion and S. Durlauf eds., p. 473–554.

[9] Banerjee, A., and B. Moll (2010), "Why Does Misallocation Persist?", *American Economic Journal: Macroeconomics*, 2(1), p.189–206.

[10] Berger, A. and G. Udell (1995), "Relationship lending and lines of credit in small firm finance", *Journal of Business*, 68, p. 351-82.

[11] Bertrand, M., P. Mehta and S. Mullainathan (2002), "Ferreting out Tunnelling: An application to Indian business groups", *Quarterly Journal of Economic*s 117(1), p.121-48

[12] Bertrand, M. and A. Schoar (2006), "The Role of Family in Family Firms", *Journal of Economic Perspectives*, 20(2), p. 73-96.

[13] Bewley, T. (1977), "The permanent income hypothesis: A theoretical formulation", *Journal of Economic Theory* 16(2), p. 252-92.

[14] Bizer, D. and P. DeMarzo (1992), "Sequential Banking", *Journal of Political Economy* 100(1), p.41-61.

[15] Bond, P. (2004), "Bank and non-bank financial intermediation", *Journal of Finance*, 59(6), p. 2489-2529.

[16] Bond, S. and C. Meghir (1994), "Dynamic investment models and the firms' financial policy", *Review of Economic Studies*, 61(2), p.197-222.

[17] Bond, S., J. Elston, J. Mairesse and B. Mulkay (2003), "Financial factors and investment in Belgium, France, Germany and the United Kingdom: A comparison using company panel data", *Review of Economics and Statistics*, 85(1), p.153-65.

[18] Boot, A. (2000), "Relationship banking: What do we know?", *Journal of Financial Intermediation*, 9, p. 7-25.

[19] Buera, F., and Y. Shin (2013), "Financial Frictions and the Persistence of History: A Quantitative Exploration", *Journal of Political Economy* 121(2), p.221–72.

[20] Carbó-Valverde, S., F. Rodríguez-Fernández and G. Udell (2008), "Bank Lending, Financing Constraints and SME Investment", *Federal Reserve Bank of Chicago WP* 2008-04.

[21] Caspar, C., A. Dias and H-P. Elsrodt (2010), "The five attributes of enduring family businesses", McKinsey & Company.

[22] Cetorelli, N. (2001), "Competition Among Banks: Good or Bad?", *Economic Perspectives* 25(2), Federal Reserve Bank of Chicago.

[23] Chava, S., and A. Purnanandam (2009), "The effect of banking crisis on bank-dependent borrowers", Working paper.

[24] Chirinko, R. and J. Elston (2006), "Finance, control and profitability: the influence of German banks", *Journal of Economic Behaviour and Organization*, 59, p. 69-88.

[25] Cleary, S. (1999), "The relationship between firm investment and financial status", *Journal of Finance*, 54, p. 673-92.

[26] Clementi, G-L. and H. Hopenhayn (2006), "A Theory of Financing Constraints and Firm Dynamics", *Quarterly Journal of Economics*, 121(1), p.229-65.

[27] Cooper, R. and J. Ejarque (2003), “Financial Frictions and Investment: A Requiem in Q”, *Review of Economic Dynamics*, 6, p. 710-28.

[28] Crespí, R. and A. Martín-Oliver (2015), “Do Family Firms have Better Access to External Finance during Crises?”, *Corporate Governance: An International Review* 23(3), p. 249–65.

[29] Cronqvist, H and M. Nilson (2003), “Agency costs and minority shareholder”, *Journal of Financial and Quantitative Analysis*, 38(4), p. 695-719.

[30] D’Espallier, B., J. Huybrechts and F. Iturriaga (2011), “Analyzing firm-varying investment-cash flow sensitivities and cash-cash flow sensitivities: A Bayesian approach”, *Spanish Journal of Finance and Accounting* 40, p.439-67.

[31] De Mel, S., D. McKenzie and C. Woodruff (2008), “Returns to Capital in Microenterprises: Evidence from a Field Experiment,” *Quarterly Journal of Economics* 123(4), p.1329-72.

[32] Degryse, H. and S. Ongena (2005), “Distance, Lending Relationships, and Competition”, *Journal of Finance* 60, p.2757-88.

[33] Degryse, H. and Van Cayseele, P. (2000), “Relationship lending with a bank-based system: Evidence from European small business data”, *Journal of Financial Intermediation*, 9, p. 90-109.

[34] Diamond, D. (1984), “Financial intermediation and delegated monitoring”, *Review of Economic Studies*, 51, p. 393-414.

[35] Dubois, P., B. Julien and T. Magnac (2008), “Formal and Informal Risk Sharing in LDCs: Theory and Empirical Evidence,” *Econometrica* 76(4), p.679–725

[36] Elston, J. (1996), “Investment, liquidity constraints and bank relationships: evidence from German manufacturing firms”, Discussion Paper 1329, CEPR.

[37] Elyasiani, E. and Goldberg, L. (2004), “Relationship lending: a survey of the literature”, *Journal of Economics and Business* 56, p. 315-30.

[38] Estrada, A. and J. Vallés (1998), “Investment and Financial Structure in Spanish Manufacturing Firms”, *Investigaciones Económicas*, 22(3), p. 337-359.

[39] Evenson, R., and D. Gollin (2003), “Assessing the Impact of the Green Revolution, 1960 to 2000”, *Science* 300(5620), p.758–62.

[40] Fazzari, F., R. Hubbard and B. Petersen (1988), “Financing Constraints and corporate investment”, *Brooking Papers on Economic Activity*, 1, 141-206.

[41] Fazzari, F., R. Hubbard and B. Petersen (2000), “Investment-cash flow sensitivities are useful: a comment on Kaplan and Zingales”, *Quarterly Journal of Economics*, 115, 2, 695-705.

[42] Fohlin, C. (1998), “Relationship banking, liquidity and investment in the German industrialization”, *Journal of Finance*, 53(5), p. 1737-58.

[43] Fohlin, C. and F. Iturriaga (2010), “Bank Relationships, Ownership Concentration, and Investment Patterns of Spanish Corporate Firms”, working paper, Johns Hopkins University.

[44] Fuss, C. and P. Vermeulen (2006), “The response of firms’ investment and financing to adverse cash flow shocks: the role of bank relationships”, Working paper 658, European Central Bank.

[45] Gan, J. (2007), “The real effects of asset market bubbles: Loan- and firm-level evidence of a lending channel”, *Review of Financial Studies*, 20(5), p. 1941-73.

[46] García-Marco, T. and C. Ocaña (1999), “The effect of bank monitoring on the investment behaviour of Spanish firms”, *Journal of Banking and Finance*, 23, p. 1579-1603.

[47] Gibson, M., (1995), “Can bank health affect investment? Evidence from Japan”, *Journal of Business* 68, p.281–308.

[48] Giné, X., and R. Townsend (2004), “Evaluation of Financial Liberalization: A General Equilibrium Model with Constrained Occupation Choice”, *Journal of Development Economics*, 74(2), p.269–307.

[49] Gomes, J., (2001), “Financing Investment”, *American Economic Review*, 90(5), p. 1263-85.

[50] Green, D. and E. Liu (2015), “Growing Pains in Financial Development: Institutional Weakness and Investment Efficiency”, working paper, MIT.

[51] Hernando, I. and A. Tiorno (2002), “Financial constraints and investment in France and Spain: A comparison using firm-level data” in *French and Spain industrial corporations over the period 1991-1999: A comparative study based on their financial statements*, Banco de España.

[52] Hoshi, T., A. Kashyap and D. Scharfstein (1990), “The role of banks in reducing the costs of financial distress in Japan”, *Journal of Financial Economics* 27, p.67-88.

[53] Houston, J. and C. James (2001), “Do relationship have limits? Bank relationships, financial constraints and investment”, *Journal of Business*, 74(3), p. 347-74.

[54] Hubbard, R. (1998), “Capital Market imperfections and investment”, *Journal of Economic Literature*, 36, March, p. 193-225.

[55] Jaffee, D. and T. Russell (1976), “Imperfect information, uncertainty and credit rationing”, *Quarterly Journal of Economics*, 91, p. 651-66.

[56] Jensen, M. and W. Meckling (1976), “Theory of the firm: managerial behaviour, agency costs, and ownership structure”, *Journal of Financial Economics*, 1 p. 305-60.

[57] Jeong, H. and R. Townsend (2007), “Sources of TFP Growth: Occupational Choice and Financial Deepening”, *Economic Theory* 32(1): p. 179–221.

[58] Jiménez, G., V. Salas and J. Saurina (2006), “Determinants of collateral”, *Journal of Financial Economics*, 81, p. 255-81.

[59] Jiménez, G., J. Lopez and J. Saurina (2009), "Empirical analysis of corporate credit lines", *Review of Financial Studies* 22, p.5069-98.

[60] Jiménez, G., S. Ongena, J. Peydró and J. Saurina (2012), "Credit supply and Monetary Policy: Identifying bank balance-sheet channel with loan applications", *American Economic Review*, 102(5), 2301-26.

[61] Jiménez, G., S. Ongena, J. Peydró and J. Saurina (2014), "Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say About the Effects of Monetary Policy on Credit Risk?", *Econometrica*, 82(2), 463-505.

[62] Jiménez, G., S. Ongena, J. Peydró and J. Saurina (2016), "Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiment", *Journal of Political Economy*, forthcoming.

[63] Kang, J., and R. Stulz (2000), "Do banking shocks affect borrowing firm performance? An analysis of the japanese experience", *Journal of Business* 73, p.1–23.

[64] Kaplan, S. and Zingales, L. (1997), "Do investment-cash flow sensitivities provide useful measures of financing constraints?", *Quarterly Journal of Economics*, 112(1), p. 169-215.

[65] Kaplan, S. and Zingales, L. (2000), "Investment-cash flow sensitivities are not valid measures of financing constraints", *Quarterly Journal of Economics*, 115(2), p.707-12.

[66] Karaivanov, A. (2012), "Financial Constraints and Occupational Choice in Thai Villages", *Journal of Development Economics* 97(2), p.201-20.

[67] Karaivanov, A. and R. Townsend (2014), "Dynamic Financial Constraints: Distinguishing Mechanism Design from Exogenously Incomplete Regimes", *Econometrica* 82(3), p.887-959.

[68] Khanna, T. and Y. Yafeh (2007), "Business Groups in emerging markets: paragons or parasites", *Journal of Economic Literature*, vol. XLV, p. 331-72.

[69] Khwaja, A., and A. Mian (2008), "Tracing the impact of bank liquidity shocks: Evidence from an emerging market", *American Economic Review* 98, p.1413–42.

[70] Kinnan, C. (2014), "Distinguishing Barriers to Insurance in Thai Villages", working paper.

[71] Kinnan, C. and R. Townsend (2012), "Kinship and Financial Networks, Formal Financial Access and Risk Reduction," *American Economic Review* 102.

[72] Ligon, E. (1998), "Risk Sharing and Information in Village Economies," *Review of Economic Studies* 66(4), p.847-64.

[73] López-Gracia, J., and S. Sánchez-Andújar (2007), "Financial structure of the family business: Evidence from a group of small Spanish firms", *Family Business Review* 20(4), p.269–87.

[74] Maury, B. (2006), "Family ownership and firm performance: empirical evidence from Western European corporations", *Journal of Corporate Finance* 12, p. 321-41.

[75] Mestieri, M., J. Schauer and R. Townsend (2016), "Human Capital Accumulation and Occupational Choice in the Process of Development", Working paper.

[76] Moll, B. (2014), "Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation?", *American Economic Review* 104(10), p.3186-3221.

[77] Morck, R. (2005), *A History of Corporate Governance around the World*, Randal K. Morck ed., University of Chicago Press.

[78] Myers, S. and Majluf, N. (1984), "Corporate financing and investment decisions when firms have information that investors do not have", *Journal of Financial Economics*, 13, p. 187-221.

[79] Paulson, A. and R. Townsend (2004), "Entrepreneurship and Financial Constraints in Thailand", *Journal of Corporate Finance* 10(2), p.229-62.

[80] Paulson, A., R. Townsend and A. Karaivanov (2006), "Distinguishing limited liability from moral hazard in a model of entrepreneurship", *Journal of Political Economy* 114(1), p.100-44.

[81] Petersen, M., and R. Rajan (1994), "The Benefits of Lending Relationships: Evidence from Small Business Data", *Journal of Finance* 49, p. 3–37.

[82] Petersen, M., and R. Rajan (1995), "The effect of credit market competition on lending relationship", *Quarterly Journal of Economics* 110, p. 407–43.

[83] Phelan, C. and R. Townsend (1991), "Computing Multi-Period, Information-Constrained Optima", *Review of Economic Studies* 58(5), p.853-81.

[84] Pindado, J. and C. De la Torre (2011), "Family control and investment–cash flow sensitivity: Empirical evidence from the Euro zone", *Journal of Corporate Finance* 17(5), p. 1389–1409.

[85] Prescott, E.C. and R. Townsend (1984), "Pareto Optima and Competitive Equilibria with Adverse Selection and Moral Hazard", *Econometrica* 52, p. 21-45.

[86] Rogerson, W. (1985), "The First-Order Approach to Principal-Agent Problems", *Econometrica* 53(6), p.1357-67

[87] Samphantharak, K. (2003), *Internal capital markets in business groups*, PhD Thesis, University of Chicago.

[88] Samphantharak, K. and R. Townsend (2016), "Risk and Return in Village Economies", working paper, MIT.

[89] Schiantarelli, F. (1996), "Financial constraints and investment: Methodological issues and international evidence", *Oxford Review of Economic Policy*, 12(2), p. 70-89.

[90] Schmid, L. (2009), "A Quantitative Dynamic Agency Model of Financing Constraints", Working paper, Duke University.

[91] Schnabl, P. (2010), “Financial globalization and the transmission of bank liquidity shocks: Evidence from an emerging market”, Working Paper.

[92] Sraer, D. and D. Thesmar (2004), “Performance and behaviour of family firms: Evidence from the French stock market”, *CEPR Discussion Paper*.

[93] Stiglitz, J. and A. Weiss (1981), “Credit rationing in markets with imperfect information”, *American Economic Review*, 71, p.393-410.

[94] Townsend, R. (1979), “Optimal contracts and competitive markets with costly state verification”, *Journal of Economic Theory*, 21, p. 265-93.

[95] Townsend, R. and K. Ueda (2010), “Welfare Gains From Financial Liberalization”, *International Economic Review* 51(3), p. 553-97

[96] Udry, C. and S. Anagol (2006), “The Return to Capital in Ghana”, *American Economic Review* 96(2), p.388-93.

[97] Vickery, J. (2005), “Banking relationship and the credit cycle. Evidence from the Asian financial crisis”, Working Paper, Federal Reserve Bank of New York.

[98] Vuong, Q. (1989), “Likelihood ratio tests for model selection and non-nested hypotheses”, *Econometrica*, 57(2), p.307-33.

[99] Williamson, S. (1987), “Costly monitoring, optimal contracts and equilibrium credit rationing”, *Quarterly Journal of Economics*, 102, p. 135-45.

[100] Zhorin, V. and R. Townsend (2014), “Spatial Competition among Financial Service Providers and Optimal Contract Design”, working paper, MIT.

Appendix A – Computation

A1. Linear Programs

We discretize the dynamic programs from Section 2.2 by assuming that all state and choice variables belong to finite grids. Dividends, c belong to the grid C, capital (k and k') belongs to the grid K, effort to the grid Z, output to the grid Q and promised utility to the grid W. In principle the grids can be arbitrarily fine, although in practice we are constrained by computer time and memory requirements.

Second, we use the discretized problems to define the joint probability distribution over the choice variables such as effort, z, capital k', etc. and net profits q, conditional on the current state (e.g., beginning-of-period capital, k) as new choice variables in a linear program. For example, acknowledging that c is not an independent choice variable but can be expressed in terms of k and k', the joint probability distribution in the autarky regime can be written as $\pi(z, k', q, |k)$ where each $\pi(\tilde{z}, \tilde{k}', \tilde{q}, |\tilde{k})$ equals the joint probability of the allocation $(\tilde{z}, \tilde{k}', \tilde{q}) \in$

$Z \times K \times Q$ in the optimal contract for given $\tilde{k} \in K$. We use the following linear program to solve the firm's dynamic investment problem in the autarky regime:

$$\begin{aligned}
\bar{\Pi}^A(k) \quad &= \quad \max_{\pi(z,k',q|k)\geq 0} \sum_{z,k',q} \pi(z,k',q|k)[u(q-\hat{g}(k,k')+(1-\delta)k-k',z)+\beta\bar{\Pi}^A(k')] \\
& \quad \text{s.t. } \pi(\overline{z},\overline{k}',\overline{q}|k) = P(\overline{q}|\overline{z},\overline{k}')\sum_{q}\pi(\overline{z},\overline{k}',q|k) \text{ for all } \overline{z},\overline{k}',\overline{q} \in Z \times K \times Q \\
& \quad \text{s.t. } \sum_{z,k',q}\pi(z,k',q|k) = 1.
\end{aligned}$$

where $\hat{g}(k,k')$ is shorthand for $g(k,k'-(1-\delta)k)$ and where we used that dividends equal $c = q - g(k,k'-(1-\delta)k) + (1-\delta)k - k'$ from the budget constraint. The constraints on the probabilities $\pi(z,k',q|k)$ ensure that they are non-negative, add up to 1, and conform with the net profits production technology represented by $P(q|z,k)$.

The **saving and borrowing** financial regime has the following linear program form:

$$\begin{aligned}
\bar{\Pi}^B(k,b) \quad &= \quad \max_{\pi(z,k',b',q|k,b)\geq 0} \sum_{z,k',b',q} \pi(z,k',b',q|k,b)[u(q-\hat{g}(k,k')+(1-\delta)k-k'+b'-Rb,z)+\beta\bar{\Pi}^B(k',b')] \\
& \quad \text{s.t. } \sum_{b'}\pi(\overline{z},\overline{k}',b',\overline{q}|k,b) = P(\overline{q}|\overline{z},\overline{k}')\sum_{b',q}\pi(\overline{z},\overline{k}',b',q|k,b) \text{ for all } \overline{z},\overline{k}',\overline{q} \in Z \times K \times Q \\
& \quad \text{s.t. } \sum_{z,k',b',q}\pi(z,k',b',q|k,b) = 1.
\end{aligned}$$

where we used $c = q - g(k,k'-(1-\delta)k) + (1-\delta)k - k' + b' - Rb$ from the firm's budget constraint. The two constraints have the same interpretation as in the autarky regime.

To compute solutions to the **moral hazard** constrained credit regime we use the joint probability distribution, $\pi(z,c,k',w',q|k,w)$ over the possible allocations for effort z, capital k', net profits, q, dividends c and future discounted ("promised") utility w', assuming that all variables belong to discrete grids. The grid bounds for the promised utility grid W are $w_{\min}$ and $w_{\max}$ where, compatible with incentive provision, $w_{\min}$ is the discounted utility of having the minimum possible dividend, $c_{\min}$ and applying the lowest possible effort level, $z_{\min}$ forever and $w_{\max}$ equals the discounted utility of having the maximum possible dividend $c_{\max}$ and lowest possible effort level, $z_{\min}$ forever. See KT (2014) for more details.

We re-write the problem in (1) as a dynamic linear program in the probabilities π. With a large number of firms, π will also correspond to the frequency distribution we see in the data, if all variables were observed. The objective function is:

$$\bar{V}^{MH}(k,w) = \max_{\pi(z,c,k',w',q|k,w)\geq 0} \sum_{z,c,k',w',q} \pi(z,c,k',w',q|k,w)[q-c-k'+(1-\delta)k+R^{-1}\bar{V}^{MH}(k',w')]$$

The incentive compatibility constraints (ICC) can be written, $\forall \overline{z}, \hat{z} \neq \overline{z}$ as

$$\sum_{c,k',w',q} \pi(\bar{z},c,k',w',q|k,w)[u\left(c-\hat{g}(k,k'),\bar{z}\right)+\beta w'] \geq$$
$$\geq \sum_{c,k',w',q} \pi(\bar{z},c,k',w',q|k,w)\frac{\text{Prob}(q|\hat{z},k')}{\text{Prob}(q|\bar{z},k')}[u\left(c-\hat{g}(k,k'),\hat{z}\right)+\beta w']$$

The promised utility w entering the period must be delivered, so for $\forall k$ we must have ("promise keeping"):

$$\sum_{z,c,k',w',q} \pi(z,c,k',w',q|k,w)[u\left(c-\hat{g}(k,k'),z\right)+\beta w'] = w$$

In addition, we also have the technological feasibility constraints:

$$\sum_{c,w'} \pi(\overline{z},c,\overline{k}',w',\overline{q}|k,w) = \text{Prob}(\overline{q}|\overline{z},\overline{k}') \sum_{c,w',q} \pi(\overline{z},c,\overline{k}',w',q|k,w) \text{ for all } \overline{z},\overline{k}',\overline{q}$$

and, finally, the "adding-up" constraint:

$$\sum_{z,c,k',w',q} \pi(z,c,k',w',q|k,w) = 1.$$

A2. Grids, parameters, and functional forms

To compute and estimate the models with our yearly data we fix the firms' and intermediary's discount factors to $\beta = .95$ and $1/R = .95$. We calibrate the depreciation rate as $\delta = .18$, which corresponds to the median value of the yearly tangible assets depreciation computed from our data.[25]

We convert the data into model units (normalize) by dividing all currency values for the assets k, investment I and cash flow q by the 90-th percentile of the distribution of tangible fixed assets (k) in the data. In the baseline estimation runs, we use a five-point grid, K for capital, corresponding to the 10th, 30th, 50th, 70th and 90th asset percentiles in the data.[26] For instance, for the 2004-07 panel, $K = \{0, .025, .084, .235, 1\}$. We construct the cash flow grid Q following the same procedure, setting its five elements to the corresponding percentiles from the data. For example, for the 2004-07 panel, $Q = \{.005, .013, .035, .087, .365\}$. The grid for investment I used in the computation of the various models is obtained from the K grid using all possible values that $k' - (1-\delta)k$ can take when $k, k' \in K$ and the grid K is defined as explained earlier. Note that this allows for both upward and downward adjustments of the capital stock. The effort grid Z is set to the three-point vector $\{.01, .505, 1\}$ which can be though of as 'low', 'medium' or 'high' effort levels.

We use the following functional form for the firms' (owners) payoff,

$$u\left(c,z\right) = c - \chi z^{\gamma}$$

[25]We estimated the empirical distribution function of firm-level depreciation rates (measured by the firms' accounting depreciation expressed as percentage of tangible fixed assets) for 1997-2007. For each year, we obtained the median depreciation rate across firms and we set the value of δ equal to the average of these median depreciation rates.

[26]We use a standard histogram function based on distance to the closest grid point (Matlab's command hist). Our methods can handle much finer grids at the cost of added computation time.

where $\chi > 0$ is a parameter governing the relative cost of effort and $\gamma > 0$ parameterizes the curvature of the disutility of effort. In a robustness check we also allow for risk aversion by using $u(c,z) = \frac{c^{1-\sigma}}{1-\sigma} - \chi z^{\gamma}$ with $\sigma > 0$.

On the production side, remember that net profits q are assumed to take on a finite number of values, q_i, $i = L, \ldots, \#Q$. We calibrate the probabilities $P(q|k,z)$ of obtaining net profit level $q \in Q$ from capital level $k \in K$ and effort level $z \in Z$ using the data as follows. The grids K and Q are determined from the data percentiles as explained above. For each possible $q_i \in Q$ and $k_j \in K$, we use a histogram function on the q and k data and take the frequency of observations with the given q_i and k_j, call it $p(q_j|k_i)$. We then assign the probabilities $P(q|k,z)$ by distributing the observed frequency in the data, $p(q_j|k_i)$ for each $k_i \in K$ over the unobserved effort levels $z \in Z$.[27] The chosen specification provides a parsimonious way of calibrating the production technology to the available data, subject to the unobservability of the variable z.[28]

The assumed functional forms are not essential for our computational and estimation methods. Our linear programming approach is extremely general and can work with any (including non-convex) functional forms for preferences and technology. The main reason we chose the specific forms used here is their parsimonious use of parameters which is important for computation speed.

Appendix B – Variables definitions

Firm characteristics

– *Age*: relative to the firm registration date.

– *Industry*: three- and four-digit CNAE-93 classification. Using the industry information we exclude financial firms.

Firm-level economic variables

– *Capital (k_t)*: firm capital stock in year t is measured by the book value of the firm's tangible fixed assets.

– *(Gross) investment* (I_t): defined as the sum of the absolute increase in the stock of tangible fixed assets between years t and $t-1$ and the depreciation in year t.

– *Cash flow* (q_t)*:* defined as the sum of operating profits/losses and depreciation.

– *Sales* (S_t): measured using total sales revenue (not used in the structural estimation, only in summary statistics).

[27] To do so we use the following matrix:

$$T = \begin{pmatrix} .7 & .5 & .25 & .1 & .05 \\ .25 & .4 & .5 & .4 & .25 \\ .05 & .1 & .25 & .5 & .7 \end{pmatrix}$$

In the matrix above the rows correspond to the three effort (z) levels and the columns correspond to the five net profits (q) levels. For example, the first column means that, for any $k \in K$, we assign .7 of the probability (obtained from the data), $p(q_1, k)$ that $q = q_1$ (the lowest net profit is realized) to $z = z_1$ (the lowest effort level), .25 of the probability to the medium effort level, $z = z_2$ and .05 to the highest effort level, $z = z_3$. The opposite order of these weights is used for $q = q_5$, the highest net profit level.

[28] In the estimation runs with capital adjustment costs we use a standard quadratic form from the literature (e.g., Bond et al., 2005),

$$g(k_t, I_t) = \frac{1}{2} b k_t \left[\frac{I_t}{k_t}\right]^2$$

where b is a parameter to be estimated.

– *Total assets* (A_t): from the firms' balance sheets (not used in the structural estimation, only in summary statistics)

Financial ratios

– *Debt-to-assets* (leverage) ratio: total debt divided by total assets

– *Liquidity* ratio: cash to short term debt ratio.

Firm bank relations

– *Number of bank relations*: number of different Spanish credit institutions granting a loan to the firm. According to the current number of bank relations, we distinguish year-by-year three types of firms: unbanked, in single bank relationship (single-banked), and in multiple bank relationships (multi-banked). Empirically, to analyze differences across groups of firms defined according to their banking status, we consider firms that maintain continously the same status over all the years they are present in the data (see Section 4)

Appendix C – The likelihood

We have panel data, $\{\hat{k}_{jt}, \hat{I}_{jt}, \hat{q}_{jt}\}$ for $j = 1, ..., n$ and $t = 0, ..., T$, where the subscripts j and t denote firm and time respectively; k is capital, I is investment, and q is cash flow. The data are assumed i.i.d. across firms. For each firm j, call $\hat{y}_j$ the vector of variables used in the estimation. In the different MLE runs we do $\hat{y}_j$ can consist of either cross-sectional variables, for example, period t capital, investment and cash flow (that is $\hat{y}_j = (\hat{k}_{jt}, \hat{I}_{jt}, \hat{q}_{jt})$) or variables from different time periods, for example, firm investment and cash flow from dates t and $t+1$, that is, $\hat{y}_j = (\hat{I}_{jt}, \hat{q}_{jt}, \hat{I}_{jt+1}, \hat{q}_{jt+1})$).

For given: (i) structural parameters of the model (preferences and technology), (ii) distribution parameters for unobserved heterogeneity (the initial distribution of debt/savings b or promised utility, w), and (iii) a distribution parameter for the measurement error, we construct the likelihood, $\Lambda^m(\phi)$ of each model $m \in \{A, B, MH\}$ with respect to the data $\{\hat{y}_j\}_{j=1}^n$ where ϕ is the vector of all estimated parameters.

Following Karaivanov and Townsend (KT, 2014), call s^1 the observed state variable (capital, k) and s^2 the unobserved state variable (debt/savings, b or promised utility, w) in the model. For given structural parameters ϕ^s for preferences and technology, the solution of each LP problem in Section 2 is a discrete joint probability distribution, $\pi(.|s^1, s^2)$, using which we can obtain the theoretical joint distribution in model regime m over any vector of variables y used in the estimation. Call this distribution $g^m(y|s^1, s^2; \phi^s)$.

We allow for the possibility that the data $\hat{y}$ contain additive Normally distributed measurement error with variance parameter γ_{me} which we estimate.[29] Next, we need to initialize the states s^1 and s^2. The observed state s^1 (capital k) is initialized using the actual data $\{\hat{k}_j\}_{j=1}^n$ from the (initial) period used in the estimation, discretized over the grid K via histogram function (see KT, 2014). Call the resulting discrete probability distribution $h(s_0^1)$. The initial distribution of the unobserved states s_0^2 is treated as unobservable heterogeneity and parametrized by ϕ^d. [30] Overall, we obtain the initial joint state distribution $h(s_0^1, s_0^2; \phi^d)$.

[29]Specifically, we assume that the measurement error of variable x has distribution $N(0, (\gamma_{me}\chi(x))^2)$ where $\chi(x)$ denotes the variable's grid range, $\chi(x) \equiv x_{\max} - x_{\min}$. More complex versions of measurement error parametrized by additional parameters can be considered at the cost of added computing time.

[30]In our baseline estimation runs we assume that the initial distributions of the state variables s^1 and s^2 are independent and that the unobserved state is distributed $\Omega(s_0^2, \phi^d) = N(\mu_{s^2}, \gamma_{s^2}^2)$. This assumption is not essential, see KT (2014).

To write the likelihood of model m with the given observations on variables y, construct

$$f^m(y;\phi^s,\phi^d)\equiv\sum_{s_0^2}g^m(y|s_0^1,s_0^2;\phi^s)h(s_0^1,s_0^2;\phi^d),$$

which is the joint distribution of the observable variables y given parameters ϕ^s,ϕ^d integrated over the distribution of the unobserved state.

Let $\Phi\left(.|\mu,\sigma\right)$ be the pdf of a Normal distribution with mean μ and variance σ^2. Given the assumed form of measurement error, the likelihood of observing data $\hat{y}_j$ (for instance $\hat{I}_j,\hat{q}_j$) relative to grid point $y_r\in Y$ for any $r=1,...,\#Y$ is,

$$\prod_{l=1}^{L}\Phi\left(\hat{y}_j^l|y_r^l,\sigma^l(\gamma_{me})\right)\tag{4}$$

where $l=1,...,L$ indexes the distinct variables and/or time periods used in the estimation (e.g., $L=2$ if $y=(I_t,q_t)$ and $L=4$ if $y=(I_t,q_t,I_{t+1},q_{t+1})$) and where $\sigma^l(\gamma_{me})$ is as defined in footnote 28.

Putting all the pieces together, the likelihood of the data $\{\hat{y}_j\}_{j=1}^n$ in model m given initial state distribution $h(s_0^1,s_0^2;\phi^d)$, at parameters $\phi\equiv(\phi^s,\phi^d,\gamma_{me})$ is,

$$\Lambda^m\left(\phi\right)\equiv\sum_{j=1}^{n}\ln[\sum_{r=1}^{\#Y}f^m(y_r;\phi^s,\phi^d)\prod_{l=1}^{L}\Phi\left(\hat{y}_j^l|y_r^l,\sigma^l(\gamma_{me})\right)].\tag{5}$$

We maximize the log-likelihood $\Lambda^m(\phi)$ by choice of the parameters ϕ for each of the three financial regimes (A, B, and MH). We first run an extensive grid search over the parameters and then use a global optimization method starting from the best-fitting candidate parameters from the grid search. Standard errors are computed via bootstrapping, repeatedly drawing with replacement from the data up to the original sample size. Finally, we follow Vuong (1989) and use the maximized likelihood for each model (A, B and MH) to compute an asymptotic test statistic and formally compare (pairwise) across the alternative financial regimes.

Table 1 - Sample comparisons

	(1)	(2)	(3)
A. all years, 1997-2007			
observations	3718286	1493181	
number of firms	805118	385539	
mean age	11	11.6	
mean assets, k	991	1446	
median k	79	105	
stdev k	29796	41723	
mean cash flow, q	303	501	
median q	35	45	
stdev q	10178	15686	
mean investment, I	196	273	
median I	10	12	
stdev I	14975	7218	
percent family firms	32%	34%	
percent unbanked	21%	24%	
percent single-banked	31%	18%	
percent multi-banked	48%	58%	
B. 2004-2007			
observations	1782431	711985	402980
number of firms	653804	290276	100745
mean age	11.4	11.7	14.5
mean assets, k	1070	1455	2073
median k	81	95	175
stdev k	32897	43627	55548
mean cash flow, q	321	510	751
median q	33	37	73
stdev q	11670	17918	20527
mean investment, I	206	272	380
median I	9	9	20
stdev I	20548	7168	8539
percent family firms	32%	33%	42%
percent unbanked	21%	27%	17%
percent single-banked	33%	22%	16%
percent multi-banked	46%	51%	67%

Notes:

(1) all observations with non-missing (k,I,q) data from any of the listed years

(2) observations of firms with non-missing (k,I,q) data from any of the listed years and continuing bank status

(3) observations of firms with non-missing (k,I,q) data present in all listed years and continuing bank status (balanced panel)

* All means, medians, standard deviations (stdev) and percentages are computed at the observation level.

Table 2 - Summary statistics by banking and family status - all balanced panels

	unbanked firms			single-banked firms			multi-banked firms		
	all	family	non family	all	family	non family	all	family	non family
observations	128147	22005	106142	107031	28271	78760	645549	326177	319372
number of firms	26601	4097	22504	21150	4884	16266	87700	40893	46807
percent of all		17.2%	82.8%		26.4%	73.6%		50.5%	49.5%
Data used in the MLE									
mean assets (k)	415	246	450	456	353	494	2556	1004	4141
median k	20	24	19	77	81	76	266	261	272
stdev k	4376	1019	4785	3077	1238	3509	58115	6592	82324
mean cash flow (q)	80	144	66	109	108	110	954	409	1511
median q	10	16	9	28	40	25	126	132	117
stdev q	2953	6979	657	657	371	733	20631	2113	29243
mean investment (I)	47	33	49	65	55	68	497	226	774
median I	1	1	1	5	8	5	45	46	43
stdev I	1191	376	1297	866	476	968	9368	2337	13101
Financial indicators and others									
mean total assets (A)	2095	1262	2268	2256	1160	2650	10235	4524	16068
median A	255	283	249	389	494	355	1477	1466	1494
stdev A	40496	10399	44242	78537	2879	91534	128585	21957	181276
mean sales revenue (S)	697	878	656	1068	1315	975	10802	5038	16745
median S	208	320	190	416	699	351	1941	2122	1660
stdev S	5278	7623	4587	4868	2135	5552	140452	22027	198737
mean q/A ratio	0.08	0.11	0.08	0.10	0.11	0.10	0.11	0.11	0.10
median q/A	0.06	0.08	0.05	0.09	0.09	0.08	0.09	0.10	0.09
stdev q/A	1.31	0.18	1.44	0.15	0.14	0.16	0.12	0.12	0.11
mean q/k ratio	2.90	3.46	2.78	3.14	2.45	3.40	2.53	2.03	3.04
median q/k	0.36	0.54	0.32	0.33	0.44	0.29	0.49	0.51	0.47
stdev q/k	54	47	55	56	27	64	73	20	102
mean debt/assets ratio (D/A)	0.38	0.42	0.37	0.60	0.60	0.60	0.70	0.71	0.69
median D/A	0.32	0.40	0.30	0.64	0.63	0.64	0.74	0.74	0.73
stdev D/A	0.31	0.30	0.31	0.26	0.25	0.26	0.19	0.18	0.20
mean liquidity ratio (LR)	3.36	2.17	3.62	0.95	0.71	1.03	0.22	0.18	0.25
median LR	0.54	0.55	0.54	0.21	0.22	0.20	0.07	0.07	0.06
stdev LR	49.6	24.5	53.6	9.0	3.4	10.2	2.1	1.1	2.7
mean age	11.6	11.7	11.6	10.7	11.2	10.6	15.1	14.7	15.5

* All means, medians, standard deviations (stdev) and percentages are computed at the observation level.

Table 2B - Summary statistics by family firm subcategories - all balanced panels

	unbanked			single-banked			multi-banked		
	pure family	fam-netw.	non family	pure family	fam-netw.	non family	pure family	fam-netw.	non family
observations	19390	2615	106142	26703	1568	78760	302971	23206	319372
number of firms	3609	491	22504	4603	285	16266	38333	2922	46807
percent of all	13.6%	1.8%	84.6%	21.8%	1.3%	76.9%	43.7%	3.3%	53.4%
Data used in the MLE									
mean assets (k)	221	429	450	300	1255	494	726	4632	4141
median k	23	31	19	78	153	76	244	854	272
stdev k	936	1487	4785	884	3667	3509	3368	21177	82324
mean cash flow (q)	57	786	66	96	305	110	299	1854	1511
median q	16	21	9	38	88	25	124	437	117
stdev q	196	20230	657	220	1270	733	917	7038	29243
mean investment (I)	30	61	49	49	154	68	175	895	774
median I	2	1	1	8	9	5	43	145	43
stdev I	335	600	1297	351	1409	968	2093	4370	13101
Financial indicators and others									
mean total assets (A)	861	4232	2268	1005	3800	2650	3239	21305	16068
median A	257	561	249	476	1174	355	1363	5778	1494
stdev A	3765	28198	44242	2123	8082	91534	10866	70230	181276
mean sales revenue (S)	701	2342	656	1272	2088	975	3945	19366	16745
median S	315	397	190	692	854	351	2011	5886	1660
stdev S	1114	22934	4587	1939	4275	5552	8574	75228	198737
mean q/A ratio	0.11	0.09	0.08	0.11	0.11	0.10	0.11	0.10	0.10
median q/A	0.08	0.04	0.05	0.09	0.08	0.08	0.10	0.09	0.09
stdev q/A	0.18	0.21	1.44	0.13	0.15	0.16	0.12	0.09	0.11
mean q/k ratio	2.65	10.57	2.78	2.17	7.64	3.40	1.84	4.58	3.04
median q/k	0.56	0.39	0.32	0.44	0.39	0.29	0.51	0.51	0.47
stdev q/k	15	140	55	14	101	64	14	55	102
mean debt/assets ratio (D/A)	0.44	0.33	0.37	0.61	0.52	0.60	0.72	0.65	0.69
median D/A	0.42	0.25	0.30	0.64	0.52	0.64	0.75	0.69	0.73
stdev D/A	0.30	0.30	0.31	0.25	0.27	0.26	0.18	0.20	0.20
mean liquidity ratio (LR)	1.96	3.81	3.62	0.68	1.12	1.03	0.19	0.14	0.25
median LR	0.57	0.33	0.54	0.22	0.20	0.20	0.07	0.05	0.06
stdev LR	10.2	66.9	53.6	3.3	5.2	10.2	1.2	0.6	2.7
mean age	11.5	13.1	11.6	11.1	12.5	10.6	14.4	18.6	15.5

* All means, medians, standard deviations (stdev) and percentages are computed at the observation level.

Table 3 - Vuong Test Model Comparisons - Firm Size and Age

	A. whole sample				B. small and young firms				C. large and old firms			
Comparison:	MH v B	MH v A	B v A	Best fit	MH v B	MH v A	B v A	Best fit	MH v B	MH v A	B v A	Best fit
1. 2004-07 data; investment (I) panel data (3 years)												
1.1 2004-06, unbanked	tie	A***	A***	**A**	tie	A***	A***	**A**	B***	MH***	B***	**B**
1.2 2004-06, single-banked	tie	MH***	B***	**MH,B**	MH***	tie	A***	**A,MH**	B***	MH***	B***	**B**
1.3 2004-06, multi-banked	B***	MH***	B***	**B**	MH***	MH***	B***	**MH**	tie	MH***	B***	**MH,B**
2. 2004-07 data; investment and cashflow (I,q) panel data (2 years)												
2.1 2004,05 unbanked	B***	A***	A***	**A**	B***	A***	A***	**A**	MH***	MH***	B***	**MH**
2.2 2004,05 single-banked	B***	MH***	B***	**B**	B***	A***	A***	**A**	MH***	MH***	B***	**MH**
2.3 2004,05 multi-banked	MH***	MH***	B***	**MH**	B***	A***	B***	**B**	MH***	MH***	B***	**MH**
2.4 2004,07 unbanked	B***	A***	A***	**A**	B***	A***	A***	**A**	MH***	MH***	B***	**MH**
2.5 2004,07 single-banked	B***	MH***	B***	**B**	B***	A***	A***	**A**	MH***	MH***	A***	**MH**
2.6 2004,07 multi-banked	MH***	MH***	B***	**MH**	B***	tie	tie	**B,A**	MH***	MH***	B***	**MH**
3. 2004-07 data; assets, investment and cashflow (k,I,q) cross-sections												
3.1 2007, unbanked	B***	A***	A***	**A**	B***	A***	A***	**A**	MH***	MH***	B***	**MH**
3.2 2007, single-banked	B***	A***	B***	**B**	B***	A***	B***	**B**	tie	MH***	B***	**MH,B**
3.3 2007, multi-banked	B***	tie	B***	**B**	B***	MH***	B***	**B**	B***	MH**	B***	**B**
3.4 2004, unbanked	MH***	A***	A***	**A**	B***	A***	A***	**A**	MH***	MH***	B***	**MH**
3.5 2004, single-banked	B***	MH***	B***	**B**	B***	A***	A***	**A**	MH*	MH***	B***	**MH**
3.6 2004, multi-banked	B***	A***	B***	**B**	B***	A***	A***	**A**	B***	A***	B***	**B**
4. 2001-03 data; assets, investment and cashflow (k,I,q) cross-sections												
4.1 2002, unbanked	B***	A***	B***	**B**	B***	A***	B***	**B**	MH***	MH***	A***	**MH**
4.2 2002, single-banked	B***	A***	B***	**B**	B***	tie	B***	**B**	B***	A***	B***	**B**
4.3 2002, multi-banked	B***	A***	B***	**B**	B***	MH***	B***	**B**	B***	MH***	B***	**B**
5. 1997-00 data; assets, investment and cashflow (k,I,q) cross-sections												
5.1 2000, unbanked	B***	A***	B***	**B**	B***	A***	A***	**A**	B***	tie	B***	**B**
5.2 2000, single-banked	B***	MH***	B***	**B**	B***	A***	B***	**B**	B***	MH**	B***	**B**
5.3 2000, multi-banked	B***	A***	B***	**B**	B***	MH***	B***	**B**	B***	MH***	B***	**B**
5.4 1997, unbanked	B***	A***	A***	**A**	B***	A***	tie	**B,A**	B***	A**	B***	**B**
5.5 1997, single-banked	B***	tie	B***	**B**	B***	A***	B***	**B**	B***	MH*	B***	**B**
5.6 1997, multi-banked	B***	A**	B***	**B**	tie	MH***	B***	**B,MH**	B***	MH***	B***	**B**

Notes: The listed regime is best fitting, including ties. ***, ** and * denote statistical significance at the 1%, 5% and 10% level respectively.

Table 4A - Vuong test model comparisons - Family status

	A. family firms				B. non-family firms			
Comparison:	MH v B	MH v A	B v A	Best fit	MH v B	MH v A	B v A	Best fit
<u>I. 2004-07 balanced panel, continuing banking status</u>								
1. investment (I) panel (3 years)								
1.1 04-06, unbanked	B***	A***	B***	**B**	MH***	A***	A***	**A**
1.2 04-06, single-banked	MH***	MH***	B***	**MH**	B***	MH***	B**	**B**
1.3 04-06, multi-banked	B***	MH***	B***	**B**	B***	MH***	B***	**B**
2. investment and cashflow (I,q) panel data (2 years)								
2.1 04,05 unbanked	B***	A***	A***	**A**	B***	A***	A***	**A**
2.2 04,05 single-banked	B***	MH***	B***	**B**	tie	A***	A***	**A**
2.3 04,05 multi-banked	MH***	MH***	B***	**MH**	MH***	MH***	B***	**MH**
2.4 04,07 unbanked	B***	A***	B**	**B**	B***	A***	A***	**A**
2.5 04,07 single-banked	tie	MH***	B***	**MH,B**	tie	A***	A***	**A**
2.6 04,07 multi-banked	MH***	MH***	B***	**MH**	MH***	MH***	A***	**MH**
3. assets, investment and cashflow (k,I,q) cross-sections								
3.1 2007, unbanked	B***	A***	B***	**B**	MH***	A***	A***	**A**
3.2 2007, single-banked	B***	MH***	B***	**B**	B***	A***	B***	**B**
3.3 2007, multi-banked	B***	MH***	B***	**B**	B***	MH***	B***	**B**
3.4 2004, unbanked	B***	A***	B***	**B**	B***	A***	B***	**B**
3.5 2004, single-banked	MH***	MH***	A***	**MH**	B***	MH***	B***	**B**
3.6 2004, multi-banked	tie	MH***	B***	**MH,B**	B***	MH***	B***	**B**
<u>II. 2001-03 balanced panel, continuing banking status</u>								
4. investment (I) panel data (3 years)								
4.1 01-03, unbanked	B***	A*	B***	**B**	MH***	A***	A***	**A**
4.2 01-03, single-banked	tie	MH***	B***	**MH,B**	B***	MH***	B***	**B**
4.3 01-03, multi-banked	B***	MH***	B***	**B**	B***	MH***	B***	**B**
5. assets, investment and cashflow (k,I,q) cross-sections								
5.1 2002, unbanked	B***	A***	B***	**B**	B***	A***	B***	**B**
5.2 2002, single-banked	B***	A***	B***	**B**	B***	A***	B***	**B**
5.3 2002, multi-banked	B***	A***	B***	**B**	B**	MH***	B***	**B**
<u>III. 1997-00 balanced panel, continuing banking status</u>								
6. assets, investment and cashflow (k,I,q) cross-sections								
6.1 2000, unbanked	tie	tie	B***	**B,MH**	tie	A***	A***	**A**
6.2 2000, single-banked	MH***	MH*	A***	**MH**	B***	MH***	B***	**B**
6.3 2000, multi-banked	B***	MH***	B***	**B**	B***	MH***	B***	**B**
6.4 1997, unbanked	B***	A***	B**	**B**	MH***	A**	A***	**A**
6.5 1997, single-banked	MH***	tie	A***	**MH,A**	B**	MH**	B***	**B**
6.6 1997, multi-banked	B***	A***	B***	**B**	B***	MH***	B***	**B**

Table 4B - Vuong test model comparisons - Family status

	A. family firms				B. non-family firms			
Comparison:	MH v B	MH v A	B v A	Best fit	MH v B	MH v A	B v A	Best fit
IV. Small and young firms, continuing banking status; (k,I,q) cross-sections								
7.1 2007, unbanked	B***	A***	A***	**A**	B***	A***	A***	**A**
7.2 2007, single-banked	B***	A**	B***	**B**	B***	A***	B***	**B**
7.3 2007, multi-banked	B***	A***	B***	**B**	B***	MH***	B***	**B**
7.4 2004, unbanked	B***	A***	A***	**A**	B***	A***	A***	**A**
7.5 2004, single-banked	tie	A***	A***	**A**	B***	A***	A***	**A**
7.6 2004, multi-banked	B***	A***	B***	**B**	B***	A***	A***	**A**
8.1 2002, unbanked	B***	A***	B**	**B**	B***	A***	A***	**A**
8.2 2002, single-banked	tie	MH***	B***	**MH,B**	B***	A***	B***	**B**
8.3 2002, multi-banked	B***	tie	B***	**B**	B***	MH***	B***	**B**
9.1 2000, unbanked	B***	A***	B*	**B**	B***	A***	B***	**B**
9.2 2000, single-banked	B***	A*	B***	**B**	B***	A***	B***	**B**
9.3 2000, multi-banked	B***	A**	B***	**B**	B***	MH***	B***	**B**
9.4 1997, unbanked	B***	A***	tie	**B,A**	B***	A***	A***	**A**
9.5 1997, single-banked	B***	tie	B***	**B**	B***	A***	B*	**B**
9.6 1997, multi-banked	tie	MH***	B***	**MH,B**	B***	MH***	B***	**B**
V. Large and old firms, continuing banking status; (k,I,q) cross-sections								
10.1 2007, unbanked	MH**	MH**	A***	**MH**	MH***	MH***	B***	**MH**
10.2 2007, single-banked	MH**	MH**	tie	**MH**	B***	MH***	B***	**B**
10.3 2007, multi-banked	B***	MH***	B***	**B**	B***	MH*	B***	**B**
10.4 2004, unbanked	MH***	MH***	A***	**MH**	MH***	MH***	B***	**MH**
10.5 2004, single-banked	MH***	MH***	tie	**MH**	B***	tie	B***	**B**
10.6 2004, multi-banked	B***	MH***	B***	**B**	B***	A**	B***	**B**
11.1 2002, unbanked	MH***	MH**	tie	**MH**	B***	A***	A***	**A**
11.2 2002, single-banked	B***	A***	B**	**B**	B***	A***	B***	**B**
11.3 2002, multi-banked	B***	MH***	B***	**B**	B***	MH***	B***	**B**
12.1 2000, unbanked	B***	tie	B***	**B**	B***	tie	B***	**B**
12.2 2000, single-banked	B***	MH**	B***	**B**	B***	MH***	B***	**B**
12.3 2000, multi-banked	B***	MH***	B***	**B**	B***	MH***	B***	**B**
12.4 1997, unbanked	tie	tie	tie	**B,MH,A**	B***	tie	B***	**B**
12.5 1997, single-banked	B***	MH***	B***	**B**	B***	tie	B***	**B**
12.6 1997, multi-banked	B***	tie	B***	**B**	B***	MH***	B***	**B**

Notes: The listed regime(s) is best fitting. ***, ** and * denote statistical significance at the 1%, 5% and 10% level respectively.

Table 5 - Vuong Test Model Comparisons - Family Firm Sub-categories

Comparison:	A. pure family firms MH v B	MH v A	B v A	Best fit	B. family networked firms MH v B	MH v A	B v A	Best fit	C. non-family firms MH v B	MH v A	B v A	Best fit
1. 2004-07 data; investment (I) panel data (3 years)												
1.1 04-06, unbanked	B***	MH***	B***	**B**	B***	A**	B***	**B**	MH***	A***	A***	**A**
1.2 04-06, single-banked	MH***	MH***	B***	**MH**	MH*	MH***	B***	**MH**	B***	MH***	B**	**B**
1.3 04-06, multi-banked	B***	MH***	B***	**B**	tie	MH***	B***	**MH,B**	B***	MH***	B***	**B**
2. 2004-07 data; investment and cashflow (I,q) panel data (2 years)												
2.1 04,05 unbanked	B***	A***	A***	**A**	B***	tie	B***	**B**	B***	A***	A***	**A**
2.2 04,05 single-banked	B***	MH***	B***	**B**	MH***	MH***	A***	**MH**	tie	A***	A***	**A**
2.3 04,05 multi-banked	MH***	MH***	B***	**MH**	tie	MH***	B***	**MH,B**	MH***	MH***	B***	**MH**
2.4 04,07 unbanked	B***	A***	B**	**B**	tie	tie	B*	**B,MH**	B***	A***	A***	**A**
2.5 04,07 single-banked	B***	A***	B***	**B**	MH***	MH**	A***	**MH**	tie	A***	A***	**A**
2.6 04,07 multi-banked	MH***	MH***	B***	**MH**	tie	MH***	B***	**MH,B**	MH***	MH***	A***	**MH**
3. 2004-07 data; assets, investment and cashflow (k,I,q) cross-sections												
3.1 2007, unbanked	B***	A***	A***	**A**	B**	A*	B*	**B**	MH***	A***	A***	**A**
3.2 2007, single-banked	B***	tie	B***	**B**	tie	tie	tie	**MH,B,A**	B***	A***	B***	**B**
3.3 2007, multi-banked	B***	A***	B***	**B**	tie	MH***	B***	**MH,B**	B***	MH***	B***	**B**
3.4 2004, unbanked	B***	A***	B***	**B**	B***	tie	tie	**B,A**	B***	A***	B***	**B**
3.5 2004, single-banked	B***	A***	B***	**B**	MH***	MH**	A***	**MH**	B***	MH***	B***	**B**
3.6 2004, multi-banked	B***	MH***	B***	**B**	B*	MH***	B***	**B**	B***	MH***	B***	**B**
4. 2001-03 data; (k,I,q) cross-sections												
4.1 2002, unbanked	B***	A***	B***	**B**	MH***	MH**	A***	**MH**	B***	A***	B***	**B**
4.2 2002, single-banked	B***	tie	B***	**B**	tie	tie	tie	**MH,B,A**	B***	A***	B***	**B**
4.3 2002, multi-banked	B***	MH***	B***	**B**	tie	MH***	B***	**MH,B**	B**	MH***	B***	**B**
5. 1997-00 data; (k,I,q) cross-sections												
5.1 1997, unbanked	B***	A***	A***	**A**	tie	tie	tie	**MH,B,A**	MH***	A**	A***	**A**
5.2 1997, single-banked	B***	A***	B***	**B**	B***	tie	B***	**B**	B**	MH**	B***	**B**
5.3 1997, multi-banked	B***	A***	B***	**B**	B***	MH*	B***	**B**	B***	MH***	B***	**B**
6. (k,I,q) cross-sections, any continuing banking status												
4.1 2004, small and young	B***	A***	A***	**A**	B***	A***	tie	**A,B**	B***	A***	A***	**A**
4.2 2004, large and old	B***	A***	B***	**B**	tie	MH***	B***	**MH,B**	B***	A***	B***	**B**

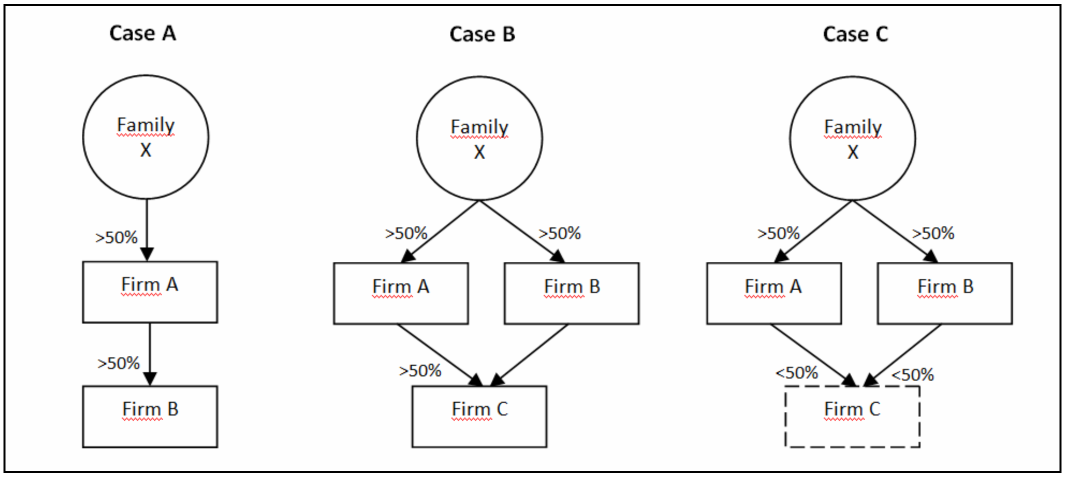
Notes: All runs above use (k,I,q) cross-section data from the listed year. The listed regime(s) is best fitting. ***, ** and * denote statistical significance at the 1%, 5% and 10% level respectively.

Table 6 - Vuong Test Model Comparisons - Robustness

Comparison:	A. family firms MH v B	MH v A	B v A	Best fit	B. non-family firms MH v B	MH v A	B v A	Best fit
1. Continuing banking status, no balanced panel								
1.1 2004, unbanked	B***	A***	B***	**B**	B***	A***	A***	**A**
1.2 2004, single-banked	MH***	MH***	A**	**MH**	MH***	A***	A***	**A**
1.3 2004, multi-banked	B***	A***	B***	**B**	B***	A***	B***	**B**
1.4 2000, unbanked	B***	A***	tie	**B,A**	B***	A***	A***	**A**
1.5 2000, single-banked	MH***	MH***	A***	**MH**	B***	A***	B**	**B**
1.6 2000, multi-banked	B***	A***	B***	**B**	B***	A***	A***	**A**
2. Any continuing banking status								
2.1 2004, all firms	MH***	MH***	B***	**MH**	B***	MH***	B***	**B**
2.2 2004, small and young	B***	A***	A***	**A**	B***	A***	A***	**A**
2.3 2004, large and old	B***	A**	B***	**B**	B***	A***	B***	**B**
3. Placebo family status								
3.1 2004, unbanked	B***	A***	B***	**B**	B***	A***	B***	**B**
3.2 2004, single-banked	B***	A***	B***	**B**	B***	A***	B***	**B**
3.3 2004, multi-banked	MH***	MH***	B***	**MH**	MH***	MH***	B***	**MH**
4. Risk aversion								
4.1 2004, unbanked	B***	A***	B***	**B**	B***	A***	A***	**A**
4.2 2004, single-banked	MH***	tie	A***	**MH,A**	B***	A***	A**	**A**
4.3 2004, multi-banked	MH***	MH***	A***	**MH**	MH***	MH***	B***	**MH**
5. Adjustment costs								
5.1 2004, unbanked	B***	MH***	B***	**B**	B***	MH***	B***	**B**
5.2 2004, single-banked	B***	MH***	B***	**B**	B***	MH***	B***	**B**
5.3 2004, multi-banked	B***	MH***	B***	**B**	B***	MH***	B***	**B**
6. Switching bank status								
6.1 2004, all firms	tie	MH***	B***	**MH,B**	B***	MH***	B***	**B**
6.2 2007, all firms	MH***	MH***	B***	**MH**	MH***	MH***	B***	**MH**
7. (k',I,q) cross-section data from 2004-05								
7.1 2004, unbanked	B***	MH***	B***	**B**	B***	MH***	B***	**B**
7.2 2004, single-banked	MH***	MH***	B***	**MH**	B***	MH***	B***	**B**
7.3 2004, multi-banked	tie	MH***	B***	**MH,B**	B***	MH***	B***	**B**

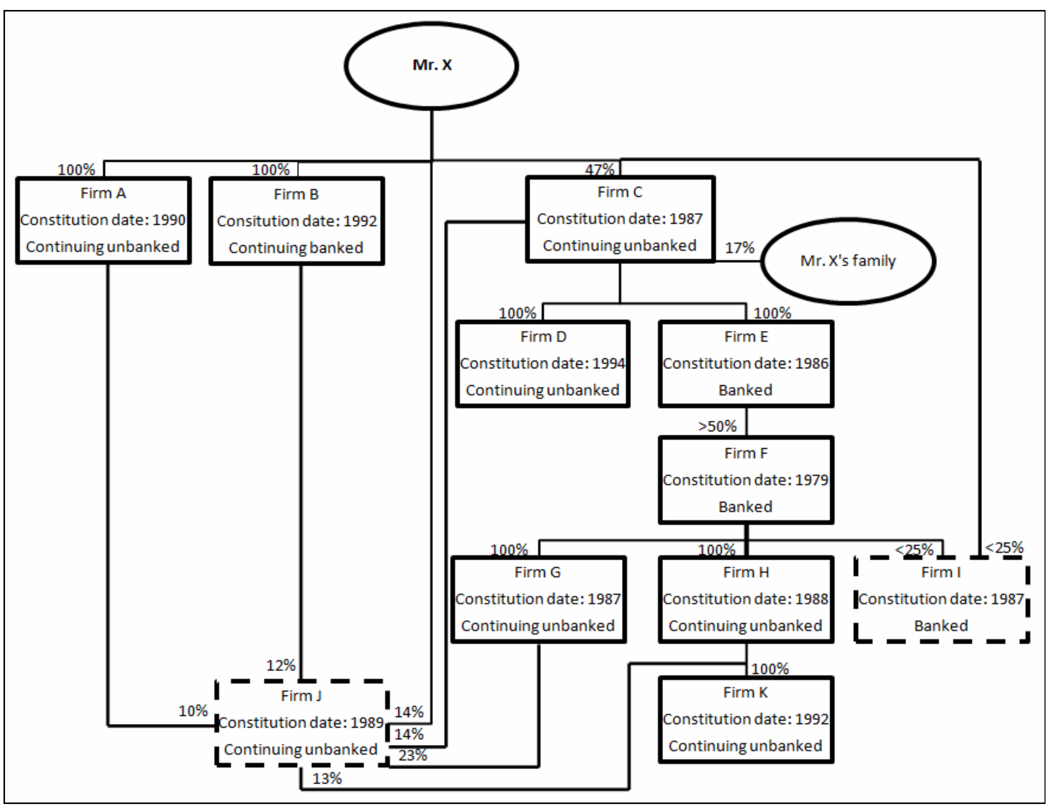
Notes: All runs above use (k,I,q) cross-section data from the listed year, unless specified otherwise. The listed regime(s) is best fitting. ***, ** and * denote statistical significance at the 1%, 5% and 10% level respectively.

Figure 2. Examples of family networks



Note: Solid lines represent firms included in the sample as network firms and dashed lines represent firms not identified as network firms.

Figure 3. Case study of a family network



Note: Solid lines represent firms included in the sample as network firms and dashed lines represent firms not identified as network firms.

Appendix Table A1 - More sample comparisons

	(1)	(2)	(3)
1997-2000			
observations	841951	353361	216060
number of firms	328336	137591	54015
mean age	10.6	11.7	13.7
mean assets, k	906	1444	1759
median k	86	129	201
stdev k	21340	31194	21490
mean cash flow, q	300	506	678
median q	43	65	106
stdev q	6882	10424	8372
mean investment, I	194	296	388
median I	13	20	34
stdev I	6335	6759	5571
percent family firms	35%	37%	45%
percent unbanked	19%	17%	9%
percent single-banked	28%	11%	7%
percent multi-banked	53%	72%	84%
2001-2003			
observations	1093904	427835	261687
number of firms	512052	211619	87229
mean age	10.5	11.4	13.7
mean assets, k	927	1433	2051
median k	73	100	183
stdev k	30064	45876	56698
mean cash flow, q	276	482	721
median q	32	42	83
stdev q	9683	15319	18658
mean investment, I	182	256	369
median I	9	11	24
stdev I	6587	7654	8927
percent family firms	31%	33%	42%
percent unbanked	23%	26%	15%
percent single-banked	31%	16%	11%
percent multi-banked	46%	58%	74%

Notes:

(1) all observations with non-missing (k,I,q) data from any of the listed years

(2) observations of firms with non-missing (k,I,q) data from any of the listed years and continuing bank status

(3) observations of firms with non-missing (k,I,q) data present in all listed years and continuing bank status (balanced panel)

* All means, medians, standard deviations (stdev) and percentages are computed at the observation level.