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# ESSAYS ON BANKING AND CORPORATE FINANCE

by

ALEV ISIL YILDIRIM

A dissertation submitted to the Graduate Faculty in Economics in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

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This manuscript has been read and accepted by the Graduate Faculty in Economics in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

**Professor Linda Allen**

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# Abstract


ESSAYS ON BANKING AND CORPORATE FINANCE

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ALEV ISIL YILDIRIM

Advisor: Professor Linda Allen

This dissertation consists of two chapters...

**Chapter 1: The Effect of Relationship Banking on Firm Efficiency**

This paper analyzes the impact of relationship bank oversight on firm operational efficiency and default risk. I find that a new loan from a relationship bank improves the technical efficiency of inefficient firms that have an elevated probability of default. Moreover, borrowing firms with elevated default risk exposure experience reductions in their probabilities of default in the years following new relationship bank loans, benefiting both banks and borrowers. Thus, the benefits of relationship bank monitoring are most apparent the higher the ex ante default risk and the lower the baseline efficiency of the borrower.

**Chapter 2: The Intangible Value of Key Talent: Decomposing Organization Capital**

Specialized firm-specific information, strategies, activities and procedures, identified as organization capital (OC), is comprised of a heterogeneous group of disparate items. We isolate firm value creation by decomposing OC into two endogenously determined components: (1) key talent comprised of disclosed compensation of top executives which creates value and (2) a residual comprised of undisclosed executive perquisites versus agency costs and empire building expenses that do not increase firm value. Whereas the first component is portable, the second is unobservable, and therefore generates rents for shareholders. Thus, only residual OC creates systematic risk exposure, whereas key talent engenders idiosyncratic risk. Furthermore, we find that systematic risk exposure is higher for firms with weak governance.

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# Chapter 1

# The Effect of Relationship Banking on Firm Efficiency

## 1.1 Introduction

This paper contributes to our understanding of how relationship banks affect borrower firms' performance. In particular, I examine whether relationship bank oversight improves firm operational efficiency and reduces default risk. In the course of lending activity, relationship banks invest in costly production of private information about their borrowers' financial performance through multiple interactions over time and/or across products (Boot, 2000). Private information production differentiates relationship banks from arm's-length lending such that in the course of collecting both hard and soft information about firm operations, relationship banks develop an expertise that can be used both to screen future loan applications to mitigate adverse selection and to monitor the borrower's ongoing performance to avoid moral hazard, thereby reducing the bank's default risk (Diamond, 1991; Rajan and Winton, 1995; Boot and Thakor, 2000; Boot, 2000; Dennis and Mullineaux, 2000; Sufi, 2007; Gustafson et al., 2017). Over time, relationship banks gain expertise that should also benefit the operation of the borrowing firm's business. This paper addresses the question of how these benefits are allocated across borrowing firms. That is, which firms realize improvements in their operational efficiency and default risk in the course of new borrowing activity from their relationship banks?

As banks hold convex cash flow claims that expose them to losses upon firm default, but do not allow sharing in upside gain of firm's profitable investments and efficient allocation of resources, the banks' incentive to invest in private information production about their borrowers is mainly to reduce the borrowers' default risks, and thereby to avoid the loss given default. However, in doing so, relationship banks intervene in borrowers' operations through regular site visits, advising the management team, assessing financial statements, monitoring covenants, renegotiating the existing loan terms and negotiating the renewal of loans and/or future loan terms (Fama, 1985; Dennis and Mullineaux, 2000). This suggests that screening and monitoring might affect not only the solvency of a firm but also its operational efficiency. Therefore, in this paper I examine how private information production by relationship banks affect both firm efficiency and default risk.

Using the Dealscan syndicated loans database for public firms in the U.S., I find that new borrowing from the firm's relationship bank increases firm efficiency on average. However, the beneficial impact of relationship bank oversight is focused on firms with an elevated risk of default, consistent with bank loss avoidance incentives. That is, firms closest to the default threshold at loan origination date experience the largest improvement in both operational efficiency and default risk in the period immediately following the new loan. Moreover, banks appear to focus on low hanging fruit in that the greatest efficiency improvement is realized for those firms that have the lowest levels of baseline operational efficiency. I also examine the persistence of the relationship bank oversight effect and find that it dissipates after one year from new loan origination. That is, I find that the operational efficiency improvement for high default risk borrowers lasts only for one year beyond loan origination.[1]

I estimate a firm's technical efficiency by comparing the firm's production and operational costs with what is feasible given the technology set for the industry, i.e. the boundary or frontier of the technology set (Bogetoft and Otto, 2011). As a measure of firm's technical efficiency, I utilize parametric stochastic frontier analysis (SFA). As a first robustness check I calculate efficiency using non-parametric and deterministic data envelopment analysis (DEA) following Demerjian et al. (2012). For a second robustness check I use semi-parametric total factor productivity (TFP) estimate of Imrohoroglu and Tuzel (2014). I use Jarrow-Merton default probabilities to calculate the default risk and estimate the effect of relationship banking on the efficiency of firms in the first and fourth quartile of Jarrow-Merton default probabilities. Furthermore, as robustness tests, I use default risk proxies of Altman's Z score (Altman, 1968) and Whited and Wu (2006) financial constraint model.[2]

However, the decision to borrow from a relationship bank is itself endogenous, and may introduce bias to my analysis. Firms can obtain funds from publicly traded debt or equity markets in lieu of syndicated bank loans. Once borrowers obtain alternative sources of funds, such as access to public debt markets, they typically face lower interest rates on bank debt as the lending bank's monopoly power is dissipated (Hale and Santos, 2009). Therefore, firms that are dependent on banks for financing may be the ones that are unable to access public debt markets because of severe adverse selection and potential moral hazard. I control for endogeneity of financing choice using Heckman's two-stage model for endogeneity in which I model the firm's choice to take a bank loan using a probit regression for the sample of firms with and without bank borrowing. I estimate the inverse Mills ratio from this probit regression and include it in the second stage of my analysis of borrowing firm efficiency

[1]This may be consistent with a hold-up problem. Alternatively, however, the impact of an individual relationship bank loan may be limited if the loan is renegotiated over time. Roberts (2015) estimates that syndicated bank loans are renegotiated every nine months on average.

[2]The results of robustness tests are available in the Appendix.

levels to control for selection bias induced by the decision to finance using bank loans. In addition, however, there is another selection bias induced by the decision to borrow from a relationship bank. To control for this problem, I estimate a second probit regression to model the probability of acquiring a relationship bank and use the probabilities from this regression as an instrument for the existence of relationship banking dummy variable in my two-stage analysis. Thus, the second stage of my analysis controls for the firm's endogenous decisions first to borrow from any bank, and second, to borrow from a relationship bank. Controlling for endogeneity, I find that low baseline efficiency firms with elevated default risk experience both improvements in efficiency and reductions in default risk in the wake of a new relationship bank loan.

Moreover, to further control for endogeneity in my analysis of the impact of relationship bank oversight on borrower default risk, I use propensity score with nearest-neighbor matching in a quasi diff-in-diff setting. That is, I compare the default risk of those firms with relationship banking (treatment group) to the default risk of those with public debt (control group) in order to observe the direct effect of relationship banking on the borrowing firm's default risk using a control group of firms that only differ in their choice of having a relationship bank. I find that reductions in the borrowing firm's probability of default in the wake of a new relationship bank loan occur for firms with higher ex ante levels of default risk. In contrast, low default-risk firms with relationship banks experience increases in default risk in the years following relationship bank lending activity. Further, borrowing on public debt markets is consistent with increases in default risk for all firms (high and low default probability). Thus, the beneficial impact of relationship bank oversight in reducing default risk over the two years following loan origination is limited to firms with higher pre-loan levels of default risk.

The remainder of the paper is organized as follows: A brief review of the literature and hypothesis development is provided in Section 1.2. Section 1.3 describes the data and variable construction. Section 1.4 introduces the model and presents the empirical findings measuring the impact of a bank relationship on borrowing firm's efficiency of operation. Section 1.5 concludes with a brief summary.

## 1.2 Literature Review and Hypothesis Development

A relationship bank invests in obtaining customer-specific information, often proprietary in nature, and evaluates the profitability of these investments through multiple interactions with the same customer over time and/or across products (Boot, 2000). As in Bharath et al. (2007), to the extent that relationship lending produces reusable and proprietary information about the borrower, a possible benefit for the relationship lender is that it would be better placed to win future loan business and other fee-generating services from its relationship borrower. They find that the probability of subsequent borrowings is 42% from a relationship bank in contrast to 3% from a non-relationship bank. Moreover, the relationship bank will tend to sell many additional services to its borrowers (e.g., deposit-taking, factoring, merger and acquisition advice, underwriting).

Theoretical debate on bank monitoring argues that compared to other private lenders banks provide more efficient monitoring than arm's-length investors do (Leland and Pyle, 1977; Diamond, 1984; Fama, 1985; Boyd and Prescott, 1986). Especially those firms that are unable to borrow from the capital markets because of information asymmetries and potential moral hazard can benefit from informed bank borrowing since banks alleviate the moral hazard problem by closely monitoring the borrower's activities (Diamond, 1991). In addition, Yosha (1995) and Bhattacharaya and Chiesa (1995) argue that firms choose bank financing if there is proprietary information to be protected for competitive purposes. In their empirical study, Bharath and Hertzel (2016) find that loan issuances have a significantly more positive effect on post-issuance productivity than bond issuances. Particularly, consistent with bank specialness in providing governance, they find that a bank loan issue causally increases total factor productivity of firms by 1% to 1.6% per year over a bond issue for up to four years after the issuance. Spyridopoulos (2017) finds that stricter loan covenants cause an increase in profitability and a reduction in operating cost. These findings suggest that banks use information obtained in the course of lending in order to impact firm performance.

Previous studies on relationship banking find evidence of private information production in stock prices (James, 1987; Li and Ongena, 2015), access to financing (Petersen and Rajan, 1994), and the cost of financing (Bharath et al., 2011). In addition, Boot and Thakor (1994) find that an infinitely repeated bank-borrower relationship is welfare enhancing and benefits the borrower. Therefore, focusing on new loans granted by relationship banks, I argue that production of private information by a relationship bank through ongoing screening and monitoring, which includes, but is not limited to, the relationship bank's intervention into borrower firm's operations by imposing covenants and possible renegotiation options will result in an increase in firm efficiency. Therefore I posit my first hypothesis as follows:

*Hypothesis 1: Ceteris paribus, relationship bank lending improves firm operational efficiency.*

As a bank is exposed to a higher default risk when it lends to an informationally opaque borrower, it will have more incentives to avoid the losses that will incur if the borrower defaults. Benmelech and Bergman (2017) find that when the underlying debt value deteriorates, debt shifts from being informationally insensitive and becomes informationally sensitive with rising information asymmetries, which result in liquidity freezes in public debt markets. These potential information asymmetries can be in two forms: an informationally opaque borrower poses an adverse selection risk ex-ante (before the borrowing takes place) and a potential moral hazard risk ex-post (after the loan is granted). In order to reduce the adverse selection, banks invest in information production in order to engage in high quality screening. After a borrower is granted the loan, the banks engage in ongoing monitoring through the collection of information to ascertain that the borrower is solvent and will repay the loan. The success of ex-ante screening activities is related to ongoing monitoring activities throughout the life of the loan to make sure that the loan covenants are not violated, the borrower is solvent and loan repayment will be made. Moreover, good ongoing monitoring can assist in future screening, as borrowers know that poor behavior will be detected and penalized in future loans and renegotiations. As Roberts (2015) argues, the frequency of renegotiation triggered by ex-ante contractual contingencies emphasizes the fundamental incompleteness of loan contracts. The finding that borrowers grant creditors strong control rights suggests that information asymmetry in conjunction with agency problems is an important element of the contracting environment. Further, the persistence of strong creditor control rights throughout the lending relationship suggests that information asymmetry about the investments, if not the borrower, is persistent. These control rights are triggered by borrower's default. Thus, banks have strong incentives to invest in private information about borrowers that have high levels of default risk. Accordingly, I test the following hypothesis:

*Hypothesis 2: Relationship banks concentrate on producing private information to improve the efficiency of those firms with elevated risk of default.*

In addition to the default risk of the borrower, the baseline efficiency at the time of relationship lending is a significant determinant for a relationship bank to invest in the private information production. Allen et al. (2008) finds that syndicated bank loan prices incorporate information about earnings approximately one month prior to public earnings announcements. The private information obtained by relationship banks, therefore, focuses on earnings as well as default risk. Therefore the third hypothesis I test is:

*Hypothesis 3: Relationship banks concentrate on producing private information to improve the efficiency of those firms with low baseline levels of operational efficiency.*

Lastly, following the findings in Fama (1985); Diamond (1991); Preece and Mullineaux

(1996); Ongena and Smith (1998), I argue that it is in the interest of both a borrower and its relationship bank to improve the borrower's solvency, thereby to avoid default and loss given default. Indeed, monopoly rents that banks may earn on relationship loans encourage their investment in information production to preserve the relationship. Phelan (2017) shows that banks earn monopoly rents by gathering private information about correlated loan outcomes and pre-committing to ongoing monitoring. Banks have incentives to keep this valuable information secret (Dang et al., 2017), thereby preventing dissipation of the bank's monopoly profits. Accordingly, I examine the impact of relationship bank oversight on borrower default risk after the new loan origination and hypothesize that:

*Hypothesis 4: The probability of default decreases in the years following a relationship bank loan for firms with elevated risks of default.*

## 1.3 Data

The data for syndicated loans comes from Loan Pricing Corporation (LPC)'s Dealscan database. I collect data on the annual financial statements of U.S. firms from the Compustat database. Focusing on the period 1991-2011, I match the firm financial statements with the syndicated loans market data using Chava and Roberts (2008) linking database. For the Jarrow-Merton default probabilities, I use KRIS database (KRIS, 2011). The matched sample consists of all firms with non-missing values of sales and total assets. I exclude firms with sales and total assets less than $5 million and that have less than three consecutive years of data. I also exclude finance (SIC codes 6000-6799) and utilities (SIC codes 4900-4942) industries since they are regulated. All the financial ratios are winsorized by 1% at both ends. The sample includes 63994 firm-year observations of 6991 firms, out of which 4918 have bank borrowing and out of these firms 2671 have relationship banks. In total there are 17067 loan facilities in the sample.

In order to introduce the lead lender relationship, following Bharath et al. (2011) and Acharya et al. (2014), I first define the Lead dummy that is equal to one if the lender role is given as or includes 'Agent', 'Arranger', 'Lead' or 'Manager'. Then, in order to get a complete definition, I use the variable 'Lead Arranger Credit', which can take values of "Yes" and "No" depending on if a particular lender receives Lead Arranger League Table credit based on Reuters LPC's League Table guidelines. I include those with "Yes" value in the Lead dummy definition as in Sufi (2007). Finally I include sole lender loans as lead banks in the Lead dummy. Next, following Bharath et al. (2011), I define the relationship dummy *(Rel_dummy)*[3], which indicates whether the firm has borrowed from the same lead-lender in the last 5 years. There are firms that have bank relationship with more than one lead lender within the same year. In order to be able to use firm-year level estimations I reduce multiple firm-year observations to single observations. Therefore for those firms with multiple relationship lenders in a given year, I use selection criteria to include the strongest relationship among a firm's relationship banks. Particularly, in a given year I choose the facility of a firm with a relationship lender with the highest relationship intensity *(Rel_intensity)*, which is defined in Bharath et al. (2011) as the amount of loans by bank m to borrower i in the last 5 years scaled by the total amount of loans by borrower i in the last 5 years. If relationship intensity between a firm and its multiple relationship banks are equal, I choose the facility of a firm with a relationship lender with the highest number of relationship loans *(Rel_number)*, which is defined as the number of loans by bank m to borrower i in the last 5 years scaled by the total number of loans by borrower i in the last 5 years (Bharath et al., 2011). Finally, for the same relationship intensity and number between a firm and its multiple relationship banks I choose the relationship lender that has the highest bank allocation, which is defined as the amount a particular lender has committed to the given facility. I follow the same rule for the facilities with more than one lead bank. As a

[3]The definitions of the variables are provided in Table 1.11.

result of this construction, I define 8412 relationship borrowings of 2671 firms. The summary statistics in Table 1 show that 26% of the sample firms have bank borrowing throughout the sample period and 13% of the firms have relationship bank borrowing.[4]

The focus on the bank relationship-firm efficiency link in the context of syndicated loans market offers a new perspective for the analysis of firm efficiency as well as the relationship banking. One of the reasons why I focus on firm efficiency rather than profitability is that the possible positive effect on profitability of a relationship bank's private information production about firm's ongoing and new investments might be delayed as returns on investments are not actualized instantaneously and therefore would be hard to observe. Moreover, increase in profitability does not always translate into operational efficiency. Lastly, the methods that explicitly model a firm's efficiency allow the econometric flexibility that profitability ratios lack. Three common measures of firm efficiency are stochastic frontier analysis (SFA), data envelopment analysis (DEA) and total factor productivity (TFP). Aigner et al. (1977); Meeusen and van den Broeck (1977) and Battese and Corra (1977) simultaneously developed a Stochastic Frontier Analysis method (SFA) that, in addition to incorporating the efficiency term into the analysis (as do the deterministic approaches) it also captures the effects of exogenous shocks beyond the control of the analyzed units. This type of model also covers errors in the observations and in the measurement of outputs (Murillo-Zamorano, 2004).

The DEA method was introduced by Farrell (1957) and improved by Charnes et al. (1978) and Banker et al. (1984). The aim of this non-parametric approach is to define a frontier envelopment surface for all sample observations. This surface is determined by those units that lie on it, that is the efficient decision-making units (DMUs). On the other hand, units that do not lie on that surface can be considered as inefficient and an individual inefficiency score will be calculated for each one of them. Unlike stochastic frontier techniques, DEA has

[4] As robustness tests, I use *Rel_intensity* and *Rel_number* as alternative relationship bank measures. I also run placebo estimations using a pseudo dummy variable for the existence of relationship bank lending. The results are robust and available in the Appendix.

no accommodation for noise, and therefore can be initially considered as a non-statistical technique where the efficiency scores and the envelopment surface are 'calculated' rather than estimated (Murillo-Zamorano, 2004). In their analysis of cost efficiency in the banking sector, Ferrier and Lovell (1990) argue that the differences between the two approaches are due to the fact that a stochastic specification had been compared with a deterministic one.

More recent studies that utilize SFA and DEA models to estimate/calculate the firm efficiency have dealt with questions such as the effect of firm efficiency on stock returns (Frijns et al., 2012), on firm performance (Baik et al., 2013) and on mergers and acquisitions performance (Leverty and Qian, 2011). They all find positive effect of efficiency on the related performance measure. Furthermore as Leverty and Grace (2012) discuss, empirical research documents a strong relationship between property-liability insurer efficiency and traditional and market measures of performance. For example, Cummins et al. (2008) find that efficiency measures are directly related to the market value performance of publicly traded insurers. Leverty and Grace (2010) find that efficiency measures are closely related to traditional measures of firm performance, such as return on assets and return on equity. Demerjian et al. (2012) introduce a new measure of managerial ability defining it as a component of firm efficiency and look at the performance of those firms with high vs. low ability managers. They show that high managerial ability increases firm performance.

Another commonly used efficiency measure in macroeconomics and corporate finance literature is total factor productivity (TFP). Imrohoroglu and Tuzel (2014) argue that it is a broader measure of firm level performance than some of the more conventional measures, such as labor productivity or firm profitability as profitability captures only the part of the value added that goes to shareholders, and labor productivity can be an inadequate measure of overall efficiency especially in capital intensive industries. They estimate firm level TFP using the semi-parametric method and find that low TFP firms are riskier and therefore earn a significant risk premium over high productivity firms in the stock market.

In this paper I use SFA method to estimate the efficiency variable.[5] SFA model assumes that the error term of the regression of firm outputs on inputs includes both randomness (statistical noise) and technical inefficiency. To estimate SFA efficiency I use translog production function, which is quadratic in logarithms and incorporates interactions of inputs in addition to the levels of inputs to control for nonlinearity in the specification. As Bogetoft and Otto (2011) discuss, when we estimate the parameters of the translog function, we estimate the second-order derivative that determines how the inputs and outputs interact. In this way, we let the data determine the latter, i.e. whether the inputs and outputs are substitutes or complements. Therefore it is more flexible than other production functions.[6] For the translog production function and in logarithmic terms, the single-output stochastic frontier can be shown as

$$lnSales_i = \beta_0 + \sum_{i=1}^{n} \beta_i lnX_i + \sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij} lnX_i lnX_j + \nu_i - u_i \tag{1.1}$$

where

$$\nu_i \sim \mathcal{N}(0, \sigma_\nu^2) \text{ and } u_i \sim \mathcal{N}_+(0, \sigma_u^2)$$

in which $Y_{it}$ represents output measured as total revenue (REVT) and $X_{n,it}$ represents the inputs. Using Demerjian et al. (2012)'s definitions the inputs are cost of goods sold (COGS) that are the costs of production; selling, general and administrative expenses (SG&A), which are operational costs also known as the costs unrelated to the production process; net property, plant and equipment (PPENT) that accounts for fixed assets; net operating leases (OpsLease) that are included to capture the expenses of the firms that lease the fixed assets rather than purchase; research and development expenses (R&D); purchased goodwill

[5] My results are robust to using DEA method and TFP estimates of Imrohoroglu and Tuzel (2014) and are available in the Appendix.

[6] The results are robust to Cobb-Douglas production function and are available upon request.

(Goodwill), which is the excess of the purchase price for a business acquisition; and other intangibles (OtherIntan) that include items such as client lists, patent costs, and copyrights. The five stock variables (PPENT, OpsLease, R&D, Goodwill and OtherIntan) are measured at the beginning of year $t$ and the two flow measures (COGS and SG&A) are measured over the year $t$. I follow Ge (2006) to calculate Net Operating Leases as the discounted present value of the next five years of required operating lease payments (MRC1-MRC5 on Compustat). I follow Lev and Sougiannis (1996), who use a five-year capitalization period of R&D expense. Other Intangible Assets item (OtherIntan) is calculated by subtracting Goodwill (GDWL) from the Other Acquired and Capitalized Intangibles (INTAN). The term $\nu_{it} - u_{it}$ is a composed error term where $\nu_{it}$ represents randomness and $u_{it}$ represents technical inefficiency. An important assumption in this model is that $\nu_{it}$ and $u_{it}$ are independent. If $u_{it} = 0$ the firm is 100% efficient, and if $u_{it} > 0$, then there is some inefficiency. The $N_+$ denotes a half-normal distribution, which is truncated at point 0 and the distribution is concentrated on the half-interval $[0, \infty)$ (Murillo-Zamorano, 2004). The analysis is done by maximum likelihood estimation of cross-sectional observations of firms within each year and industry using Fama-French 12 industry classification. The firm-specific technical efficiency is given by

$$TE_i = \frac{f(lnX_i, lnX_i lnX_j; \hat{\beta}_n) - \hat{u}_i}{f(lnX_i, lnX_i lnX_j; \hat{\beta}_n)} = 1 - \frac{\hat{u}_i}{f(lnX_i, lnX_i lnX_j; \hat{\beta}_n)} \tag{1.2}$$

The summary statistics are given in Table 1.1. Mean (median) SFA efficiency scores are 0.89 (0.92) with a standard deviation of 0.11.

To control for firm-specific features that might affect efficiency through channels other than existence of banking relationship, I use leverage, size, square of size, profitability, cash holdings, market to book, tangibility, interest coverage, capital expenditures, firm age and rating dummy, which are standard control variables in debt contracting literature (Dass and Massa, 2011; Denis and Mihov, 2003). *Leverage* is the ratio of public debt to equity; the two forms of firm's outside financing. It is defined as the ratio of book value of debt to the total of market value of equity and book value of debt.[7] *Firm size* is the natural log of total assets. I also control for square of size to include possible nonlinear effect of firm size on efficiency. Profitability is the return on assets *(ROA)* defined as the ratio of earnings before interest, taxes, depreciation and amortization to book value of assets. *Cash holdings* are measured as total cash and equivalents scaled by total assets. I define market to book ratio *(M/B)* as market value of equity plus book value of debt scaled by total assets. *Tangibility* is the ratio of net property, plant and equipment divided by total assets. *Interest coverage* is earnings before interest, tax, depreciation and amortization scaled by total interest payments. *Capital expenditures* ratio is total capital expenditures scaled by total assets. *Firm age* is the number of years since the initial public offering. *Rating* is a dummy variable equal to one if the firm has S&P domestic long-term issuer credit rating and zero otherwise.

According to the summary statistics in Table 1.1 mean (median) size of firms in the sample is about $2.5billion$(261 million). Average profitability is 10%. Tangibility, which measures the riskiness of the firm in terms of the fixed assets, has a mean (median) of 29% (22%). 25% of the sample has S&P domestic long-term issuer credit rating. The market-to-book ratio (M/B) measures the growth opportunities of the firm, which has a mean (median) of 1.47 (1.11) in the sample. Mean (median) leverage ratio is 25% (18%).

In order to analyze the impact of the existence of relationship banking on firms with low vs. high probability of default I use Jarrow Merton (JM) Hybrid Model, which is a statistical hazard model that relates the probability of firm default to the same explanatory variables as the Jarrow-Chava Model (firm financial ratios, other firm attributes, industry classification, interest rates, macroeconomic factors, and information about firm and market

[7] The results are unchanged when book leverage is used instead of market leverage.

equity price levels and behavior), and incorporates the default probability of the Merton Structural Model as an additional explanatory variable. The Merton Structural Model uses option-pricing methods to relate the probability of firm default to its financial structure and information about the firm's market price of equity. The explanatory variables include a measure of the firm's outstanding debt, its market valuation, and information about firm and market equity price behavior. In this model firm default occurs when the market value of the firm's assets decline below a threshold related to the firm's outstanding debt (KRIS, 2011). For yearly default probabilities I use one-year estimations of the model and include the value of the last day of a firm's reporting month (*fyr* in Compustat). The mean (median) value for a one-year default probability estimate is 1.33% (0.15%). As a robustness test, I estimate firms' default risks using Altman's Z-score and Whited-Wu financial constraint index. The mean (median) default risk value using the former is 1.75 (2.04) and latter is -0.27 (-0.26).

The syndicated loans market provides an opportunity to the researchers to analyze firms with varying levels of information asymmetries (Dennis and Mullineaux, 2000). Sufi (2007) shows that the borrowers with little or no credit reputation obtain syndicated loans that are similar to sole-lender bank loans. In these loans, the lead arranger retains a larger share of the loan and there are fewer participant lenders on the syndicate. More transparent borrowers obtain syndicated loans that are similar to public debt; i.e., the syndicate is dispersed and the lead arranger retains a smaller share of the loan.[8] In Table 1.2 I explore the univariate

[8]Using syndicated loans market data has become very common in the empirical relationship banking analysis (such as Bharath et al. (2007); Dass and Massa (2011)). Yet, firms that have access to syndicated loans market are larger in size, more profitable and transparent and have more tangible assets, which shows that syndicated loans market is not a perfect representation of the Compustat sample. This suggests that the implications of theoretical banking literature, that opaque firms with intermediate levels of default risk are the ones with the highest benefit out of relationship lending (such as Fama (1985); Diamond (1991); Rajan and Winton (1995)), are not observed in the syndicated loans market database. In order to mitigate this selection bias, I model a firm's decision to borrow in the syndicated loans market using all Compustat firms. Then I model the decision to have a relationship banking conditional on having borrowed in the syndicated loans market. In addition, in Section 1.4.3 I use all Compustat firms' data to compare the default risk of firms with relationship banking to that of those only with public debt after the borrowing takes place.

analysis of syndicated loan terms and syndicate structure for the subsamples of firms I define according to their baseline efficiencies (below vs. above median SFA efficiency) and default probabilities (first vs. fourth quartile of Jarrow-Merton default probabilities). This allows me to gauge the type of firms that the relationship banks would have highest incentive to produce private information. In Panel A columns 1, 2 and 3, I evaluate the differences in means of low efficiency subsamples with low PD vs. high PD (elevated risk of default). The differences of low PD vs. high PD and the t-statistics of the differences show that among the low baseline efficiency firms, low PD firms have lower loan spreads, longer loan maturities and lower lead bank share of the loan when compared to high PD firms. For the high efficiency subsample in columns 4, 5 and 6 of Panel A, I find that low PD firms have lower loan spreads, larger loan amounts and longer loan maturity when compared to high PD firms' syndicated loans and syndicate structure. These results show that high PD subsample is the one that relationship banks will screen and monitor more closely. To assess further, I look at the subsample of high PD firms with low vs. high baseline efficiencies in Panel B. I find that among the high PD firms, those with low baseline efficiency receive a higher loan spread, smaller loan amount, larger lead bank share and lower number of lead banks in the syndicate. Therefore I find that relationship banks evaluate low baseline efficiency firms with elevated risk of default (high PD) more closely, since lenders of these firms are exposed to the highest loss given default in the sample.

## 1.4 Model and Results

### 1.4.1 Two-Stage Analysis

I analyze the effect of relationship banking on the borrowing firm's efficiency using the *Rel_dummy* variable that is equal to one if the firm has borrowed from the same lead-lender in the last 5 years. However, the decision to borrow from a bank is endogenous, and may introduce bias to my analysis. The firms that can obtain funds from publicly traded debt or equity markets may choose to do so in lieu of syndicated bank loans since they typically face higher interest rates on bank debt. Therefore, firms that are dependent on banks for financing may be the ones that are unable to access public debt markets because of severe adverse selection and potential moral hazard, thereby injecting endogeneity into my analysis. In order to mitigate this concern, I endogenize the loan taking decision and define a *Bor_dummy* variable, which is equal to one if a firm has borrowed in any given year in the syndicated loans market and zero otherwise. Conditional on taking a loan in the syndicated loans market, having a relationship bank is also endogenous as not all firms borrowing in the syndicated loans market choose to have a relationship bank. Therefore I also endogenize the *Rel_dummy* variable and estimate the likelihood of the existence of relationship so that the results reflect the effect of likelihood of relationship banking on firm efficiency controlling for both sources of endogeneity in the borrowing decision (Bharath et al., 2011; Dass and Massa, 2011; Elsas, 2005).

Following Wooldridge (2010), I use a Heckman's two-step correction model for endogeneity. I estimate the probability of syndicated loan borrowing and use the inverse Mills ratio (lambda) from the probit regression to control for endogeneity in the second step of my analysis. Then, I estimate another probit regression for having a relationship bank conditional on borrowing in the syndicated loans market, and use the probabilities from this regression as instruments in the second stage of the two-stage model. Following Papke and Wooldridge (1993); Ramalho et al. (2010) and Ramalho et al. (2011), in the second stage estimation of SFA efficiency I use fractional response regression since SFA efficiency score is a continuous variable within the unit interval and OLS estimation does not guarantee that the predicted values of the dependent variable are restricted to the unit interval. Using lagged levels of all control variables in the first step probit estimations to alleviate reverse causality concerns, I estimate below first probit estimation model:

$$Prob(Bor\_dummy_{it} = 1|X_{it-1}) = \Phi(\alpha X_{it-1} + YearFE + IndustryFE) \qquad (1.3)$$

in which $X_{it-1}$ includes two instruments: number of previous bank relationships in the industry a firm operates and a dummy variable that indicates an outstanding relationship bank borrowing from the previous period. The first instrument controls for the industry effect on a firm's decision to take a loan each year. As it is measured at the industry and year level and lagged, it is not related to current firm level efficiency. The second instrument is to account for the existence of prior bank relationships, consistent with Bharath et al. (2007), who find that subsequent borrowings are more likely following earlier syndicated bank loans for both relationship and non-relationship banks (40% and 3%, respectively). Therefore I define the second instrument as a *Dummy for outstanding relationship from previous period*, which includes a firm's outstanding relationship borrowing from any lead-lender. Consistent with literature, I find that both instruments increase the probability of having a bank loan. In addition to these instruments, I control for leverage, size, square of size (to allow for non-linearity), profitability, cash holdings, market to book, tangibility, interest coverage, capital expenditures, firm age and rating dummy. The results of the first step analyses are presented in the first column of Table 1.3. Similar to the findings of Dass and Massa (2011), younger firms with credit rating, low cash holdings, high profitability and growth opportunities (M/B), low interest coverage, high capital expenditures and low tangibility have a higher likelihood of borrowing from a bank. Furthermore, size has an inverted u-shape impact on loan taking decision suggesting that it initially has a positive effect on the likelihood of loan taking but as firms get larger in size, they are less likely to borrow from banks. These suggest that larger firms and firms with credit rating have access to syndicated loans market. Those firms with higher growth opportunities, lower tangibility and lower liquidity have higher probability of borrowing in the syndicated loans market.

The second column of Table 1.3 presents the results of the second probit regression estimated to control for relationship bank endogeneity as follows:

$$Prob(Rel\_dummy_{it} = 1|C_{it-1}) = \Phi(\gamma C_{it-1} + YearFE + IndustryFE) \tag{1.4}$$

Following the findings in Bharath et al. (2007), I use the *Dummy for outstanding loan from previous period* variable for existence of bank loan from any lead-lender in the previous periods to instrument the likelihood of establishment of a relationship. My results show that outstanding loans from previous periods have a positive and statistically significant effect at 1% level on the existence of relationship banking. Moreover, I find that large firms with credit rating, low cash holdings and leverage ratio, high profitability and growth opportunities (M/B), low interest coverage, high capital expenditures and low tangibility have a higher likelihood of having a relationship bank. These suggest that among the firms borrowing in the syndicated loans market those with low information asymmetries that have low liquidity have higher probability of having a relationship bank.

Wooldridge (2010) argues that (1) using valid instruments for the second step probit *(Dummy for outstanding loan from previous period)*, (2) nonlinearity of probit model and (3) using estimated probabilities as instruments for existence of relationship bank in the two-stage regression rather than using instruments as regressors directly in the second step, satisfy exclusion restrictions. Using inverse Mills ratio (lambda) from column 1 of Table 1.3 and the fitted value of the estimated relationship probability from column 2 of Table 1.3, I estimate a two-stage model with fractional response regression in the second stage in order to study the effect on firm efficiency of a new loan from a relationship bank:

$$SFA\ Efficiency_{it} = \alpha + \beta Z_{it} + \gamma \bar{X}_{i[t-1,t-5]} + \delta Lambda_{it} + YearFE + IndustryFE + \epsilon_{it} \tag{1.5}$$

in which $Z_{it}$ is the *Rel_dummy*, which is instrumented using estimated probabilities from second probit regression in equation (1.4). Following Dass and Massa (2011), $\bar{X}_{i[t-1,t-5]}$ indicates the five-year average values of the same control variables from the first step probit specification.[9] I use bootstrapping at the firm level in all regressions to correct the standard errors.

Table 1.4 presents the first stage results of the two-stage model for all sample (column 1), low probability of default (Low PD) (column 2), elevated probability of default (High PD) (column 3), low baseline efficiency (column 4) and high baseline efficiency subsamples (column 5). Estimated probabilities from the equation (1.4) are significant at 1% level in all five estimations. F-statistic of the excluded instrument in all columns rejects the null hypothesis of weak instrument. Column 1 in Table 1.5 presents the second stage results of the estimation of equation (1.5), which exhibits support for *Hypothesis 1*. Particularly, according to all sample results in column 1, borrowing firm technical efficiency increases, on average, as a result of a new loan from a relationship bank. These results are both statistically and economically significant such that a 1% increase in the likelihood of existence of relationship banking increases SFA efficiency by 0.7 percentage points, significant at 1% level. This corresponds to an increase of 2.51 percentage points in average SFA efficiency score. The average annual growth rate of SFA efficiency scores throughout the sample period is -0.07%. Therefore the results in Table 1.5 indicate economically meaningful efficiency gains.

[9] Average maturity of relationship bank loans is 43 months in the sample. It corresponds to about 3.5 years. However I define the existence of relationship banking if the firm has borrowed from the same lead-lender in the last 5 years. Therefore I use the average of 5 years lags of control variables. The results are robust to using 3-year lagged averages of controls.

All sample results also show that an increase in the five-year average profitability and efficiency increase firms' efficiency during the year of a newly active syndicated bank loan. Both size and the square of size have positive and significant impact on a firm's efficiency. Moreover, the results shows that increase in cash holdings increase a firm's efficiency in the year of borrowing. Firms with more growth opportunities (M/B) also operate more efficiently. Increase in default risk of a firm reduces its efficiency. Higher tangibility in the previous five years has a positive impact on a firm's efficiency, suggesting that firms with less information asymmetries operate more efficiently. In addition, firms with higher interest coverage have higher operational efficiency. Higher investment (Capex/TA) does not have an impact on firms' efficiency. Firm efficiency also decreases, as firms get older. Firms with credit rating operate more efficiently when a new loan from a relationship bank is initiated. A positive and significant coefficient on lambda shows that there is selection bias in firms' decision to borrow from a bank and that without controlling for lambda the effect of relationship banking would be biased.

### 1.4.2 Efficiency Effects Controlling for Distance to Default and Baseline Efficiency

The convex nature of the bank's return function may cause the bank to focus only on borrowers in elevated risk of default. I test *Hypothesis 2* for the subsamples of low vs. elevated default risk firms defined by the first and fourth quartile of Jarrow Merton default probabilities. Columns 2 and 3 in Table 1.5 present the second stage results of the estimation of equation (1.5) for subsamples of low vs. elevated default risk firms, respectively. The results provide evidence for *Hypothesis 2* that relationship banks concentrate on producing private information to improve the efficiency of those firms with elevated risk of default. Specifically, 1% increase in the likelihood of existence of relationship banking increases the efficiency of low PD subsample firms by 0.6 percentage points, whereas a similar change increases the efficiency of high PD subsample firms by 1.1%, both statistically significant at 1% level.

Relationship banks improve borrower outcome through intervening in the borrower's operations during the course of private information production via screening and monitoring. This intervention requires assessment of efficient use of resources while evaluating the default risk. Therefore the baseline efficiency of a borrower at the time of a relationship lending is also a significant determinant for a relationship bank to invest in the private information production. To test *Hypothesis 3*, I define the subsamples according to below and above median baseline SFA efficiency scores. The results in columns 4 and 5 of Table 1.5 indicate that low baseline efficiency firms experience higher increase in their efficiency when they borrow from a relationship bank. 1% increase in the likelihood of existence of relationship bank increases the efficiency of low baseline efficiency firms by 1.2 percentage points at 1% statistical significance level, while a similar increase in the likelihood of relationship bank increases the efficiency of high baseline efficiency firms by 0.1 percentage points at 5% significance level. Therefore these results present support for *Hypothesis 3* that relationship banks concentrate on producing private information to improve the efficiency of those firms with low baseline efficiency.

I also argue that among the firms with elevated risk of default, increases in efficiency in the presence of relationship bank loans are highest for firms that have low baseline levels of operational efficiency. In order to test this, I estimate equation (1.5) for the subsamples of firms defined as low baseline efficiency firms with low default risk, high baseline efficiency firms with low default risk, low baseline efficiency firms with elevated default risk and high baseline efficiency firms with elevated default risk. Table 1.6 presents the results for each subsample for the first stage estimation of equation (1.5) using estimated probabilities from the second step probit regression as instruments for existence of relationship banking.

Table 1.7 reports the second stage results of the estimation of equation (1.5). The coefficient of *Rel_dummy* is statistically significantly positive (at the 1% significance level), and economically important with a 1% increase in the likelihood of existence of bank relationship increasing the efficiency of low efficiency firms that have an elevated probability of default (column 3) by 1.1 percentage points at 1% statistical significance level. A similar increase in the likelihood of existence of relationship banking increases the efficiency of high baseline efficiency that have an elevated probability of default (column 4) by 0.5 percentage points. In comparison, while firms with high baseline efficiency and low default risk (column 2) do not experience significant change in their efficiencies as a result of relationship bank borrowing, firms with low baseline efficiency with low default risk (column 1) experience 1 percentage point increase in their efficiency when the likelihood of relationship banking increases by 1%. These results show that among the firms with elevated risk of default increases in efficiency in the presence of relationship bank loans are highest for firms that have low baseline levels of operational efficiency. In addition, these results show additional support for *Hypothesis 3* that relationship banks concentrate on producing private information to improve the efficiency of those firms with low baseline efficiency.

In order to test the persistence of the impact of relationship bank oversight on borrower performance, I use 5-year window around the year a new loan from a relationship bank is granted. Particularly, I estimate equation (1.5) for two years before and after the borrowing takes place as well as for the year of borrowing for subsamples of low efficiency firms substantially above the default threshold and low efficiency firms that have an elevated probability of default. Table 1.8 shows that both low PD and high PD firms experience statistically significant (at the 1% level) increases in technical efficiency in the year of a new relationship bank loan. However, the efficiency improving effect of the relationship bank loan persists for one more year after the loan origination for firms that have an elevated probability of default whereas it disappears for firms above default threshold after the loan is originated.

Table 1.9 shows the 5-year window results for high baseline efficiency firms. Similar to low baseline efficiency firms with elevated default risk, high baseline efficiency firms with elevated default risk experience an improvement in their efficiency for one more year after the loan origination. The effect disappears thereafter. Therefore, these findings suggest that the benefits of relationship bank information production in generating efficiency improvements offer diminishing returns over time.

One alternative explanation to the insignificant results for low baseline efficiency firms with elevated risk of default two years after the relationship bank borrowing could be that it corresponds to the loan maturity. Therefore banks may not have an incentive to monitor the borrower any more. However, as Panel B of Table 1.2 shows, the average maturity of the relationship bank loans for low baseline efficiency firms with elevated risk of default is 36 months. This means that although the relationship bank is still monitoring, it does not have further incentive to improve the borrower outcome. A second and more plausible explanation is that the loans are restructured very frequently during the life of a loan. Therefore efficiency-increasing incentives might disappear as a loan approaches maturity. In fact, Roberts (2015) estimates that syndicated bank loans are renegotiated every nine months on average. Moreover, Garleanu and Zwiebel (2008) suggest that renegotiation is a response to initially tight contracts designed to mitigate information-related problems.

### 1.4.3 Examining the Impact on Default Risk

It would be reasonable to expect that banks' investments in information production should pay off in terms of improved loan outcome, i.e., reduced default risk. I examine this in my test of *Hypothesis 4*, presented in Table 1.10. I estimate a propensity score matching with nearest neighbor matching approach[10] and compare the year-to-year difference in the probability of

[10] I also use Mahalanobis matching technique as a robustness check. The results are statistically and economically similar and available in the Appendix.

default of firms that have relationship banking with those of matched control firms that have public debt. I match the firms according to their propensity score (using 0.1 as the maximum distance criteria), estimated as the probability of having a relationship banking one period before the borrowing took place. I estimate equation (1.4) using logistic regression, where the dependent variable is equal to one for the firms that have relationship banking during the sample period (treatment group) and zero for the firms, which do not have relationship banks during the sample period but have issued public debt (control group). Following Rosenbaum and Rubin (1985) I check the standardized percentage bias for the matched treated and non-treated groups' covariates before and after the matching. The bias after matching is reduced to below 25%, which is the accepted limit. After matching I define the difference of default probabilities between year *0* and *-1*, where *0* is the year of borrowing and *-1* is the prior year. Similarly I check the difference of default probabilities between year *1* and *-1* and year *2* and *-1*.

Results in Panel A of Table 1.10 show a reduction in default risk over years *1* and *2* (as compared to year *-1*) only for the high default risk borrowers with bank relationships. That is, default risk declined by 0.79% both one year and two years after the origination of a relationship bank loan. These measures are all statistically significant at the 1% and 5% levels, respectively, and imply economic significance of -19.03% (-0.79%/4.15%)[11] of mean default risk in year *1* and 19.94% (-0.79%/3.96%) of mean default risk in year *2*. In contrast, Panel B of Table 1.10 shows that default risk actually increases for both relationship bank borrowers (treatment group) and public debt issuers (control group) that are far from the default threshold.

Finally, I perform a quasi diff-in-diff estimation by comparing the treatment group to the control group in the years before and after the debt issuance. These results are presented

[11] The mean of Jarrow-Merton default probability in the fourth quartile is 4.15% in year *1* and 3.96% in year *2*. For the first quartile of Jarrow-Merton default probabilities the mean is 0.017% in both year *1* and *2*.

in boldface in Table 1.10. As shown in Panel A of Table 1.10, relationship bank borrowers experience significant decreases in default risk as compared to bond issuers in the year of new debt issuance as compared to the year before. The mean of -1.16% (significant at the 1% level) indicates a decrease in default risk of 27.95% (-1.16%/4.15%) in mean default risk. The magnitude of this effect increases in the year following the debt issuance, with relationship bank borrowers experiencing a -1.24% decline in default risk relative to bond issuers, corresponding to -31.31% (-1.24%/3.96%) in mean default risk. The differences are not significant for the low default risk subsample shown in Panel B. These results provide support for *Hypothesis 4* that the probability of default decreases for firms with elevated default risk in the years following a new loan from a relationship bank.

## 1.5 Conclusion

I analyze the impact of relationship banking in the syndicated loans market on firm efficiency, as measured by Stochastic Frontier Analysis method. In particular, I determine whether a firm that borrows a new loan from a banking relationship is more or less likely to operate efficiently in the years before, during and after the loan is granted. This permits an examination of whether a relationship bank's information production is narrowly focused on firm default risk or more broadly related to overall firm performance even when the probability of default is low.

I find that relationship banks' value added in improving outcomes appears to be limited to borrowing firms with elevated risks of default. In addition, the results show that relationship banks appear to invest efficiency-improving information resources in low baseline efficiency firms even if they have low probabilities of default. Moreover, I find evidence that among firms with low efficiency, relationship banks have the most impact for the borrowers that have elevated risks of default. The results also provide evidence that the impact of relationship banking on firm efficiency disappears one year after the new borrowing from a relationship bank takes place.

Lastly, I find that relationship banking appears to reduce the probability of default only for firms closer to the default threshold. That is, low default-risk firms with relationship banks experience increases in default risk in the years following bank-lending activity, consistent with their increased leverage. Further, borrowing on public debt markets is consistent with increases in default risk for all firms (high and low default probability). Thus, my results suggest that relationship banks are successful in reducing default risk on syndicated bank loans for less creditworthy borrowing firms with low baseline levels of technical efficiency.

One important caveat of this analysis is the absence of exogenous variation. I mitigate this concern by conducting Heckman's two-step estimation model for endogeneity. Further research can focus on how an exogenous shock to existence, intensity and/or frequency of relationship banking affects firm performance. In addition, further research can shed light on how relationship bank oversight impacts firm innovation, growth and riskiness.

**Table 1.1:** Summary Statistics

| **Variable** | **Obs** | **Mean** | **Std.Dev.** | **Q1** | **Median** | **Q3** |
|---|---|---|---|---|---|---|
| SFA efficiency | 63,994 | 0.89 | 0.11 | 0.85 | 0.92 | 0.96 |
| DEA efficiency | 63,994 | 0.71 | 0.22 | 0.56 | 0.74 | 0.88 |
| TFP (Imrohoroglu and Tuzel (2014)) | 46,203 | -0.34 | 0.47 | -0.53 | -0.32 | -0.10 |
| Total Assets (TA) ($ millions) | 63,994 | 2,544.43 | 8,050.12 | 62.51 | 261.48 | 1,214.02 |
| Size | 63,994 | 5.70 | 2.06 | 4.13 | 5.56 | 7.10 |
| $Size^2$ | 63,994 | 36.77 | 25.46 | 17.10 | 30.98 | 50.43 |
| Cash/TA | 63,994 | 0.13 | 0.16 | 0.02 | 0.07 | 0.18 |
| Leverage | 63,994 | 0.25 | 0.23 | 0.05 | 0.18 | 0.38 |
| ROA | 63,994 | 0.10 | 0.16 | 0.06 | 0.11 | 0.17 |
| Interest coverage | 63,994 | 41.83 | 173.87 | 2.34 | 6.45 | 17.93 |
| M/B | 63,994 | 1.47 | 1.16 | 0.78 | 1.11 | 1.72 |
| Capex/TA | 63,994 | 0.06 | 0.06 | 0.02 | 0.04 | 0.07 |
| Tangibility | 63,994 | 0.29 | 0.23 | 0.11 | 0.22 | 0.41 |
| Rating | 63,994 | 0.25 | 0.43 | 0 | 0 | 1 |
| Firm age | 63,994 | 15.02 | 15.36 | 4 | 10 | 21 |
| Jarrow-Merton (JM) default probability (%) | 63,994 | 1.33 | 4.33 | 0.04 | 0.15 | 0.64 |
| Whited-Wu financial constraint index | 63,994 | -0.27 | 0.12 | -0.34 | -0.26 | -0.18 |
| Altman's z-score | 63,994 | 1.76 | 2.36 | 1.20 | 2.04 | 2.81 |
| Bor_dummy | 63,994 | 0.26 | 0.44 | 0 | 0 | 1 |
| Rel_dummy | 63,994 | 0.13 | 0.34 | 0 | 0 | 0 |
| Dummy for outstanding loan from previous period | 63,994 | 0.48 | 0.50 | 0 | 0 | 0 |
| Dummy for outstanding relationship from previous period | 63,994 | 0.13 | 0.33 | 0 | 0 | 1 |
| Total number of industry loans | 63,994 | 0.13 | 0.34 | 0 | 0 | 0 |

**Table 1.2:** Univariate Analysis of Syndicate Structure and Loan Terms

**Panel A: All sample**

| | **Low Efficiency** | | | **High Efficiency** | | |
|---|---|---|---|---|---|---|
| | Low PD | High PD | Low PD - High PD (t-stat) | Low PD | High PD | Low PD - High PD (t-stat) |
| Loan Spread (bps) | 125.18 | 248.44 | -123.26*** | 73.07 | 161.61 | -88.54*** |
| | | | (-14.61) | | | (-16.99) |
| Loan Amount ($ millions) | 391 | 416 | -25 | 825 | 585 | 240*** |
| | | | (-0.34) | | | (2.88) |
| Maturity (months) | 46.41 | 36.37 | 10.04*** | 39.14 | 35.22 | 3.92** |
| | | | (6.00) | | | (2.48) |
| Lead Share (%) | 24.03 | 47.55 | -23.51*** | 18.21 | 20.82 | -2.60 |
| | | | (-7.18) | | | (-1.31) |
| Number of Lead Banks | 4.52 | 4.04 | 0.48 | 5.52 | 5.53 | -0.01 |
| | | | (1.26) | | | (-0.03) |

**Panel B: High PD firms**

| | Low Efficiency | High Efficiency | Low Efficiency - High Efficiency (t-stat) |
|---|---|---|---|
| Loan Spread (bps) | 248.44 | 161.61 | 86.83*** |
| | | | (8,22) |
| Loan Amount ($ millions) | 416 | 585 | -169** |
| | | | (-2.02) |
| Maturity (months) | 36.37 | 35.22 | 1.15 |
| | | | (0.53) |
| Lead Share (%) | 47.55 | 20.82 | 26.73*** |
| | | | (7.17) |
| Number of Lead Banks | 4.04 | 5.53 | -1.49*** |
| | | | (-3.00) |

**Table 1.3:** First step probit regressions

The dependent variable in the first column is *Bor_dummy* variable, which is equal to one if a firm has borrowed in any given year in the syndicated loans market and zero otherwise. The dependent variable in the second column is *Rel_dummy* variable, which is equal to one if a firm has borrowed from the same lead-lender within the previous five-year window. The coefficients correspond to semi-elasticities ($dy/ex$). All variable definitions are in the Appendix. The period of analysis is between 1991-2011. All regressions include industry and year fixed effects. The standard errors are clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| Dependent variable: | $Bor\_exists_t$ | $Rel\_dummy_t$ |
|---|---|---|
| *Dummy for outstanding relationship from previous period* | 0.013*** | |
| | (12.28) | |
| *Total number of industry loans* | 0.023** | |
| | (2.13) | |
| *Dummy for outstanding loan from previous period* | | 0.174*** |
| | | (33.47) |
| $ROA_{t\text{-}1}$ | 0.012*** | 0.011*** |
| | (5.06) | (3.40) |
| $Size_{t\text{-}1}$ | 0.526*** | 0.314*** |
| | (13.16) | (6.18) |
| $Size^2_{t\text{-}1}$ | -0.195*** | -0.030 |
| | (8.52) | (1.09) |
| $Cash_{t\text{-}1}$ | -0.041*** | -0.021*** |
| | (23.61) | (12.64) |
| $M/B_{t\text{-}1}$ | 0.008*** | 0.010*** |
| | (2.63) | (3.03) |
| $JM\ probability\ of\ default_{t\text{-}1}$ | -0.000 | -0.001 |
| | (0.07) | (1.21) |
| $Tangibility_{t\text{-}1}$ | -0.042*** | -0.020*** |
| | (10.25) | (4.91) |
| $Interest\ Coverage_{t\text{-}1}$ | -0.002*** | -0.002*** |
| | (5.23) | (5.03) |
| $Capex/Total\ assets_{t\text{-}1}$ | 0.023*** | 0.007** |
| | (8.17) | (2.57) |
| $Leverage_{t\text{-}1}$ | -0.002 | -0.007** |
| | (0.72) | (2.10) |
| *Rated dummy* | 0.041*** | 0.021*** |
| | (17.65) | (7.38) |
| *Firm age* | -0.007*** | -0.001 |
| | (2.61) | (0.33) |
| *N* | 54,814 | 43,981 |

**Table 1.4:** First Stage Results

The table shows the first stage OLS results of two-stage model for the subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) and below and above median baseline SFA efficiency scores. The dependent variable is *Rel_dummy*, which is equal to one if a firm has borrowed from the same lead-lender within the previous five-year window. The instrument is the estimated probabilities from the second probit regression in equation (1.4). The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| Dependent variable: $Rel\_dummy_t$ | All sample | Low PD subsample | High PD subsample | Low Efficiency subsample | High Effiiency subsample |
|---|---|---|---|---|---|
| *Prob. of* $Rel\_dummy_t$ (instrument) | 0.671*** | 0.633*** | 0.707*** | 0.693*** | 0.665*** |
| | (34.84) | (17.03) | (14.22) | (22.12) | (25.25) |
| *ROA* | 0.066*** | 0.069 | 0.019 | 0.065** | 0.084 |
| | (2.65) | (1.31) | (0.41) | (2.28) | (1.58) |
| *Efficiency* | 0.029 | 0.029 | 0.111 | 0.029 | 0.185 |
| | (0.61) | (0.29) | (1.23) | (0.53) | (1.64) |
| *Size* | 0.044*** | 0.060*** | 0.026** | 0.053*** | 0.047*** |
| | (7.72) | (4.59) | (2.15) | (7.34) | (3.43) |
| $Size^2$ | -0.003*** | -0.004*** | -0.002* | -0.004*** | -0.003*** |
| | (6.80) | (4.62) | (1.77) | (6.14) | (3.64) |
| *Cash/TA* | -0.108*** | -0.135*** | -0.153*** | -0.122*** | -0.083** |
| | (5.47) | (3.68) | (3.40) | (5.31) | (2.40) |
| *M/B* | 0.001 | -0.002 | 0.005 | 0.005 | -0.005 |
| | (0.38) | (0.42) | (0.80) | (1.55) | (1.00) |
| *JM prob. of default* | -0.001 | 0.003 | 0.000 | -0.001 | -0.001 |
| | (0.76) | (0.61) | (0.14) | (0.67) | (0.37) |
| *Tangibility* | -0.015 | -0.047* | -0.001 | -0.020 | -0.005 |
| | (1.17) | (1.86) | (0.03) | (1.16) | (0.26) |
| *Interest coverage* | -0.000*** | -0.000 | -0.000* | -0.000*** | -0.000*** |
| | (4.20) | (1.32) | (1.84) | (3.32) | (2.66) |
| *Capex/TA* | 0.041 | 0.125 | 0.007 | 0.128* | -0.117 |
| | (0.70) | (1.12) | (0.06) | (1.74) | (1.19) |
| *Leverage* | 0.014 | 0.057* | -0.027 | 0.011 | 0.009 |
| | (1.04) | (1.78) | (1.11) | (0.69) | (0.44) |
| *Firm age* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.35) | (0.86) | (1.04) | (0.22) | (0.68) |
| *Rating dummy* | 0.017*** | 0.012 | 0.011 | 0.019** | 0.012 |
| | (2.79) | (1.19) | (0.79) | (2.03) | (1.45) |
| *Lambda* | -1.243*** | -1.291*** | -1.141*** | -1.229*** | -1.251*** |
| | (125.74) | (88.40) | (47.26) | (69.82) | (104.67) |
| F-statistics | 708.52 | 180.55 | 154.49 | 369.02 | 334.28 |
| (p-value) | (<0.0000) | (<0.0000) | (<0.0000) | (<0.0000) | (<0.0000) |
| $R^2$ | 0.63 | 0.70 | 0.53 | 0.56 | 0.66 |
| $N$ | 23,711 | 6,864 | 5,081 | 11,679 | 12,032 |

**Table 1.5:** Second Stage Results of SFA Efficiency

The table shows the semi-elasticities ($dy/ex$) of the second stage results of two-stage model using fractional response regression and SFA efficiency as dependent variable for the whole sample as well as subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) (columns (2) and (3)) and below and above median baseline SFA efficiency scores (columns (4) and (5)). The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| Dependent variable: SFA efficiency | All sample | Low PD subsample | High PD subsample | Low Efficiency subsample | High Efficiency subsample |
|---|---|---|---|---|---|
| *Rel_dummy (instrumented)* | 0.007*** | 0.006*** | 0.011*** | 0.012*** | 0.001** |
| | (6.80) | (3.99) | (4.46) | (6.40) | (2.06) |
| *ROA* | 0.006*** | -0.002 | 0.006*** | 0.006*** | 0.002*** |
| | (8.10) | (1.53) | (6.73) | (6.20) | (4.00) |
| *Efficiency* | 0.188*** | 0.153*** | 0.152*** | 0.381*** | -0.106*** |
| | (16.72) | (11.06) | (5.74) | (21.83) | (8.50) |
| *Size* | 0.069*** | 0.065*** | 0.070*** | 0.083*** | 0.023*** |
| | (7.49) | (5.03) | (3.82) | (6.62) | (3.24) |
| *Size*$^2$ | 0.013*** | 0.012** | 0.018** | -0.023*** | 0.021*** |
| | (3.25) | (2.02) | (2.51) | (4.42) | (6.49) |
| *Cash/TA* | 0.002** | 0.002** | 0.001 | 0.003*** | 0.000 |
| | (2.46) | (2.46) | (0.71) | (2.96) | (0.04) |
| *M/B* | 0.004*** | 0.006*** | 0.002 | 0.004** | 0.002*** |
| | (3.65) | (3.01) | (0.90) | (2.50) | (3.83) |
| *JM prob. of default* | -0.001*** | 0.000** | -0.001 | -0.001** | -0.000*** |
| | (3.63) | (2.15) | (1.29) | (2.29) | (2.67) |
| *Tangibility* | 0.003*** | 0.002 | 0.002 | 0.004** | -0.001* |
| | (2.94) | (1.53) | (1.15) | (2.54) | (1.83) |
| *Interest coverage* | 0.000*** | 0.000 | 0.001** | 0.001*** | 0.000 |
| | (3.09) | (1.10) | (2.11) | (3.14) | (0.83) |
| *Capex/TA* | -0.000 | 0.004*** | -0.002 | -0.003* | 0.000 |
| | (0.23) | (3.38) | (0.73) | (1.90) | (1.30) |
| *Leverage* | -0.001 | -0.001 | 0.006*** | -0.000 | -0.001*** |
| | (1.39) | (1.18) | (2.91) | (0.10) | (2.91) |
| *Firm age* | 0.042*** | 0.024*** | 0.095*** | 0.085*** | 0.004* |
| | (6.06) | (3.54) | (4.29) | (5.82) | (1.74) |
| *Rating dummy* | -0.002*** | -0.002*** | -0.003** | -0.004*** | -0.001*** |
| | (4.34) | (3.52) | (2.30) | (3.15) | (4.16) |
| *Lambda* | 0.001*** | 0.001** | 0.001 | 0.000 | 0.000 |
| | (2.98) | (2.08) | (1.53) | (0.51) | (0.92) |
| *N* | 23,711 | 6,864 | 5,081 | 11,679 | 12,032 |

**Table 1.6:** First Stage Results of Low vs. High SFA Efficiency and Low vs. High PD Subsamples

The table shows the first stage OLS results of two-stage model for the subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) and below and above median baseline SFA efficiency scores. The subsample in column (1) is low PD - low efficiency, (2) is low PD - high efficiency, (3) is high PD - low efficiency, and (4) is high PD - high efficiency. The dependent variable is *Rel_dummy*, which is equal to one if a firm has borrowed from the same lead-lender within the previous five-year window. The instrument is the estimated probabilities from the second probit regression in equation (1.4). The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Low PD | | High PD | |
|---|---|---|---|---|
| Dependent variable: $Rel\_dummy_t$ | Low Efficiency | High Efficiency | Low Efficiency | High Efficiency |
| *Prob. of* $Rel\_dummy_t$ (instrument) | 0.733*** | 0.595*** | 0.680*** | 0.764*** |
| | (11.92) | (12.58) | (10.73) | (9.13) |
| *ROA* | 0.173** | -0.066 | 0.032 | -0.032 |
| | (2.34) | (0.87) | (0.65) | (0.25) |
| *Efficiency* | 0.046 | 0.149 | 0.052 | 0.412** |
| | (0.35) | (0.55) | (0.47) | (2.16) |
| *Size* | 0.084*** | 0.030 | 0.035** | 0.017 |
| | (5.04) | (1.24) | (2.27) | (0.52) |
| $Size^2$ | -0.007*** | -0.002 | -0.002 | -0.001 |
| | (5.20) | (1.41) | (1.54) | (0.64) |
| *Cash/TA* | -0.130*** | -0.113** | -0.155*** | -0.154 |
| | (2.61) | (2.11) | (3.32) | (1.39) |
| *M/B* | -0.016** | 0.008 | 0.009 | -0.005 |
| | (2.03) | (1.30) | (1.49) | (0.31) |
| *JM prob. of default* | 0.003 | 0.004 | -0.002 | 0.003 |
| | (0.49) | (0.44) | (1.16) | (0.97) |
| *Tangibility* | -0.100** | -0.010 | 0.025 | -0.045 |
| | (2.49) | (0.30) | (0.84) | (0.89) |
| *Interest coverage* | -0.000 | -0.000 | -0.000** | -0.000 |
| | (1.07) | (1.06) | (2.09) | (0.26) |
| *Capex/TA* | 0.236 | -0.031 | 0.091 | -0.148 |
| | (1.46) | (0.20) | (0.76) | (0.60) |
| *Leverage* | 0.060 | 0.047 | 0.001 | -0.087* |
| | (1.18) | (1.15) | (0.05) | (1.86) |
| *Firm age* | -0.000 | 0.000 | 0.000 | 0.000 |
| | (0.74) | (1.60) | (1.34) | (0.02) |
| *Rating dummy* | 0.011 | 0.016 | 0.012 | 0.009 |
| | (0.56) | (1.21) | (0.62) | (0.42) |
| *Lambda* | -1.293*** | -1.290*** | -1.094*** | -1.176*** |
| | (44.32) | (77.53) | (27.46) | (37.37) |
| F-statistics | 93.04 | 93.89 | 68.05 | 76.22 |
| (p-value) | (<0.0000) | (<0.0000) | (<0.0000) | (<0.0000) |
| $R^2$ | 0.65 | 0.71 | 0.46 | 0.57 |
| $N$ | 2,602 | 4,262 | 3,280 | 1,801 |

**Table 1.7:** Second Stage Results of Low vs. High SFA Efficiency and Low vs. High PD Subsamples

The table shows the semi-elasticities ($dy/ex$) of the second stage results of two-stage model using fractional response regression and SFA efficiency as dependent variable for the subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) and below and above median baseline SFA efficiency scores. The subsample in column (1) is low PD - low efficiency, (2) is low PD - high efficiency, (3) is high PD - low efficiency, and (4) is high PD - high efficiency. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Low PD | | High PD | |
|---|---|---|---|---|
| Dependent variable: SFA Efficiency | Low Efficiency | High Efficiency | Low Efficiency | High Efficiency |
| *Rel_dummy (instrumented)* | 0.010*** | 0.001 | 0.011*** | 0.005*** |
| | (3.61) | (0.67) | (3.46) | (3.21) |
| *ROA* | -0.002 | -0.000 | 0.005*** | 0.003*** |
| | (1.07) | (0.25) | (4.74) | (3.09) |
| *Efficiency* | 0.340*** | -0.094*** | 0.289*** | -0.079*** |
| | (12.50) | (5.35) | (9.35) | (3.53) |
| *Size* | 0.113*** | 0.024** | 0.088*** | -0.009 |
| | (5.04) | (2.06) | (4.01) | (0.72) |
| *Size*$^2$ | -0.040*** | 0.022*** | -0.018** | 0.032*** |
| | (3.62) | (3.98) | (1.96) | (5.71) |
| *Cash/TA* | 0.005*** | -0.000 | 0.001 | 0.000 |
| | (3.74) | (0.33) | (0.65) | (0.46) |
| *M/B* | 0.005 | 0.002*** | 0.002 | -0.000 |
| | (1.55) | (3.53) | (0.48) | (0.03) |
| *JM prob. of default* | 0.001** | 0.000 | -0.002 | -0.000 |
| | (2.32) | (1.22) | (1.39) | (1.47) |
| *Tangibility* | 0.002 | -0.001 | 0.003 | -0.000 |
| | (0.80) | (1.17) | (1.02) | (0.11) |
| *Interest coverage* | 0.000 | 0.000 | 0.001** | -0.000 |
| | (0.31) | (1.05) | (2.09) | (0.48) |
| *Capex/TA* | 0.007*** | 0.001* | -0.004 | -0.001 |
| | (3.06) | (1.78) | (1.25) | (1.11) |
| *Leverage* | -0.001 | -0.001** | 0.011*** | -0.001 |
| | (0.48) | (2.24) | (4.02) | (1.09) |
| *Firm age* | -0.005*** | -0.001*** | -0.002 | -0.000 |
| | (2.96) | (4.37) | (1.15) | (0.55) |
| *Rating dummy* | 0.002* | 0.000 | 0.001 | -0.001 |
| | (1.96) | (0.50) | (1.12) | (1.08) |
| *Lambda* | 0.053*** | 0.002 | 0.122*** | 0.018*** |
| | (3.42) | (0.60) | (3.48) | (2.83) |
| *N* | 2,602 | 4,262 | 3,280 | 1,801 |

**Table 1.8:** Regression results for low SFA Efficiency subsample of firms

The table shows the semi-elasticities ($dy/ex$) of the second stage results of two-stage model using fractional response regression and SFA efficiency as dependent variable for the subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) and below median baseline SFA efficiency scores. In the period $t-2$ *Rel_dummy* is lagged for two-period and in $t-1$ analysis *Rel_dummy* is lagged for one-period. In $t+1$ analysis one-period forward dependent variable is used and in $t+2$ analysis two-period forward dependent variable is used. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Low PD | | | | | High PD | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *t-2* | *t-1* | *t* | *t+1* | *t+2* | *t-2* | *t-1* | *t* | *t+1* | *t+2* |
| *Rel_dummy$_{t-2}$ (instrumented)* | -0.001 | | | | | -0.004* | | | | |
| | (0.68) | | | | | (1.83) | | | | |
| *Rel_dummy$_{t-1}$ (instrumented)* | | 0.003 | | | | | 0.001 | | | |
| | | (1.34) | | | | | (0.42) | | | |
| *Rel_dummy$_t$ (instrumented)* | | | 0.010*** | 0.000 | 0.004 | | | 0.011*** | 0.008** | 0.005 |
| | | | (3.61) | (0.03) | (0.80) | | | (3.46) | (2.06) | (1.20) |
| *ROA* | -0.002 | -0.002 | -0.002 | -0.000 | -0.007* | 0.006*** | 0.006*** | 0.005*** | 0.006*** | 0.005*** |
| | (0.82) | (0.76) | (1.07) | (0.06) | (1.96) | (5.51) | (5.53) | (4.74) | (3.54) | (2.71) |
| *Efficiency* | 0.344*** | 0.342*** | 0.340*** | 0.177*** | 0.141*** | 0.296*** | 0.294*** | 0.289*** | 0.174*** | 0.210*** |
| | (12.71) | (12.66) | (12.50) | (6.66) | (3.00) | (9.60) | (9.53) | (9.35) | (4.02) | (4.16) |
| *Size* | 0.133*** | 0.131*** | 0.113*** | 0.149*** | 0.099** | 0.113*** | 0.113*** | 0.088*** | 0.085*** | 0.057* |
| | (6.18) | (6.06) | (5.04) | (4.78) | (2.57) | (5.43) | (5.42) | (4.01) | (3.04) | (1.66) |
| *Size$^2$* | -0.043*** | -0.045*** | -0.040*** | -0.023 | 0.015 | -0.016* | -0.021** | -0.018** | 0.009 | 0.027** |
| | (3.97) | (4.11) | (3.62) | (1.56) | (0.82) | (1.70) | (2.21) | (1.96) | (0.88) | (2.12) |
| *Cash/TA* | 0.003* | 0.004*** | 0.005*** | 0.002 | 0.001 | -0.003 | -0.001 | 0.001 | -0.000 | -0.001 |
| | (1.92) | (2.72) | (3.74) | (0.92) | (0.57) | (1.45) | (0.61) | (0.65) | (0.06) | (0.46) |
| *M/B* | 0.006* | 0.005* | 0.005 | 0.007** | 0.008* | 0.003 | 0.002 | 0.002 | 0.002 | -0.004 |
| | (1.94) | (1.73) | (1.55) | (2.32) | (1.96) | (0.97) | (0.67) | (0.48) | (0.36) | (0.76) |
| *JM prob. of default* | 0.001** | 0.001** | 0.001** | 0.001 | 0.001 | -0.003** | -0.003* | -0.002 | -0.001 | 0.001 |
| | (2.06) | (2.25) | (2.32) | (1.11) | (1.36) | (2.11) | (1.70) | (1.39) | (0.35) | (0.46) |
| *Tangibility* | 0.001 | 0.001 | 0.002 | -0.002 | 0.000 | -0.000 | 0.001 | 0.003 | 0.003 | 0.001 |
| | (0.27) | (0.58) | (0.80) | (0.48) | (0.00) | (0.07) | (0.49) | (1.02) | (0.87) | (0.14) |
| *Interest coverage* | -0.000 | -0.000 | 0.000 | 0.000 | 0.001** | 0.000 | 0.001* | 0.001** | 0.001* | 0.000 |
| | (0.81) | (0.52) | (0.31) | (0.27) | (2.23) | (1.53) | (1.75) | (2.09) | (1.75) | (0.35) |
| *Capex/TA* | 0.007*** | 0.007*** | 0.007*** | 0.005* | 0.005 | -0.002 | -0.003 | -0.004 | -0.002 | 0.004 |
| | (3.30) | (3.15) | (3.06) | (1.68) | (1.28) | (0.63) | (0.98) | (1.25) | (0.49) | (0.95) |
| *Leverage* | -0.000 | -0.001 | -0.001 | 0.001 | -0.001 | 0.011*** | 0.011*** | 0.011*** | 0.009** | 0.003 |
| | (0.29) | (0.42) | (0.48) | (0.45) | (0.57) | (4.25) | (3.99) | (4.02) | (2.44) | (0.65) |
| *Firm age* | -0.005*** | -0.005*** | -0.005*** | -0.005** | -0.002 | -0.003 | -0.003 | -0.002 | -0.003 | -0.007*** |
| | (3.36) | (3.34) | (2.96) | (2.31) | (0.85) | (1.54) | (1.46) | (1.15) | (1.45) | (2.71) |
| *Rating dummy* | 0.003*** | 0.002*** | 0.002* | 0.002** | 0.002 | 0.003*** | 0.002** | 0.001 | 0.003** | 0.003*** |
| | (3.14) | (2.65) | (1.96) | (2.08) | (1.14) | (3.00) | (2.46) | (1.12) | (2.49) | (2.69) |
| *Lambda* | -0.003 | -0.002 | 0.053*** | -0.001 | 0.021 | -0.002 | 0.003 | 0.122*** | 0.085** | 0.047 |
| | (0.98) | (0.57) | (3.42) | (0.03) | (0.75) | (0.29) | (0.35) | (3.48) | (2.05) | (1.07) |
| *N* | 2,602 | 2,602 | 2,602 | 2,052 | 1,629 | 3,280 | 3,280 | 3,280 | 2,650 | 2,234 |

**Table 1.9:** Regression results for high SFA Efficiency subsample of firms

The table shows the semi-elasticities ($dy/ex$) of the second stage results of two-stage model using fractional response regression and SFA efficiency as dependent variable for the subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) and above median baseline SFA efficiency scores. In the period $t-2$ $Rel\_dummy$ is lagged for two-period and in $t-1$ analysis $Rel\_dummy$ is lagged for one-period. In $t+1$ analysis one-period forward dependent variable is used and in $t+2$ analysis two-period forward dependent variable is used. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Low PD | | | | | High PD | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *t-2* | *t-1* | *t* | *t+1* | *t+2* | *t-2* | *t-1* | *t* | *t+1* | *t+2* |
| *Rel_dummy$_{t-2}$ (instrumented)* | -0.001 | | | | | -0.001 | | | | |
| | (1.37) | | | | | (0.69) | | | | |
| *Rel_dummy$_{t-1}$ (instrumented)* | | 0.000 | | | | | 0.001 | | | |
| | | (0.35) | | | | | (1.08) | | | |
| *Rel_dummy$_t$ (instrumented)* | | | 0.001 | 0.000 | -0.002 | | | 0.005*** | 0.008** | 0.002 |
| | | | (0.67) | (0.04) | (0.87) | | | (3.21) | (2.47) | (0.58) |
| *ROA* | -0.000 | -0.000 | -0.000 | -0.003** | -0.004*** | 0.003*** | 0.003*** | 0.003*** | 0.004* | 0.004* |
| | (0.11) | (0.20) | (0.25) | (2.12) | (2.73) | (3.45) | (3.40) | (3.09) | (1.72) | (1.82) |
| *Efficiency* | -0.094*** | -0.094*** | -0.094*** | 0.081*** | 0.004 | -0.079*** | -0.080*** | -0.079*** | 0.090** | 0.031 |
| | (5.36) | (5.33) | (5.35) | (2.65) | (0.11) | (3.53) | (3.52) | (3.53) | (2.13) | (0.70) |
| *Size* | 0.025** | 0.025** | 0.024** | 0.087*** | 0.083*** | 0.001 | -0.001 | -0.009 | 0.015 | 0.024 |
| | (2.25) | (2.18) | (2.06) | (4.40) | (3.83) | (0.06) | (0.09) | (0.72) | (0.43) | (0.72) |
| *Size$^2$* | 0.021*** | 0.021*** | 0.022*** | -0.007 | -0.001 | 0.030*** | 0.029*** | 0.032*** | 0.029* | 0.032** |
| | (4.00) | (3.96) | (3.98) | (0.78) | (0.14) | (5.39) | (5.32) | (5.71) | (1.81) | (2.01) |
| *Cash/TA* | -0.000 | -0.000 | -0.000 | 0.000 | -0.001 | -0.000 | -0.000 | 0.000 | 0.001 | 0.002 |
| | (0.97) | (0.48) | (0.33) | (0.71) | (1.21) | (1.02) | (0.34) | (0.46) | (0.74) | (1.32) |
| *M/B* | 0.002*** | 0.002*** | 0.002*** | 0.005*** | 0.007*** | 0.000 | 0.000 | -0.000 | 0.002 | 0.004* |
| | (3.74) | (3.59) | (3.53) | (4.36) | (5.43) | (0.54) | (0.22) | (0.03) | (1.22) | (1.94) |
| *JM prob. of default* | 0.000 | 0.000 | 0.000 | 0.000** | 0.000*** | -0.000** | -0.000* | -0.000 | -0.000 | -0.001 |
| | (1.14) | (1.22) | (1.22) | (2.01) | (2.87) | (2.05) | (1.70) | (1.47) | (0.21) | (0.75) |
| *Tangibility* | -0.001 | -0.001 | -0.001 | 0.002** | 0.001 | -0.001 | -0.000 | -0.000 | 0.002 | 0.002 |
| | (1.51) | (1.22) | (1.17) | (2.40) | (1.15) | (0.90) | (0.51) | (0.11) | (1.36) | (1.25) |
| *Interest coverage* | 0.000 | 0.000 | 0.000 | -0.000 | 0.000 | -0.000 | -0.000 | -0.000 | 0.000 | -0.001* |
| | (0.76) | (0.97) | (1.05) | (0.17) | (0.30) | (0.68) | (0.61) | (0.48) | (0.68) | (1.78) |
| *Capex/TA* | 0.001* | 0.001* | 0.001* | -0.001 | -0.001 | -0.000 | -0.001 | -0.001 | 0.000 | -0.002 |
| | (1.92) | (1.80) | (1.78) | (1.25) | (0.52) | (0.54) | (0.84) | (1.11) | (0.23) | (1.15) |
| *Leverage* | -0.001** | -0.001** | -0.001** | -0.003*** | -0.002** | -0.001 | -0.001 | -0.001 | 0.002 | -0.000 |
| | (2.08) | (2.23) | (2.24) | (3.03) | (2.28) | (0.98) | (1.16) | (1.09) | (1.18) | (0.11) |
| *Firm age* | -0.001*** | -0.001*** | -0.001*** | -0.003*** | -0.003*** | -0.000 | -0.000 | -0.000 | -0.001 | -0.001 |
| | (4.41) | (4.42) | (4.37) | (4.68) | (4.24) | (0.58) | (0.61) | (0.55) | (1.35) | (0.60) |
| *Rating dummy* | 0.000 | 0.000 | 0.000 | 0.001 | 0.003*** | 0.000 | 0.000 | -0.001 | 0.001 | 0.002* |
| | (1.23) | (0.70) | (0.50) | (1.62) | (3.04) | (0.72) | (0.02) | (1.08) | (0.88) | (1.79) |
| *Lambda* | -0.001 | -0.000 | 0.002 | 0.002 | -0.005 | -0.003** | -0.002* | 0.018*** | 0.036** | 0.008 |
| | (0.92) | (0.31) | (0.60) | (0.22) | (0.68) | (2.27) | (1.87) | (2.83) | (2.39) | (0.46) |
| *N* | 4,262 | 4,262 | 4,262 | 3,639 | 3,023 | 1,801 | 1,801 | 1,801 | 1,538 | 1,360 |

**Table 1.10:** Propensity Score Matching of Probability of Default

The matching is done on the year before the relationship borrowing takes place ($year = -1$) using nearest neighbor matching technique. The matching the probabilities are estimated in equation (1.4) using the dummy variable defined as one for the treatment group firms ($PD_t$), which have only relationship bank borrowing and zero for the control group firms ($PD_c$), which have only public debt borrowing. Panel A shows results for firms in the fourth quartile of Jarrow-Merton default probabilities. Panel B includes firms that are in the first quartile of Jarrow-Merton default probabilities. The results in bold are quasi diff-in-diff estimations of differences in default probabilities of treatment and control groups for the year of borrowing and one year and two years after the borrowing takes place. The period of analysis is between 1991-2011. *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Obs. | Mean | St.Error | T-Stat |
|---|---|---|---|---|
| **High Probability of Default Firms** | | | | |
| $\Delta PD_{t,0} = \bar{PD}_{bank\_relationship,0} - \bar{PD}_{bank\_relationship,-1}$ | 1,125 | 0.0169 | 0.2769 | 0.06 |
| $\Delta PD_{c,0} = \bar{PD}_{public\_debt,0} - \bar{PD}_{public\_debt,-1}$ | 1,125 | 0.1607 | 0.1572 | 1.02 |
| $\Delta PD_{t,0} - \Delta PD_{c,0}$ | 1,125 | -0.1437 | 0.3149 | -0.45 |
| $\Delta PD_{t,1} = \bar{PD}_{bank\_relationship,1} - \bar{PD}_{bank\_relationship,-1}$ | 1,049 | -0.7987 | 0.2982 | -2.67*** |
| $\Delta PD_{c,1} = \bar{PD}_{public\_debt,1} - \bar{PD}_{public\_debt,-1}$ | 1,049 | 0.3626 | 0.1743 | 2.08** |
| $\Delta PD_{t,1} - \Delta PD_{c,1}$ | 1,049 | -1.1614 | 0.3315 | -3.50*** |
| $\Delta PD_{t,2} = \bar{PD}_{bank\_relationship,2} - \bar{PD}_{bank\_relationship,-1}$ | 887 | -0.7977 | 0.3285 | -2.42** |
| $\Delta PD_{c,2} = \bar{PD}_{public\_debt,2} - \bar{PD}_{public\_debt,-1}$ | 887 | 0.4507 | 0.2046 | 2.20** |
| $\Delta PD_{t,2} - \Delta PD_{c,2}$ | 887 | -1.2485 | 0.3630 | -3.43*** |
| **Low Probability of Default Firms** | | | | |
| | Obs. | Mean | St.Error | T-Stat |
| $\Delta PD_{t,0} = \bar{PD}_{bank\_relationship,0} - \bar{PD}_{bank\_relationship,-1}$ | 2,313 | 0.1007 | 0.0107 | 9.37*** |
| $\Delta PD_{c,0} = \bar{PD}_{public\_debt,0} - \bar{PD}_{public\_debt,-1}$ | 2,313 | 0.1615 | 0.0704 | 2.29** |
| $\Delta PD_{t,0} - \Delta PD_{c,0}$ | 2,313 | -0.0608 | 0.0706 | -0.86 |
| $\Delta PD_{t,1} = \bar{PD}_{bank\_relationship,1} - \bar{PD}_{bank\_relationship,-1}$ | 1,860 | 0.2876 | 0.0405 | 7.09*** |
| $\Delta PD_{c,1} = \bar{PD}_{public\_debt,1} - \bar{PD}_{public\_debt,-1}$ | 1,860 | 0.4784 | 0.0896 | 5.33*** |
| $\Delta PD_{t,1} - \Delta PD_{c,1}$ | 1,860 | -0.1908 | 0.0975 | -1.95* |
| $\Delta PD_{t,2} = \bar{PD}_{bank\_relationship,2} - \bar{PD}_{bank\_relationship,-1}$ | 1,690 | 0.5236 | 0.0728 | 7.18*** |
| $\Delta PD_{c,2} = \bar{PD}_{public\_debt,2} - \bar{PD}_{public\_debt,-1}$ | 1,690 | 0.5769 | 0.0979 | 5.88*** |
| $\Delta PD_{t,2} - \Delta PD_{c,2}$ | 1,690 | -0.0532 | 0.1216 | -0.43 |

**Table 1.11:** Variable Definitions

| Variable name | Definition |
|---|---|
| SFA efficiency score | Parametric, stochastic efficiency score calculated by Stochastic Frontier Analysis method for each year and industry. |
| DEA efficiency score | Non-parametric, deterministic efficiency score calculated by Data Envelopment Analysis method for each year and industry. |
| TFP estimate | Imrohoroglu and Tuzel (2014) estimate of firm level efficiency using a semi-parametric method. |
| Size | Natural logarithm of total assets. |
| Size$^2$ | Square of firm size. |
| Cash/TA | Cash and short-term investments scaled by total assets. |
| Leverage | Ratio of book value of debt to the sum of market value of equity and book value of debt. |
| ROA | Profitability measure defined as the ratio of earnings before interest, taxes, depreciation and amortization to book value of assets. |
| Interest coverage | Ratio of earnings before interest, taxes, depreciation and amortization to total interest expenses. |
| Market-to-Book ratio (M/B) | Ratio of sum of market value of equity and book value of debt to book value of assets. |
| Capex/TA | Ratio of capital expenditures divided by total assets |
| Tangibility | Ratio of net property, plant and equipment divided by total assets |
| Rating | Dummy variable equal to one if firm has S&P domestic long-term issuer credit rating and zero otherwise. |
| Firm age | Number of years since initial public offering. |
| Jarrow-Merton (JM) default probability (%) | Default probability estimate of a statistical hazard model that relates the probability of firm default to the same explanatory variables as the Jarrow-Chava Model and incorporates the default probability of the Merton Structural Model as an additional explanatory variable. |
| Whited-Wu financial constraint index | Financial constraint index created by Whited and Wu (2006) |
| Altman's z-score | Bankruptcy score created by Altman (1968). |
| Bor_dummy | Dummy variable equals to one if a firm has borrowed in any given year in the syndicated loans market and zero otherwise. |
| Rel_dummy | Dummy variable equals to one if the firm has borrowed from the same lead-lender in the last 5 years. |
| Rel_intensity | The amount of loans by bank m to borrower i in the last 5 years scaled by the total amount of loans by borrower i in the last 5 years |
| Rel_number | The number of loans by bank m to borrower i in the last 5 years scaled by the total number of loans by borrower i in the last 5 years. |
| Dummy for outstanding loan from previous period | Dummy variable for existence of an outstanding bank loan from any lead-lender in the previous period. |
| Dummy for outstanding relationship from previous period | Dummy variable that indicates an outstanding relationship bank borrowing from any lead-lender from the previous period. |
| Total number of industry relationships | Total number of relationship borrowings in an industry within a year. |

# Chapter 2

# The Intangible Value of Key Talent: Decomposing Organization Capital

## (with Linda Allen)

*"The manner in which information is accumulated in a firm offers an explanation for the firm's existence. Information is an asset to the firm, since it affects the production possibility set and is produced jointly with output. We call this asset of the firm its organization capital." Prescott and Visscher (1980)*

## 2.1 Introduction

A firm is more than a collection of assets. There is something intangible that identifies each firm and differentiates an Apple from a Microsoft. This intangible asset, denoted organization capital (OC) constitutes the firm's culture, internal knowledge and language, firm-specific policies and procedures, growth opportunities and information technology, brand name and any other aspects that are not directly related to the production process and are unique to the firm itself. A critical component of the OC intangible asset is the firm's key talent. For example, Bloom and Van Reenen (2007) and Bertrand and Schoar (2003) show that OC value creation resides in the firm's key talent, thereby generating economic rents, which are shared by the firm's top executives and stockholders. Executive compensation contracts include the value of economic rents from OC generated by key talent. However, the executive compensation contract is not fully observable to outside firms that might want to expropriate OC by hiring a firm's top managers. Firms disclose payments to top executives in the form of cash (i.e., salary and bonus) and non-cash (i.e., stock and options). However, firms may also offer perquisites and special arrangements as additional compensation to attract strategic executives. These arrangements are sometimes not publicly disclosed. For example, during Jeff Immelt's sixteen-year tenure at General Electric, a spare jet routinely accompanied the corporate jet on overseas trips. This was not even revealed to GE's Board.[1] The presence of perquisites and other cash and non-cash emoluments complicates measures of the OC component of key talent. Was the spare jet a perquisite required to elicit the full OC contribution of GE's chief executive to enhance firm value or was it a value reducing agency cost? Indeed, the challenge is to differentiate payment for value-enhancing OC embedded in key talent from value-reducing agency costs in the perquisite component of the executive compensation contract.

In this paper, we dichotomize OC value from key talent into the disclosed executive compensation contract (comprised of cash, stock and options) in contrast to the undisclosed emoluments and perquisites that form a portion of executive compensation. Because the portion of these undisclosed perquisites that generates OC value is unobservable and indistinguishable from agency costs, outside firms are unable to determine the full OC value of a firm's executives. This unobservable component of OC, therefore, cannot be expropriated by

[1]Wall Street Journal, October 29, 2017, https://www.reuters.com/article/us-ge-airplane/ge-board-did-not-know-about-ceos-extra-plane-wsj-idUSKBN1CY0RI

managers when they leave the firm. Indeed, it is destroyed when the firm key talent switches from one firm to another, since it is determined by the unique combination of firm assets and managerial skill, i.e., it is manager- and firm-specific OC. In terms of the theoretical model of Lustig et al. (2011), hereinafter LSV, this component is not portable. The portability (denoted $''\varphi''$ ) of OC is a key exogenous component of the LSV and other theoretical models (e.g., Eisfeldt and Papanikolaou (2013) who assume that all OC is 100% portable). LSV performs comparative statics on portability assumed to vary discreetly from 0% to 50% to 75%. We build on these theoretical models by endogenizing OC portability and suggesting an empirical measure of OC portability.

To empirically estimate these components of OC, we follow studies that have measured OC using overhead and non-allocated expenses as empirical measures of the firm's investment in the firm itself, rather than in the products it produces and sells (e.g., Lev and Radhakrishnan (2005), Eisfeldt and Papanikolaou (2013)). Selling, general and administrative (SG&A) expenses are considered the inputs into an intangible organization capital production function since these costs relate to the firm's operation but are not directly connected to the firm's outputs. If we consider the components contained within SG&A to be the factors in an organization capital production function, we must specify the output. Since organization capital represents an investment in the firm itself, the output is firm value. Thus, in this paper, we examine the impact of organization capital on the firm's Tobin's Q (market to book value). Our results are consistent with other studies that show that organization capital is positively related to firm performance (Lev et al., 2009; Lev and Radhakrishnan, 2005; Banker et al., 2011; Chen et al., 2012; Eisfeldt and Papanikolaou, 2013).

However, SG&A expenditures encompass many different factors of production, ranging from personnel costs (i.e., for top executives and other non-allocated employees) to advertising, office rent, corporate perquisites, etc. We differentiate between disclosed key talent OC compensation and the remaining components of OC, which include undisclosed key talent

OC compensation. This decomposition allows us to differentiate observable payments to key talent in the form of executive compensation from other unobservable costs aggregated into SG&A. We utilize Execucomp data on executive compensation in order to isolate the disclosed component of key talent in organization capital that accrues entirely to managers. Our approach disentangles the observable component of OC embedded in top management's disclosed compensation from the human capital OC component that may contain undisclosed empire building and entrenched management agency problems.

To accomplish the decomposition, we divide organization capital into two empirical measures: (1) the disclosed human capital component, defined as the capitalized value of compensation paid to top executives or key talent (denoted HC_OC), and (2) the residual comprised of all other elements of organization capital (denoted Residual_OC), which includes an undisclosed component of perquisites and other emoluments paid to key talent. This decomposition allows us to determine which component of organization capital drives firm value. In particular, higher investment in HC_OC may be value enhancing if executives are paid to diligently and effectively manage the firm. Alternatively, however, agency problems may lead to higher measures of Residual_OC as highly remunerated and entrenched management pursues empire building or risk diversification strategies at odds with shareholder value.[2] We find that the key talent component of organization capital (HC_OC) enhances firm value (as measured by market to book value), whereas Residual_OC expenditures do not contribute to firm value.

The decision to pay for key talent in the form of disclosed cash and stock compensation as opposed to unobservable perquisites is endogenous. Indeed, shareholders may retain some rents from OC value creation if they shift the composition of the compensation contract away from disclosed payments to implicit, undisclosed payments, thereby creating informa-

[2]For example, Venieris et al. (2015) find that costs are stickier when OC is high as management delays reductions in intangible investments in response to decreases in the firm's production level.

tion asymmetries about the OC contribution of key talent. This reduces the ability of executives to communicate the full value of their OC contribution to outside firms.[3] We utilize a two-stage analysis to endogenously estimate the breakdown between observable and unobservable OC compensation, employing three instrumental variables. The first instrument exploits the observation that over recent years, the job market has changed dramatically in terms of labor mobility and job polarization, thereby impacting the decomposition of OC (but not market to book directly) via changing labor supply and demand conditions. As one of our instrumental variables, we utilize the classification of Donangelo (2014), which measures the degree of worker specialization, thereby impacting the breakdown between key talent (HC_OC) and white-collar support personnel (Residual_OC). A second instrumental variable follows Jaimovich and Siu (2012) in measuring the ratio of non-routine, high wage employees (HC_OC) to routine, low wage employees (Residual_OC) as firms reallocate their work force to the polar extremes away from higher paying middle level employment. Our third instrumental variable relates the firm's executive compensation (HC_OC) to industry median levels. Using these instrumental variables to address endogeneity, we find a positive correlation between firm value (Tobin's Q) and HC_OC, but not for Residual_OC. The results are more robust for firms with high institutional ownership, which is a proxy for strong governance, whereas firms with low institutional ownership do not experience increase in firm value as a result of an increase in HC_OC.

Our decomposition of organization capital allows us to extend work of Eisfeldt and Papanikolaou (2013), hereinafter EP, and to more precisely measure the risk associated with key talent. We create five value-weighted portfolios sorted on HC_OC and Residual_OC individually in order to assess the risk characteristics of each component. We utilize CAPM,

[3]Top executives compensate themselves for their undiversifiable risk in the firm through consumption of perquisites and empire building. Moreover, restrictions on executive compensation in the wake of SOX and Dodd-Frank regulations could also encourage the shift from disclosed compensation to undisclosed implicit compensation in the form of perquisites.

Fama-French three-factor model Fama and French (1993) and the Carhart four-factor model Carhart (1997) for portfolios created using the quintiles of HC_OC and Residual_OC separately. The results show that high HC_OC firms do not have higher returns on average than low HC_OC firms, whereas high Residual_OC firms have positive and statistically significant average returns throughout the sample period. That is, high-minus-low HC_OC portfolios have no significant systematic risk incorporated into returns, whereas high-minus-low Residual_OC portfolios have a systematic risk premium amounting to from 4.05% to 6.46% p.a. Furthermore, consistent with managerial power argument of Bebchuk et al. (2002), we find that the systematic risk premium in high-minus-low Residual_OC portfolios is highest for firms in the lowest quintile of institutional ownership amounting to 8.73% to 10.40% p.a., suggesting that weak governance increases agency costs. For the highest quintile of institutional ownership, high-minus-low Residual_OC portfolios do not generate systematic risk.

The paper proceeds as follows. The literature on organization capital is discussed in Section 2.2. Our empirical decomposition methodology and the impact of each of the components of organization capital on firm Tobin's Q are analyzed in Section 2.3. Section 2.4 estimates the risk characteristics of each of the components of organization capital. Section 2.5 concludes.

## 2.2 Literature Review and Hypothesis Construction

The concept of organization capital dates back to economists' attempts to justify the existence of firms. Organizing assets into distinct companies occurs because these assets are more productive in unison than in isolation. That is, there is an intangible glue, called organization capital that connects the assets and makes them more productive. Organization capital incorporates the non-production related unique knowledge produced within the firm using the interaction of human capital and production technologies within themselves and among each other. Prescott and Visscher (1980) model the firm's organization capital in terms of improvements in the productivity of the firm's human capital, since the firm's knowledge of the capabilities of its individual employees improves efficiency by matching the worker to the best job, by creating effective teams of employees and by investment in on-the-job training. Evenson and Westphal (1995) summarize the organization capital as: "the knowledge used to combine human skills and physical capital into systems for producing and delivering want-satisfying products". Carlin et al. (2012) view organization capital as a form of intra-firm language. This captures the idea that the value of organization capital depends on its being shared across managers and that it must be transmitted to the next generation of employees to be preserved. A firm's language includes informal work routines, convenient technical jargons, and a vocabulary of patterns remembered from past experiences. They show that firms with more organization capital have less employee turnover, and therefore, can invest over the long term. Eisfeldt and Papanikolaou (2013, 2014) identify the value of key talent as critical to the role of organization capital in creating firm value. Berk et al. (2016) find that actively managed mutual funds create value by reallocating funds based on the firm's private information about the skill of its money managers.

Organization capital encompasses the firm's know-how embedded in its work force. However, it is more than that. Indeed, Atkeson and Kehoe (2005) estimate that the payments to intangible capital represent about 8% of U.S. manufacturing output, with return on organization capital encompassing 40% of those payments. Corrado et al. (2009) attribute 30% of all intangible assets in the U.S. to organization capital (in their terms "firm-specific economic competencies"), representing the largest category. Moreover, Leung et al. (2016) find that organization capital impacts stock returns in 20 OECD countries. Organization capital includes the firm's intellectual capital embodied in research and development, growth opportunities and corporate culture with respect to innovations. Francis et al. (2015) connect the firm's organization capital to the number of patents granted. Martín-Oliver and

Salas-Fumás (2012) show that organization capital increases firm value through the optimal deployment of the firm's investment in information technology and other material assets.

Whether investment in organization capital increases or decreases firm value is an empirical question. Oshima et al. (2009) view organization capital as entrepreneurial human capital that has been transformed from a non-tradable asset into tradable capital that is embedded in firm value. However, there are limits to the ability to write contracts based on this entrepreneurial talent. Organization capital is an intangible asset, and therefore, susceptible to agency problems which may reduce firm value. For example, Eisfeldt and Papanikolaou (2013) highlight the role of key talent in building the firm's organization capital. However, these talented executives have an outside option to leave the firm and use their expertise at another firm. Thus, the firm's shareholders are exposed to the risk that key talent will depart, thereby taking valuable organization capital with them. Eisfeldt and Rampini (2008) show that capital is less efficiently reallocated during downturns because executives have capital control rights as a result of their private information about asset productivity. Venieris et al. (2015) also find that selling, general and administrative expenses are sticky due to managerial reluctance to reallocate capital during downturns. Thus, key talent can pursue private objectives (such as empire building or risk diversification) at odds with value maximization. Firms' shareholders provide incentive pay to induce managers to relinquish control rights. Eisfeldt and Papanikolaou (2013) find that organization capital makes firms riskier, resulting in a 4.5% p.a. increase in risk-adjusted returns. Lustig et al. (2011) find that shareholders must share economic rents to key talent to prevent them from leaving the firm. This takes the form of pay for performance and greater inequality of income among the firm's employees. Further, Boguth et al. (2016) find that organization capital is fragile, thereby exposing the firm to risk of loss. They estimate a 6% p.a. risk premium for organizational capital fragility, as measured by the size of the management team (the smaller the team, the more fragile the firm's OC).

Previous studies find significant association of higher executive compensation (included in SG&A expenses) with increasing agency problems between managers and shareholders of a firm. Agency theory argues that misalignment of interests between shareholders and managers could lead to agency problems, so that managers engage in activities for their own benefits rather than the benefits of the firm's shareholders (Jensen and Meckling, 1976). One well-known agency problem is managerial empire building, which refers to managers' tendencies to grow the firm beyond its optimal size or to maintain unutilized resources with the purpose of increasing personal utility from status, power, compensation, and prestige (Jensen, 1986; Stulz, 1990; Bebchuk et al., 2002; Masulis et al., 2007; Hope and Thomas, 2008; Chen et al., 2012). For example, in his seminal paper on managers' utility-maximizing tendencies, Williamson (1963) specifically uses the expansion of staff (proxied by SG&A costs) beyond optimal levels as an example to illustrate the effects of managerial discretion on managers' opportunistic behavior.

Another agency problem is the managers' disincentives to downsize as they derive monetary and nonmonetary benefits from managing larger and more complex organizations. Since any benefits from downsizing accrue primarily to shareholders rather than managers, managers may prefer the quiet life and try to avoid the difficult decisions and costly efforts associated with downsizing (Bertrand and Mullainathan, 2003; Datta et al., 2010; Chen et al., 2012).

There are a significant number of studies on the effect of executive compensation on firm performance. Some of these focus on the executive compensation structure and find evidence that equity compensation and managerial ownership have a positive relationship with firm value (Mehran, 1995; Chang et al., 2010; Frydman and Saks, 2010) while, others show that the relationship has a nonlinear inverted-U shape (Morck et al., 1988; McConnell and Servaes, 1990; McConnell et al., 2008; Coles et al., 2012). There is also evidence in the literature that the relationship between managerial ownership and firm value is asymmetric in the sense that large increases in managerial ownership increases firm value, whereas large decreases do not result in decrease in firm value (Fahlenbrach and Stulz, 2009).

Another strand of this literature discusses the effect of CEOs on firm performance. Adams et al. (2009) and citetVillalongaAmit2006 find evidence that founder-CEOs increase firm value. Malmendier and Tate (2008) find evidence that award-winning CEOs subsequently underperform and that the ex-post consequences of media-induced superstar status for shareholders are negative. Bebchuk et al. (2011) find that an increase in the fraction of aggregate compensation of the top-five executive team captured by the CEO leads to decreases in firm value.

In this paper, we utilize a novel decomposition of organization capital in order to resolve some of the disagreements in the literature. Indeed, we hypothesize that the executive compensation component of OC has a different relationship with firm value than other fixed costs (such as R&D, staffing, perquisities, etc.). To test this, we hypothesize that:

*Hypothesis 1: The key talent component of organization capital (HC_OC) enhances firm value whereas the Residual_OC does not contribute to firm value.*

If executive compensation reflects the second best opportunity cost of key talent, then the firm retains the differential between the idiosyncratic value to the firm and the alternative use of key talent. This explains the positive contribution of key talent (measured by HC_OC) to firm value. However, if executives take back some of this firm value in the form of perquisite consumption and empire building, the Residual_OC component of organization capital will not contribute to increases in firm value. This agency problem (measured by Residual_OC) exposes firm shareholders to systematic risk, whereas executive compensation (measured by HC_OC) creates only an idiosyncratic risk exposure. Thus, we hypothesize:

*Hypothesis 2: There are two components of organization capital risk: idiosyncratic and systematic. High-minus-low HC_OC portfolios have no significant systematic risk incorporated into returns, whereas high-minus-low Residual_OC portfolios have a systematic risk* *premium.*

Existence of agency problems impact executive compensation contracts. Bebchuk et al. (2002) and Bebchuk, Fried and Walker (2002) and Bebchuk and Fried (2003) argue that, in contrast to "optimal contracting" approach to executive compensation, which argues that boards are assumed to design compensation schemes to provide managers with efficient incentives to maximize shareholder value, the "managerial power" approach suggests that boards do not operate at arm's length in formulating executive compensation arrangements; rather, executives have power to influence their own pay, and they use that power to extract rents. Furthermore, according to the "managerial power" approach, compensation arrangements approved by boards often deviate from optimal contracting because directors are captured or subject to influence by management, sympathetic to management, or simply ineffectual in overseeing compensation. As a result of such deviations from optimal contracting, executives can receive pay in excess of the level that would be optimal for shareholders; this excess pay constitutes rents. More importantly, to camouflage or facilitate the extraction of rents, managerial power can lead to the use of inefficient pay structures that weaken or distort incentives and that thus, in turn, further reduce shareholder value. One of the governance mechanisms to limit managerial power is the existence of large shareholders. Shleifer and Vishny (1986a) argue that large shareholders have large enough stake to monitor an incumbent management. Therefore firms with large shareholders play an active role in corporate governance. We posit our third hypothesis as:

*Hypothesis 3: The value-increasing impact of HC_OC is highest for firms with strong governance, whereas firms with weak governance experience the highest systematic risk generated by Residual_OC.*

## 2.3 OC and Firm Value

### 2.3.1 Theoretical Discussion

Let us assume that $OC_{ij}$ is the portion of OC value that is created by key talent by manager $i$ in firm $j$. A portion (denoted $1-\varphi_j$) of this total key talent $OC_{ij}$ is generated by managerial skills in combination with firm specific assets, and therefore cannot be replicated outside of the firm. If all OC is completely independent of the specific firm and is portable or can be replicated in any outside firm, then $\varphi_j$ and the executive can fully expropriate all OC value (i.e., $1 - \varphi_j = 0$), thereby limiting the economic rents that remain for firm shareholders.[4] However, as portability declines ($\varphi_j \to 0$), more of the manager's OC value is trapped in the firm, thereby reducing the component of OC rents paid to managers and increasing the OC rents to shareholders. We suggest that information asymmetries determine the degree of OC portability. If managers are paid an observable compensation contract, outside firms can completely evaluate the manager's OC contribution, and hire her away from their firm, thereby increasing the portability of managerial OC, and reducing shareholder rents from OC. However, if a component of managerial compensation is in the form of unobservable perquisites, then outside firms cannot bid away managers using this portion of their compensation. The manager's opportunity cost wage, therefore, is limited to the observable, and therefore portable, component of their executive compensation. Thus, the breakdown of the managerial compensation contract into observable (cash, stock, bonus, etc.) and unobservable (perquisites and other emoluments) determines the breakdown of OC into portable and non-portable components. That is, the firm's shareholders endogenously determine the degree of OC portability by allocating managerial compensation between observable and unobservable components.

[4] In the LSV model, shareholders retain some economic rents even when $\varphi_j = 1$ since (1) they insure risk averse managers by back loading the long term managerial compensation contract, and (2) they absorb the risk that their firm will not survive due to insufficient growth.

To see how this operates, assume a world of full information (as in the LSV model), where each manager $i$ - firm $j$ pair is endowed with an observable manager-firm specific total OC value of $OC_{ij}$. In a world of perfect information, all firms perfectly observe both the cash and remaining component of the OC value and the shareholders receive all economic rents from OC value creation. In such an environment manager will get a portion of economic rents from OC value creation, $OC_{ij}$, in the form of disclosed compensation ($\varphi_j OC_{ij}$) and the firm's shareholders retain economic rents equal to $(1 - \varphi_j)OC_{ij}$.

We introduce information asymmetries in the form of the breakdown of the managerial compensation contract into observable and unobservable components. Suppose that there is perfect information within the firm, but that outside firms can only observe the observable cash component of the manager's OC compensation. Then the manager's opportunity cost wage (disclosed) is limited to $\varphi_j OC_{ij}$ and the firm's shareholders and managers share the remaining rents $(1 - \varphi_j)OC_{ij}$. Under this setting, managers can negotiate to retain the portion of these rents with firm shareholders. If managers have complete bargaining power, they expropriate all rents and $\varphi_j = 1$. On the other hand, if managers have low bargaining power, firm shareholders can reduce the portability of the manager's OC by adjusting the proportion of compensation paid in the form of cash versus perquisites, i.e., by adjusting $\varphi_j$. The lower the $\varphi_j$, the less portable is managerial OC and the smaller the percentage of cash in the management compensation contract. We denote this optimum $\varphi_j$ in the absence of within firm information asymmetries as $\varphi_j^*$ such that $\varphi_j^* > \varphi_j$.

Now let us assume information asymmetries within the firm so that managers know their own OC value contribution ($\varphi_j$), but shareholders do not, relying instead on managers to inform them about their OC value contribution ($\hat{\varphi}_j$). Under this scenario, managers can deceive shareholders into assessing a higher value of their OC ($\hat{\varphi}_j$), where $\hat{\varphi}_j > \varphi_j^* > \varphi_j$, by incorporating agency costs and empire building objectives into their management compensation contract, thereby generating compensation in excess of the manager's optimum disclosed and undisclosed OC value ($\hat{\varphi}_j$). Let $\delta = (1-\hat{\varphi}_j)/(1-\varphi_j^*)$ be the ratio of the optimal OC rent that accrues to shareholders in the presence of information asymmetries as a result of the biased estimate of $\varphi_j^*$ such that $\hat{\varphi}_j > \varphi_j^*$ and $\delta \in (0,1)$ by definition. Therefore shareholders' rent is defined as $(1-\hat{\varphi}_j)OC_{ij} = \delta(1-\varphi_j^*)OC_{ij}$. Accordingly, managers' private benefits (such as empire building, risk diversification, perquisite consumption) will be $(\hat{\varphi}_j - \varphi_j^*)OC_{ij} = (1-\delta)(1-\varphi_j^*)OC_{ij}$. Thus, managers can expropriate some portion of shareholders' OC rent through undisclosed private benefits by a fraction of $(1-\delta)$ and thereby reduce shareholders' rent by a fraction of $\delta$ by increasing information asymmetries and pursuing activities with private managerial benefits that increase within firm information asymmetries. Under this scenario, shareholders' optimum OC rent $(1-\varphi_j^*)OC_{ij}$ includes both value-enhancing OC ($\delta(1-\varphi_j^*)OC_{ij}$) and value-destroying private benefits to managers ($(1-\delta)(1-\varphi_j^*)OC_{ij}$). Moreover, as Bebchuk et al. (2002) argues these information asymmetries will exacerbate in the presence of weak governance by increasing $\hat{\varphi}_j$ and decreasing $\delta$.

### 2.3.2 Sample Construction

We obtain financial data concerning firms and executive compensation from Compustat, CRSP, ExecuComp and Thomson Reuters Form 13F filings databases for the period from 1992 to 2015.[5] The Compustat sample consists of all firms with sales and total assets higher than \$5 million excluding financial firms and utilities, as these industries are highly regulated. Our final sample consists of 9,060 firm-year observations of 965 firms.

### 2.3.3 Variable Definitions

We follow Faleye (2007) and measure Tobin's Q as the market value of equity plus the book values of debt and preferred equity, all divided by the book value of assets. Our main

[5] The period is restricted to 1992 because it is the earliest year ExecuComp data is available.

variables of interest are the OC measure and its components: human capital (HC_OC) and residual (Residual_OC). Previous studies use selling, general and administrative expenses item (SG&A) of the income statement as a proxy for OC measure (Lev et al., 2009; Eisfeldt and Papanikolaou, 2013). Following Eisfeldt and Papanikolaou (2013) we construct the stock of OC using the perpetual inventory method. Therefore, we calculate the following:

$$O_{it} = (1 - \delta)O_{it-1} + (SGA_{it}/cpi_t) \tag{2.1}$$

in which $cpi_t$ denotes the consumer price index and $\delta$ is the depreciation rate. In order to implement the law of motion, we choose an initial stock by:

$$O_{i0} = SGA_{i1}/(g_{OC} + \delta_{OC}) \tag{2.2}$$

As in Eisfeldt and Papanikolaou (2013), we use the depreciation rate of 15%, which is equal to the depreciation rate used by the BEA in its estimation of R&D capital in 2006 and match the growth rate, g, with average annual real growth rate of firm-level SG&A expenditures, which is 8% in our sample. We scale this *OCstock* by the firm's book value of assets and denote this ratio as *OC*.

For the human capital component of OC measure, we capitalize the total executive compensation (item TDC1[6] in Execucomp) of top five executives that a firm reports on annual proxy (DEF14A SEC form).[7] We construct the HC_OC measure following the same procedure used in Equations (2.1) and (2.2). As it is a proxy for the human capital of a firm, we

[6] This item includes both cash compensation and the value of stocks and options granted. However, SG&A expenses did not include the value of options granted until 2005 when FAS 123r statement came into effect. Therefore, in our construction, we exclude the value of options granted from total executive compensation until 2005.

[7] To avoid heterogeneity of firms' reporting in ExecuComp, we limit our sample to firms with five executives listed in ExecuComp. Our results are robust to including total compensation to three or more executives listed in ExecuComp.

use 1% depreciation rate[8] and a 20% real growth rate of executive compensation.[9] Similar to *OCstock*, we scale this measure by firm's book value of assets. To construct Residual_OC, we subtract the dollar amount of total executive compensation from SG&A expenses and follow the procedure in equations (2.1) and (2.2) using a 15% depreciation rate and an annual real growth rate of 9%.[10] [11]

Besides organization capital and its components, there are other variables that affect firm value such as governance and firm performance measures. We measure firm governance using institutional ownership (Bethel et al., 1998) and insider ownership (Morck et al., 1988). We also include square of insider ownership to capture nonlinearities in the relationship between governance and firm value. The institutional ownership data are obtained from Thomson Reuters Form 13F filings. We collect data on insider ownership from the Execucomp database. Firm performance measures are constructed using Compustat variables. We follow Yermack (1996) and include profitability measured by return on assets (ROA), which is defined as the ratio of operating income before depreciation to total assets.[12] We also include tangibility, defined as net property, plant and equipment scaled by total assets; leverage, defined as the ratio of long term debt to total assets; capital expenditures scaled by total assets; and firm age, defined as the number of years since IPO. We also control for industry-median adjusted firm size.[13] To control for industry variations, we include 48

[8] Previous studies find human capital depreciation rate between 0.1% and 0.8%. (Browning et al., 1999; Ludwig et al., 2012). Arrazola and Hevia (2004) find the depreciation rate to be 1% and 1.5% in Spain. Our results are robust to a depreciation rate in 0-1% interval as well as 15% as in the construction of OC. The robustness tests with $\delta = 0$ can be found in the Appendix.

[9] Average annual real growth rate of firm-level executive compensation is 20% in our sample.

[10] Firm level Residual_OC has a real growth rate of 9% per year in the sample. We use 15% depreciation rate as in the construction of OC.

[11] Alternatively, we define Residual_OC2 from the regression of OC on HC_OC variable to estimate a residual component of OC that is orthogonal to HC_OC. Our results are robust to either definition and are available in the Appendix.

[12] Our results are robust to excluding ROA from the control variables due to potential endogeneity concerns.

[13] We use this measure instead of natural logarithm of book value of assets in order to alleviate collinearity between OC components and firm size. In the untabulated results using size as a control, although the statistical significance in fixed effects results are reduced, our two-stage results remain unchanged.

industry classifications from Fama and French (1997).

Table 2.1 presents summary statistics for the variables described above. As the table shows, the mean Tobin's Q in our sample is 1.78. The SG&A item has a mean of $1,153.38 million, and total executive compensation is $9.02 million on average. Therefore, the executive compensation component constitutes approximately 1% of SG&A expenses on average. Accordingly, the total OC measure has an average of 0.75. This is decomposed into HC_OC with a mean of 0.05, and Residual_OC, which has a mean of 0.71.[14] Average firm size is approximately $2 billion of total assets with 14.9% annual return on assets and long-term debt constituting 20.7% of the total assets. On average, institutional ownership is 68.7% of the firm's outstanding shares, whereas managerial ownership is 2.6% of a firm's shares on average.

### 2.3.4 Empirical Analysis

#### 2.3.4.1 Components of OC and firm value analysis

In order to validate the results of earlier studies, we first perform OLS analysis using the aggregate measure of organization capital, OC. We use the Tobin's Q proxy for firm value as the dependent variable. Table 2.2 presents our results. Using the OC coefficient shown in column (1) of Table 2.2, a one standard deviation increase in OC (equal to 0.65 from Table 2.1) increases firm value by 11.05% (0.65*0.17), statistically significant at the 1% significance level. Controlling for firm fixed effects in columns (2) and (3) to reduce omitted variable bias, a one standard deviation increase in OC (equal to 0.27 using within standard deviation)[15] increases firm value by 8.04% (0.27*0.302) in column (2) and 5.80% (0.27*0.215) in column

[14] The sum of these two components is not equal to average OC measure (0.75) as the real annual growth rate and depreciation rate of OC, HC_OC and Residual_OC are not equal.

[15] In the fixed effects regression the variables are transformed to estimate within variation (Baltagi, 2008). Therefore, in order to analyze the magnitude of the effect of OC or components of OC on firm value, we use the standard deviation of within transformation of $x_{it}$. That is, the estimation uses $\tilde{x}_{it} = x_{it} - \bar{x}_i$ and the within standard deviation is equal to 0.27 for OC and 0.01 for HC_OC.

(3), both significant at the 1% level.

In the aggregate, our results suggest that an increase in organization capital is correlated with increased firm value. However, to determine the source of that value creation, we decompose OC into two components (HC_OC and Residual_OC) as outlined in Section 2.3.2. To test our first hypothesis, we estimate fixed effects regressions of firm value on our two components of OC and present the results in columns (4), (5) and (6) of Table 2.2. Our results show a significant and positive impact on firm value related to executive compensation for key talent (HC_OC), whereas the residual component (Residual_OC) remains insignificant in all three estimations. Using the standard deviation of HC_OC from Table 2.1 (equal to 0.05), column (4) of Table 2.2 shows that a one standard deviation increase in HC_OC increases firm value by 20.26% (0.05*4.052), statistically significant at the 1%. In column (5), using the within standard deviation of HC_OC (equal to 0.01), a one standard deviation increase in HC_OC increases firm value by 7.40% (0.01*7.406), statistically significant at the 1% level. After controlling for the lagged Tobin's Q in column (6), a one standard deviation increase in HC_OC increases firm value by 3.01% (0.01*3.015), statistically significant at the 1% level. These results are consistent with *Hypothesis 1* that there is a statistically and economically significant increase in firm value from the key talent component of organization capital. In contrast, the residual component of organization capital has an insignificant effect on firm value in all specifications. Our fixed effects model does not suffer from the lack of time variation in the total executive compensation since it has increased significantly during the sample period (1992-2015) although the standard deviation is 0.01. According to Bebchuk and Grinstein (2005), equity-based compensation tripled during the period 1993-2003 and cash compensation increased by 40% during the same period. Similarly, Shue and Townsend (2017) report that option compensation grew by more than six fold between 1992-2011, whereas non-option compensation remained relatively flat during the same period. However, the model does not fully address endogeneity problems.

#### 2.3.4.2 Resolving the endogeneity problem

The results presented in Table 2.2 suffer from potential sample selection bias as a result of the endogenous choice to hire key talent and pay the required level of executive compensation. For example, if successful firms have the financial resources to hire expensive executives, we may find a spurious connection that reflects reverse causality between key talent compensation and firm value. We address the endogeneity problem in the Tobin's Q regressions utilizing a two-stage estimation approach. We identify three sets of instrumental variables for our decomposition of OC. Our first instrumental variable is the industry specific labor mobilization measure (*Labor mobility*) of Donangelo (2014). The more industry-specific the skill set required in a particular industry, the lower the degree of labor mobility. This creates systematic risk as firms with inflexible labor supply face frictions in adjusting to industry shocks. We utilize the time-varying, industry level classification of Donangelo (2014) in which workers in occupations concentrated in a few industries are associated with industry specialists with low labor mobility, while workers in occupations dispersed across the economy are associated with generalists with high labor mobility. We argue that firms in high labor mobility industries face more frequent turnover, which is reflected in their hiring and training costs incorporated in Residual_OC. Moreover, attracting and retaining key talent requires the offering of more perquisites and emoluments, thereby increasing Residual_OC for high mobility industries. On the other hand, more frequent turnover and lower average tenure would reduce HC_OC in high mobility industries.

Our second instrumental variable utilizes the measure of *Job polarization* developed in Jaimovich and Siu (2012) that identifies the increasing concentration of jobs in high wage and low wage extremes coupled with a declining secular trend in middle level employment. We hypothesize that the growing reliance on routine, low level employees in the work force reduces firm's salary expenditures for non-routine middle level workers, as well as reduces the firm's incentive to expend ongoing resources for labor support and training activities, thereby reducing Residual_OC. An increase in the job polarization instrumental variable also implies greater reliance on non-routine labor, which includes but is not limited to key talent. We hypothesize a positive relationship with HC_OC as a result of the greater expenditures for high wage employees in general administrative expenses. We construct the Job Polarization ratio of non-routine cognitive occupations to routine cognitive occupations in each year using the occupational classification system obtained from the St. Louis Federal Reserve Bank FRED monthly database.[16] We use the end of December values to proxy annual employment numbers.[17] [18]

We utilize *Relative_Salary_OC* as our third instrumental variable. The salary component of total executive compensation (TDC1 on Execucomp) constitutes about 25% of total executive compensation on average and its annual real growth rate is 2.6% during our sample period. Therefore, it is a fairly stable component of HC_OC. In addition, as Berger et al. (1997) argue CEO's salary and bonus compensation has extremely low sensitivity to changes in firm value. We calculate the total salary component of the top five executives on Execucomp and follow the same procedure outlined in Equations (2.1) and (2.2) to construct Salary_OC. Then, we define *Relative_Salary_OC* as the difference between Salary_OC of firm $i$ and the industry median Salary_OC, excluding firm $i$ in each year.[19] This variable directly

[16]Non-routine cognitive workers are defined as those employed in "management, business, and financial operations occupations" and "professional and related occupations" and routine cognitive workers are those in "sales and related occupations" and "office and administrative support occupations." Routine manual occupations are "production occupations," "transportation and material moving occupations," "construction and extraction occupations," and "installation, maintenance, and repair occupations." Non-routine manual occupations are "service occupations." We only use non-routine cognitive occupations and routine cognitive occupations to construct the job polarization variable since only these two categories' wages are included in the SG&A expenses.

[17]Our results are robust to measuring the ratio using total of all months' employment as well as the mean value of all months' employment during each year.

[18]*Job Polarization* variable is reported yearly at the aggregate level. Therefore we cannot use time fixed effects in our regressions. However in the untabulated robustness tests the results are unchanged when we use time fixed effects instead of *Job Polarization* variable.

[19]As a robustness test, we define *Relative_Salary_OC2* as the difference between Salary_OC of firm $i$ and the industry mean Salary_OC, excluding firm $i$ in each year. We also use *Next_Salary_OC* as an instrument,

impacts the HC_OC component of organization capital by construction. It also impacts Residual_OC as increases in cash salary may be met with increases in perquisites and empire building especially when other components of executive compensation do not grow proportionately, thereby contributing to increases in Residual_OC. Increases in the components of the executive pay package will impact the components of organization capital without directly impacting the firm's Tobin's Q. The Sargan-Hansen test statistic fails to reject the null that overidentifying restrictions are valid. Furthermore, the Sanderson and Windmeijer (2016) multivariate F tests of excluded instruments rejects the null that instruments are weak at 1% significance level for IVs of both components of OC. These show that both the exclusion restriction and relevance conditions are met for our IV estimations. We present the first stage of our two-stage estimation in Table 2.3. Consistent with our expectations, we find that *Labor Mobility* increases Residual_OC but reduces HC_OC. The effect is significant at 5% significance level for both Residual_OC and HC_OC. *Job polarization* ratio reduces Residual_OC but does not have an impact on HC_OC. Finally, the coefficient estimate on the *Relative_Salary_OC* variable is significantly positive (at the 1% level) in Table 2.3, indicating that higher cash salaries paid to top executives relative to the industry contribute directly to higher HC_OC and to higher Residual_OC.

Our second stage results, presented in Table 2.4, provides evidence that after controlling for endogeneity, we find strong evidence supporting our hypothesis that the value-enhancing component of organization capital is HC_OC. A one standard deviation increase in HC_OC (equal to 0.05) increases Tobin's Q by 22.14% (0.05*4.428) at 1% level of statistically significance. On the other hand, we find that the coefficient on Residual_OC is statistically insignificant. Thus, the two-stage analysis suggests that HC_OC enhances firm value, whereas Residual_OC does not contribute to firm value.

which is the nearest competitor's Salary_OC, where nearest competitor is defined by revenue sorting in each year and industry. Our results in Table 2.3 and 2.4 are robust to either alternative specification.

#### 2.3.4.3 Impact of governance

To test our third hypothesis, we analyze the subsamples of firms according to governance using institutional ownership as proxy for governance following Shleifer and Vishny (1986b). Weak (strong) governance subsample includes firms with below (above) the median institutional ownership. We estimate both OLS and 2SLS regressions using our instruments defined in Section 2.3.4.2. The results in Table 2.5 show that in both estimations, firms with strong governance experience increase in their Tobin's Q as a result of an increase in HC_OC. In column 4 one standard deviation increase in HC_OC (equal to 0.05) increases Tobin's Q by 40.2% (0.05*8.040) at 1% level of statistically significance. The positive and significant impact of HC_OC in OLS results disappears in the weak governance subsample when we control for endogeneity in 2SLS regressions (column 3). Furthermore, we find that Residual_OC does not have a significant impact on firm value in either subsample. These findings are consistent with our third hypothesis that the value-increasing impact of HC_OC is highest for firms with strong governance.

## 2.4 The Risk of Organization Capital Components

To test our second hypothesis, we analyze the risk of each of the two components of organization capital to distinguish between priced systematic risk and idiosyncratic risk. In order to test this, we estimate CAPM, Fama-French three-factor model (Fama and French, 1993) and Carhart four-factor model (Carhart, 1997) for five portfolios of firms sorted on HC_OC and Residual_OC separately within each year and industry.

### 2.4.1 Sample Construction

Data on risk factors are from Kenneth French's website. We obtain monthly stock returns data from CRSP and match each year's HC_OC and Residual_OC, calculated using the

Compustat data described in Section 2.2 for the period from 1992 to 2015. Our sample includes all non-financial and non-utilities firms in Compustat with fiscal year ending in December with common shares that are traded on NYSE, AMEX, or NASDAQ and that have non-missing SIC codes and nonzero values of HC_OC and Residual_OC.

Following Eisfeldt and Papanikolaou (2013) we first group firms into 17 industries based on the Fama and French (1997) classification. Then, within each industry and each year, we sort firms into five subportfolios based on HC_OC (Residual_OC). We then pool the subportfolios across industries and years to form five portfolios of firms sorted on HC_OC (Residual_OC), where the breakpoints are industry and year specific. Finally, we form five value-weighted portfolios based on each firm's within-industry HC_OC (Residual_OC) rank in each year, and rebalance these portfolios in June every year.[20] Therefore, portfolio 1 (5) contains firms in the lowest (highest) HC_OC or Residual_OC quintile in each year and industry.

### 2.4.2 Asset Prices of Portfolios Sorted on Components of OC

We present our asset pricing results for portfolios sorted on HC_OC in Table 2.6 and on Residual_OC in Table 2.7. As in Eisfeldt and Papanikolaou (2013), in addition to estimating CAPM, Fama and French three-factor and Carhart four-factor models[21], we also use high-minus-low portfolio of both HC_OC and Residual_OC as additional risk factors in panel B of Table 2.6 and 2.7, respectively. These results show that the beta of high-minus-low HC_OC and Residual_OC portfolios increases from low to high quintile portfolios suggesting that both components of OC are sources of risk that increase monotonically from low to high portfolios. However, when controlling for other factors in Panel C (3-factor) and Panel D (4-factor), the

[20] Our results using equal-weighted portfolio returns are stronger and statistically significant at 1% level. We provide those results in the Appendix.

[21] As robustness tests we also estimate Fama and French five-factor model (Fama and French, 2015) and Q-factor model of Hou et al. (2015). The results are robust and available in the Appendix.

alpha of high-minus-low HC_OC portfolio (5-1) becomes negative and insignificant whereas, alpha of high-minus-low Residual_OC portfolio (5-1) becomes positive and significant. In the four-factor model presented in panel D of Table 2.7 the statistical significance of alpha in high-minus-low (5-1) is at 10%. Our results suggest that the risk premium of high-minus-low Residual_OC portfolio (5-1) corresponds to 6.46% higher annual returns in three-factor model (i.e., 12 times the monthly alpha coefficient of 0.539 in Panel C of Table 2.7) and 4.05% higher annual return in four-factor model (i.e., 12 times the monthly alpha coefficient of 0.338 in Panel D of Table 2.7). These results support our second hypothesis that HC_OC fluctuations engender firm-specific idiosyncratic risk since there is no risk premium required for diversifiable risk. However, Residual_OC encompasses systematic risk that exposes firms with high Residual_OC portfolios to the risks associated with agency costs from empire building and perquisite consumption.

### 2.4.3 Asset Prices of Portfolios Sorted on Institutional Ownership and Components of OC

We argue that weak governance exacerbates the riskiness of the firm embedded in Residual_OC by increasing the potential agency component. In order to test this, we form quintile portfolios sorted on institutional ownership and OC components. First we form quintile portfolios of institutional ownership within each year and industry. Then, for each portfolio in each quintile we form quintile portfolios sorted on HC_OC. The results for value-weighted portfolios are provided in Table 2.8. We find that while low institutional ownership (IO=1) high-minus-low HC_OC portfolios do not have significant alphas in all three models, high institutional ownership (IO=5) high-minus-low HC_OC portfolios have negative and significant alphas in CAPM and four-factor models, suggesting that HC_OC reduces firms' riskiness for firms with strong governance.

Table 2.9 presents results for value-weighted portfolios sorted on institutional ownership and high-minus-low Residual_OC. According to these results, low institutional ownership (IO=1) high-minus-low Residual_OC portfolios have significant and positive alphas in all three models corresponding to 10.4% in CAPM (i.e., 12 times the monthly alpha coefficient of 0.867 in Panel A of Table 2.9), 9.25% in three-factor model (i.e., 12 times the monthly alpha coefficient of 0.771 in Panel B of Table 2.9) and 8.73% in four-factor model (i.e., 12 times the monthly alpha coefficient of 0.728 in Panel C of Table 2.9). These results disappear as institutional ownership increases in quintiles 2 to 5 providing evidence to our third hypothesis that the systematic risk generated by Residual_OC is highest for firms with weak governance whereas, Residual_OC of firms with strong governance do not generate systematic risk.[22]

## 2.5 Conclusion

We introduce a new decomposition of the aggregate organization capital measure used in the literature to explain intangible firm value. We distinguish the contribution of key talent, as measured by executive compensation, from the remainder of organization capital, which includes perquisite consumption and empire building costs. We find that key talent is an important value creation vehicle for firms. However, investment in the remaining component of organization capital does not contribute to firm value.

We also examine the risk characteristics of each of our newly introduced components of organization capital. We find that the human capital component of organization capital exposes shareholders to company-specific, idiosyncratic risk. Thus, there is no key talent

[22] We present our results with equal-weighted portfolios in the online appendix. The results for institutional ownership - high-minus-low Residual_OC are qualitatively and quantitatively similar. However institutional ownership - high-minus-low HC_OC portfolio results suggest positive and significant alphas for first quintile of institutional ownership portfolios. This finding is still consistent with our discussion and the significant effect disappears as institutional ownership increases in quintiles 2 to 5.

systematic risk premium. In contrast, however, the residual component of organization capital engenders systematic risk, offering a risk premium that is significant both economically and statistically. We attribute this to the inclusion of agency costs in Residual_OC. That is, the Residual_OC includes perquisite consumption, agency building and other non-value increasing activities pursued by key talent. The value created by executives empowers them to demand these intangible benefits, thereby exposing shareholders to systematic risk.

Furthermore, consistent with managerial power argument, we find that HC_OC increases firm value especially for firms with strong governance while the value-increasing effect of HC_OC disappears for firms with weak governance. In accordance with these results, we find evidence that the systematic risk engendered by Residual_OC is higher for firms with weak governance, whereas firms with strong governance do not expose shareholders to systematic risk.

**Table 2.1:** Summary Statistics

| **Variable** | **Obs** | **Mean** | **Std.Dev.** | **Q1** | **Median** | **Q3** |
|---|---|---|---|---|---|---|
| Tobin's Q | 9,060 | 1.78 | 1.36 | 0.97 | 1.37 | 2.05 |
| SG&A expenses ($ millions) | 9,060 | 1153.38 | 3021.04 | 112.92 | 296.83 | 844.55 |
| Total Executive Compensation ($ millions) | 9,060 | 13.73 | 15.02 | 4.94 | 9.02 | 16.83 |
| OC | 9,060 | 0.75 | 0.65 | 0.28 | 0.55 | 1.01 |
| HC_OC | 9,060 | 0.05 | 0.06 | 0.01 | 0.02 | 0.05 |
| Residual_OC | 9,054 | 0.71 | 0.62 | 0.26 | 0.52 | 0.95 |
| Institutional ownership | 9,060 | 0.69 | 0.22 | 0.57 | 0.72 | 0.84 |
| Managerial ownership | 9,060 | 0.03 | 0.07 | 0.00 | 0.00 | 0.01 |
| Managerial ownership$^2$ | 9,060 | 0.00 | 0.02 | 0.00 | 0.00 | 0.00 |
| Size | 9,060 | 7.65 | 1.57 | 6.51 | 7.53 | 8.69 |
| Tangibility | 9,055 | 0.31 | 0.23 | 0.12 | 0.24 | 0.43 |
| Leverage | 9,060 | 0.21 | 0.19 | 0.06 | 0.16 | 0.30 |
| ROA | 9,560 | 0.15 | 0.11 | 0.10 | 0.14 | 0.19 |
| Firm Age | 9,060 | 27.37 | 22.89 | 10 | 20 | 39 |
| Capex/TA | 9,012 | 0.06 | 0.06 | 0.02 | 0.04 | 0.07 |
| Labor mobilization | 8,014 | 0.23 | 0.87 | -0.51 | 0.28 | 0.89 |
| Job polarization | 9,060 | 1.42 | 0.16 | 1.27 | 1.39 | 1.56 |
| Relative Salary_OC | 9,003 | 0.02 | 0.07 | -0.01 | 0.00 | 0.03 |

**Table 2.2:** Regressions of Tobin's Q on OC and Components of OC

The dependent variable in all regressions is Tobin's Q, defined as the market value of equity plus the book values of debt and preferred equity, all divided by the book value of assets. Regressions in columns (1) and (4) are OLS estimations with industry and year fixed effects. Other estimations include firm and year fixed effects. Columns (3) and (6) include lagged dependent variable as a control. All independent variables are one period lagged. In all estimations the standard errors are clustered at the firm level. The sample period is 1992 to 2015. *, ** and *** indicate 10%, 5% and 1% significance levels, respectively.

| Dependent variable: Tobin's Q | OLS | FE | FE | OLS | FE | FE |
|---|---|---|---|---|---|---|
| $OC_{t-1}$ | 0.170*** | 0.298*** | 0.215*** | | | |
| | (3.43) | (4.01) | (4.36) | | | |
| $HC\_OC_{t-1}$ | | | | 4.052*** | 7.406*** | 3.015*** |
| | | | | (5.56) | (5.53) | (3.85) |
| $Residual\_OC_{t-1}$ | | | | 0.023 | -0.059 | 0.083 |
| | | | | (0.45) | (0.67) | (1.46) |
| $M/B_{t-1}$ | | | 0.535*** | | | 0.523*** |
| | | | (17.47) | | | (17.19) |
| $Institutional\,Ownership_{t-1}$ | 0.030 | -0.195** | -0.257*** | 0.051 | -0.126 | -0.229*** |
| | (0.28) | (1.98) | (3.29) | (0.49) | (1.34) | (3.02) |
| $Managerial\,Ownership_{t-1}$ | 2.489* | 3.402** | 2.161** | 2.257* | 3.211** | 2.122** |
| | (1.91) | (2.13) | (2.04) | (1.71) | (2.11) | (2.04) |
| $Managerial\,Ownership^2_{t-1}$ | -6.232* | -6.974 | -5.036* | -5.725 | -6.982* | -5.108* |
| | (1.73) | (1.62) | (1.82) | (1.59) | (1.73) | (1.89) |
| $Size_{t-1}(Ind.med.adjusted)$ | -0.043** | -0.278*** | -0.145*** | -0.020 | -0.280*** | -0.148*** |
| | (2.20) | (2.78) | (2.69) | (1.09) | (2.79) | (2.70) |
| $Tangibility_{t-1}$ | -0.770*** | -0.759*** | -0.236 | -0.668*** | -0.661** | -0.216 |
| | (3.87) | (2.70) | (1.49) | (3.55) | (2.46) | (1.36) |
| $Leverage_{t-1}$ | -1.440*** | -1.012*** | -0.162* | -1.314*** | -0.948*** | -0.153* |
| | (9.41) | (7.15) | (1.74) | (9.25) | (6.79) | (1.65) |
| $ROA_{t-1}$ | 4.078*** | 2.244*** | 0.454** | 4.215*** | 2.258*** | 0.501** |
| | (6.31) | (3.80) | (2.12) | (6.74) | (4.01) | (2.34) |
| $Firm\,age_{t-1}$ | -0.004*** | -0.001 | -0.002 | -0.002 | -0.014*** | -0.008** |
| | (2.90) | (0.25) | (0.71) | (1.32) | (2.69) | (2.10) |
| $Capex/TA_{t-1}$ | 0.649 | 0.188 | -0.401* | 0.540 | 0.159 | -0.409* |
| | (1.15) | (0.49) | (1.73) | (0.99) | (0.45) | (1.75) |
| $Intercept$ | 1.535*** | 1.657*** | 0.855*** | 1.340*** | 1.816*** | 0.940*** |
| | (8.18) | (5.24) | (3.69) | (7.23) | (6.02) | (4.17) |
| $Industry\ Fixed\ Effects$ | YES | NO | NO | YES | NO | NO |
| $Year\ Fixed\ Effects$ | YES | YES | YES | YES | YES | YES |
| $R^2$ | 0.41 | 0.19 | 0.43 | 0.43 | 0.21 | 0.43 |
| $N$ | 9,015 | 9,015 | 9,015 | 9,009 | 9,009 | 9,009 |

**Table 2.3:** First Stage Results of Two-Stage Least Squares Estimations

The instruments for HC_OC and Residual_OC are *Labor mobilization, Job polarization* and *Relative_Salary_OC*. All instruments and control variables are one period lagged. In all estimations the standard errors are clustered at the firm level. The sample period is 1992 to 2015. *, ** and *** indicate 10%, 5% and 1% significance levels, respectively.

| | HC_OC | Residual_OC |
|---|---|---|
| $Labor\,mobilization_{t-1}$ | -0.003** | 0.051** |
| | (2.18) | (2.56) |
| $Job\,polarization_{t-1}$ | 0.006 | -0.776*** |
| | (1.25) | (9.29) |
| $Relative\,Salary\,OC_{t-1}$ | 0.501*** | 1.769*** |
| | (15.87) | (5.09) |
| $Institutional\,ownership_{t-1}$ | 0.008* | -0.279*** |
| | (1.66) | (4.14) |
| $Managerial\,ownership_{t-1}$ | -0.044 | 1.068 |
| | (0.81) | (1.54) |
| $Managerial\,ownership^2_{t-1}$ | 0.039 | -2.198 |
| | (0.20) | (1.00) |
| $Size_{t-1}(Ind.med.adjusted)$ | -0.004*** | -0.047*** |
| | (4.20) | (3.76) |
| $Tangibility_{t-1}$ | -0.051*** | -0.883*** |
| | (8.74) | (10.07) |
| $Leverage_{t-1}$ | -0.018** | -0.239*** |
| | (2.48) | (2.82) |
| $ROA_{t-1}$ | -0.041** | 0.272* |
| | (2.43) | (1.65) |
| $Firm\,age_{t-1}$ | -0.000*** | 0.002** |
| | (3.99) | (2.22) |
| $Capex/TA_{t-1}$ | 0.028* | 0.616** |
| | (1.92) | (2.36) |
| $SW\,F - statistic\,of\,excluded\,instruments$ | 33.35 | 32.81 |
| $(p - value)$ | (0.0000) | (0.0000) |
| $R^2$ | 0.53 | 0.28 |
| $N$ | 7,436 | 7,436 |

**Table 2.4:** Second Stage Results of Two-Stage Least Squares Estimations

The dependent variable in all regressions is Tobin's Q, defined as the market value of equity plus the book values of debt and preferred equity, all divided by the book value of assets. HC_OC and Residual_OC variables are the estimates from the first stage regressions in Table 2.3. The instruments for HC_OC and Residual_OC are *Labor mobilization, Job polarization* and *Relative_Salary_OC*. All independent variables are one period lagged. In all estimations the standard errors are clustered at the firm level. The sample period is 1992 to 2015. *, ** and *** indicate 10%, 5% and 1% significance levels, respectively.

| | |
|---|---|
| $HC\_OC_{t-1}$ | 4.428*** |
| | (3.19) |
| $Residual\_OC_{t-1}$ | 0.078 |
| | (0.49) |
| $Institutional\,ownership_{t-1}$ | -0.315** |
| | (2.35) |
| $Managerial\,ownership_{t-1}$ | -0.750 |
| | (0.49) |
| $Managerial\,ownership^2_{t-1}$ | 2.091 |
| | (0.47) |
| $Size_{t-1}(Ind.med.adjusted)$ | -0.003 |
| | (0.12) |
| $Tangibility_{t-1}$ | -0.441** |
| | (2.55) |
| $Leverage_{t-1}$ | -1.769*** |
| | (10.65) |
| $ROA_{t-1}$ | 4.204*** |
| | (5.84) |
| $Firm\,age_{t-1}$ | -0.001 |
| | (0.52) |
| $Capex/TA_{t-1}$ | 0.274 |
| | (0.51) |
| $Sargan\,overidentification\,test\,statistic$ | 1.177 |
| $(p-value)$ | (0.2780) |
| $R^2$ | 0.29 |
| $N$ | 7,436 |

**Table 2.5:** Tobin's Q regressions of weak vs. strong governance firms

The dependent variable in all regressions is Tobin's Q, defined as the market value of equity plus the book values of debt and preferred equity, all divided by the book value of assets. Column 1 and 3 include firms below the median institutional ownership (weak governance) and columns 2 and 4 include firms above the median institutional ownership (strong governance). HC_OC and Residual_OC variables in columns 3 and 4 are the estimates from the first stage regressions in Table 2.3. The instruments for HC_OC and Residual_OC in columns 3 and 4 are *Labor mobilization, Job polarization* and *Relative_Salary_OC*. All independent variables are one period lagged. In all estimations the standard errors are clustered at the firm level. The sample period is 1992 to 2015. *, ** and *** indicate 10%, 5% and 1% significance levels, respectively.

| | OLS | | 2SLS | |
|---|---|---|---|---|
| Dependent variable: Tobin's Q | Weak Governance | Strong Governance | Weak Governance | Strong Governance |
| $HC\_OC_{t-1}$ | 1.670** | 4.645*** | 1.346 | 8.040*** |
| | (2.34) | (5.64) | (0.98) | (3.94) |
| $Residual\_OC_{t-1}$ | 0.031 | 0.035 | -0.065 | 0.003 |
| | (0.45) | (0.54) | (0.38) | (0.01) |
| $Institutional\,ownership_{t-1}$ | -0.142 | -0.280 | -0.429* | -0.898*** |
| | (0.78) | (1.17) | (1.76) | (3.41) |
| $Managerial\,ownership_{t-1}$ | 1.189 | -0.113 | -0.138 | -6.003*** |
| | (0.91) | (0.08) | (0.08) | (3.01) |
| $Managerial\,ownership^2_{t-1}$ | -2.019 | -1.176 | 1.768 | 23.079*** |
| | (0.59) | (0.25) | (0.40) | (2.71) |
| $Size_{t-1}(Ind.med.adjusted)$ | -0.022 | -0.036 | -0.029 | 0.043 |
| | (1.01) | (0.91) | (1.27) | (0.82) |
| $Tangibility_{t-1}$ | -0.461** | -0.952*** | -0.652*** | -0.657*** |
| | (2.17) | (4.26) | (2.84) | (3.21) |
| $Leverage_{t-1}$ | -1.651*** | -1.132*** | -2.284*** | -1.188*** |
| | (11.78) | (6.62) | (12.06) | (6.49) |
| $ROA_{t-1}$ | 2.502*** | 4.899*** | 2.646*** | 4.980*** |
| | (4.13) | (7.13) | (4.03) | (6.50) |
| $Firm\,age_{t-1}$ | -0.002 | -0.003*** | -0.001 | -0.005*** |
| | (1.15) | (3.03) | (0.22) | (3.10) |
| $Capex/TA_{t-1}$ | 0.883 | 0.699 | 0.875 | 0.492 |
| | (1.14) | (1.49) | (1.22) | (1.07) |
| $Intercept$ | 1.890*** | 1.511*** | - | - |
| | (6.91) | (5.46) | - | - |
| $Sargan\,overidentification\,test\,statistic$ | - | - | 2.712 | 1.124 |
| $(p-value)$ | - | - | (0.0996) | (0.2891) |
| $R^2$ | 0.35 | 0.45 | 0.24 | 0.34 |
| $N$ | 5,936 | 5,996 | 4,768 | 4,894 |

**Table 2.6:** Asset Pricing: Five portfolios sorted on HC_OC

This table shows asset-pricing estimations for five portfolios sorted on HC_OC over book value of assets relative to their industry peers within each year. In Panel A we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio. In Panel B we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and high-minus-low HC_OC factor (HMLHC). In Panel C we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and Fama and French (1993) SMB and HML factors. In Panel D we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio, Fama and French (1993) SMB and HML factors and Carhart (1997) MOM factor. Data on SMB, HML, and MOM are from Kenneth French's website. The sample period is June 1992 to December 2015. All portfolio returns correspond to value-weighted returns by firm market capitalization.

| Portfolio | Low | 2 | 3 | 4 | High | High-Low |
|---|---|---|---|---|---|---|
| | | | Panel A. CAPM Model | | | |
| $\alpha$ | 0.205* | 0.325** | 0.139 | 0.128 | -0.024 | -0.229 |
| | (1.70) | (2.28) | (0.92) | (0.76) | (0.11) | (0.86) |
| $\beta_{MKT}$ | 0.898*** | 0.864*** | 0.991*** | 1.043*** | 1.263*** | 0.365*** |
| | (26.18) | (18.96) | (19.33) | (22.32) | (18.90) | (4.46) |
| $R^2$ | 0.81 | 0.74 | 0.78 | 0.73 | 0.70 | 0.12 |
| | | | Panel B. Two-Factor Model | | | |
| $\alpha$ | 0.145 | 0.287** | 0.144 | 0.158 | 0.145 | |
| | (1.48) | (2.09) | (0.96) | (0.95) | (1.48) | |
| $\beta_{MKT}$ | 0.994*** | 0.924*** | 0.983*** | 0.993*** | 0.994*** | |
| | (34.99) | (21.11) | (18.80) | (22.47) | (34.99) | |
| $\beta_{HMLHC}$ | -0.263*** | -0.164*** | 0.022 | 0.135 | 0.737*** | |
| | (10.01) | (4.32) | (0.60) | (1.56) | (28.02) | |
| $R^2$ | 0.88 | 0.77 | 0.78 | 0.74 | 0.95 | |
| | | | Panel C. Fama-French Three-Factor Model | | | |
| $\alpha$ | 0.228** | 0.298** | 0.097 | 0.101 | 0.037 | -0.191 |
| | (2.19) | (2.22) | (0.65) | (0.64) | (0.19) | (0.88) |
| $\beta_{MKT}$ | 0.949*** | 0.910*** | 0.988*** | 0.988*** | 1.135*** | 0.186*** |
| | (32.97) | (22.41) | (19.63) | (23.08) | (21.41) | (3.10) |
| $\beta_{SMB}$ | -0.300*** | -0.138** | 0.131*** | 0.323*** | 0.409*** | 0.709*** |
| | (6.07) | (2.43) | (3.05) | (4.65) | (3.58) | (7.28) |
| $\beta_{HML}$ | -0.019 | 0.130* | 0.129** | 0.029 | -0.314*** | -0.295** |
| | (0.33) | (1.78) | (2.17) | (0.37) | (3.09) | (2.43) |
| $R^2$ | 0.85 | 0.77 | 0.79 | 0.77 | 0.78 | 0.45 |
| | | | Panel D. Fama-French-Carhart Four-Factor Model | | | |
| $\alpha$ | 0.317*** | 0.325** | 0.141 | 0.264* | 0.074 | -0.243 |
| | (3.06) | (2.43) | (0.90) | (1.75) | (0.42) | (1.19) |
| $\beta_{MKT}$ | 0.905*** | 0.897*** | 0.966*** | 0.907*** | 1.117*** | 0.212*** |
| | (31.54) | (21.30) | (19.22) | (23.78) | (19.02) | (3.01) |
| $\beta_{SMB}$ | -0.284*** | -0.133** | 0.139*** | 0.352*** | 0.416*** | 0.700*** |
| | (6.72) | (2.40) | (3.44) | (6.67) | (3.87) | (7.18) |
| $\beta_{HML}$ | -0.057 | 0.118 | 0.110* | -0.042 | -0.330*** | -0.273** |
| | (1.10) | (1.63) | (1.88) | (0.66) | (3.74) | (2.58) |
| $\beta_{MOM}$ | -0.112*** | -0.035 | -0.055 | -0.205*** | -0.047 | 0.065 |
| | (3.00) | (0.84) | (1.55) | (4.66) | (0.79) | (0.90) |
| $R^2$ | 0.87 | 0.77 | 0.79 | 0.80 | 0.78 | 0.46 |

**Table 2.7:** Asset Pricing: Five portfolios sorted on Residual_OC

This table shows asset-pricing estimations for five portfolios sorted on Residual_OC over book value of assets relative to their industry peers within each year. In Panel A we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio. In Panel B we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and high-minus-low Residual_OC factor (HMLRes). In Panel C we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and Fama and French (1993) SMB and HML factors. In Panel D we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio, Fama and French (1993) SMB and HML factors and Carhart (1997) MOM factor. Data on SMB, HML, and MOM are from Kenneth French's website. The sample period is June 1992 to December 2015. All portfolio returns correspond to value-weighted returns by firm market capitalization.

| Portfolio | Low | 2 | 3 | 4 | High | High-Low |
|---|---|---|---|---|---|---|
| | | | Panel A. CAPM Model | | | |
| $\alpha$ | -0.184 | 0.251** | 0.252** | 0.251* | 0.398*** | 0.583*** |
| | (1.27) | (1.98) | (2.13) | (1.92) | (2.63) | (2.91) |
| $\beta_{MKT}$ | 1.067*** | 0.920*** | 0.858*** | 0.802*** | 0.659*** | -0.408*** |
| | (28.48) | (29.05) | (27.15) | (21.52) | (15.95) | (7.89) |
| $R^2$ | 0.80 | 0.79 | 0.79 | 0.74 | 0.59 | 0.24 |
| | | | Panel B. Two-Factor Model | | | |
| $\alpha$ | 0.096 | 0.348*** | 0.236* | 0.199 | 0.096 | |
| | (0.84) | (2.64) | (1.91) | (1.54) | (0.84) | |
| $\beta_{MKT}$ | 0.870*** | 0.852*** | 0.869*** | 0.838*** | 0.870*** | |
| | (25.24) | (23.59) | (24.10) | (23.15) | (25.24) | |
| $\beta_{HMLRes}$ | -0.482*** | -0.166*** | 0.028 | 0.089** | 0.518*** | |
| | (11.06) | (2.86) | (0.70) | (2.15) | (11.90) | |
| $R^2$ | 0.89 | 0.80 | 0.80 | 0.75 | 0.78 | |
| | | | Panel C. Fama-French Three-Factor Model | | | |
| $\alpha$ | -0.177 | 0.284** | 0.218* | 0.249** | 0.362** | 0.539*** |
| | (1.28) | (2.34) | (1.94) | (2.09) | (2.48) | (2.83) |
| $\beta_{MKT}$ | 1.100*** | 0.947*** | 0.892*** | 0.855*** | 0.703*** | -0.397*** |
| | (29.77) | (32.99) | (32.84) | (25.97) | (18.07) | (7.75) |
| $\beta_{SMB}$ | -0.168*** | -0.218*** | -0.059 | -0.240*** | -0.099* | 0.069 |
| | (2.90) | (4.36) | (1.39) | (4.89) | (1.92) | (0.98) |
| $\beta_{HML}$ | 0.011 | -0.076* | 0.143*** | 0.057 | 0.158** | 0.147 |
| | (0.16) | (1.82) | (3.06) | (0.93) | (2.18) | (1.51) |
| $R^2$ | 0.81 | 0.81 | 0.81 | 0.79 | 0.62 | 0.25 |
| | | | Panel D. Fama-French-Carhart Four-Factor Model | | | |
| $\alpha$ | -0.066 | 0.380*** | 0.271** | 0.289** | 0.271* | 0.338* |
| | (0.49) | (2.87) | (2.39) | (2.41) | (1.87) | (1.86) |
| $\beta_{MKT}$ | 1.044*** | 0.900*** | 0.866*** | 0.836*** | 0.748*** | -0.296*** |
| | (29.33) | (26.11) | (28.75) | (23.69) | (18.59) | (6.35) |
| $\beta_{SMB}$ | -0.148*** | -0.201*** | -0.049 | -0.233*** | -0.115** | 0.033 |
| | (2.99) | (4.52) | (1.23) | (4.94) | (2.21) | (0.54) |
| $\beta_{HML}$ | -0.037 | -0.117** | 0.120*** | 0.039 | 0.197*** | 0.234*** |
| | (0.67) | (2.54) | (2.70) | (0.66) | (2.75) | (2.69) |
| $\beta_{MOM}$ | -0.139*** | -0.120** | -0.067** | -0.050 | 0.114*** | 0.254*** |
| | (4.27) | (2.35) | (2.30) | (1.46) | (3.37) | (6.28) |
| $R^2$ | 0.83 | 0.83 | 0.82 | 0.79 | 0.64 | 0.36 |

**Table 2.8:** Asset Pricing: Five portfolios sorted on institutional ownership (IO) and HC_OC

This table shows asset-pricing estimations for five portfolios sorted on institutional ownership (IO) and HC_OC over book value of assets relative to their industry peers within each year. In Panel A we report high-minus-low HC_OC portfolios (sorted on IO) alphas and betas of the regressions of excess portfolio returns on excess returns of the market portfolio. In Panel B we report high-minus-low HC_OC portfolios (sorted on IO) alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and Fama and French (1993) SMB and HML factors. In Panel C we report high-minus-low HC_OC portfolios (sorted on IO) alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio, Fama and French (1993) SMB and HML factors and Carhart (1997) MOM factor. Data on SMB, HML, and MOM are from Kenneth French's website. The sample period is June 1992 to December 2015. All portfolio returns correspond to value-weighted returns by firm market capitalization.

| Portfolio | IO=low | IO=2 | IO=3 | IO=4 | IO=high |
|---|---|---|---|---|---|
| | | | Panel A. CAPM Model | | |
| $\alpha$ | 0.382 | -0.274 | -0.403 | -0.033 | -0.756* |
| | (0.66) | (0.62) | (1.12) | (0.08) | (1.70) |
| $\beta_{MKT}$ | 0.578*** | -0.031 | 0.035 | 0.033 | 0.087 |
| | (3.21) | (0.25) | (0.40) | (0.28) | (0.76) |
| $R^2$ | 0.06 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | Panel B. Fama-French Three-Factor Model | | |
| $\alpha$ | 0.586 | -0.329 | -0.444 | -0.003 | -0.621 |
| | (1.05) | (0.77) | (1.33) | (0.01) | (1.46) |
| $\beta_{MKT}$ | 0.287** | -0.126 | -0.060 | -0.123 | -0.101 |
| | (2.14) | (1.07) | (0.70) | (1.10) | (0.93) |
| $\beta_{SMB}$ | 0.745*** | 0.588*** | 0.540*** | 0.604*** | 0.474*** |
| | (3.23) | (3.76) | (4.41) | (3.48) | (2.92) |
| $\beta_{HML}$ | -0.925*** | 0.079 | 0.032 | -0.288 | -0.608*** |
| | (3.07) | (0.35) | (0.21) | (1.64) | (3.76) |
| $R^2$ | 0.23 | 0.07 | 0.09 | 0.08 | 0.14 |
| | | | Panel C. Fama-French-Carhart Four-Factor Model | | |
| $\alpha$ | 0.440 | -0.605 | -0.445 | -0.213 | -0.896** |
| | (0.84) | (1.40) | (1.28) | (0.51) | (2.09) |
| $\beta_{MKT}$ | 0.360** | 0.012 | -0.059 | -0.027 | 0.036 |
| | (2.12) | (0.10) | (0.67) | (0.25) | (0.31) |
| $\beta_{SMB}$ | 0.719*** | 0.539*** | 0.540*** | 0.606*** | 0.425*** |
| | (3.09) | (3.77) | (4.36) | (3.75) | (3.01) |
| $\beta_{HML}$ | -0.862*** | 0.198 | 0.032 | -0.222 | -0.489*** |
| | (3.20) | (0.90) | (0.21) | (1.34) | (3.24) |
| $\beta_{MOM}$ | 0.184 | 0.347*** | 0.002 | 0.252** | 0.346*** |
| | (1.01) | (3.12) | (0.02) | (2.20) | (3.91) |
| $R^2$ | 0.24 | 0.13 | 0.09 | 0.11 | 0.19 |

**Table 2.9:** Asset Pricing: Five portfolios sorted on institutional ownership (IO) and Residual_OC

This table shows asset-pricing estimations for five portfolios sorted on institutional ownership (IO) and Residual_OC over book value of assets relative to their industry peers within each year. In Panel A we report high-minus-low Residual_OC portfolios (sorted on IO) alphas and betas of the regressions of excess portfolio returns on excess returns of the market portfolio. In Panel B we report high-minus-low Residual_OC portfolios (sorted on IO) alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and Fama and French (1993) SMB and HML factors. In Panel C we report high-minus-low Residual_OC portfolios (sorted on IO) alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio, Fama and French (1993) SMB and HML factors and Carhart (1997) MOM factor. Data on SMB, HML, and MOM are from Kenneth French's website. The sample period is June 1992 to December 2015. All portfolio returns correspond to value-weighted returns by firm market capitalization.

| Portfolio | IO=low | IO=2 | IO=3 | IO=4 | IO=high |
|---|---|---|---|---|---|
| Panel A. CAPM Model | | | | | |
| $\alpha$ | 0.867** | 0.350 | 0.405 | 0.259 | -0.026 |
| | (2.33) | (0.77) | (1.32) | (0.73) | (0.06) |
| $\beta_{MKT}$ | -0.260*** | -0.561*** | -0.338*** | -0.052 | -0.185** |
| | (2.97) | (4.55) | (3.80) | (0.55) | (2.03) |
| $R^2$ | 0.04 | 0.11 | 0.09 | 0.00 | 0.01 |
| Panel B. Fama-French Three-Factor Model | | | | | |
| $\alpha$ | 0.771** | 0.151 | 0.364 | 0.275 | 0.013 |
| | (2.19) | (0.37) | (1.25) | (0.77) | (0.03) |
| $\beta_{MKT}$ | -0.337*** | -0.456*** | -0.382*** | -0.081 | -0.300*** |
| | (4.12) | (4.59) | (4.43) | (0.83) | (3.34) |
| $\beta_{SMB}$ | 0.624*** | 0.084 | 0.319** | 0.081 | 0.403*** |
| | (5.50) | (0.60) | (2.36) | (0.62) | (2.64) |
| $\beta_{HML}$ | 0.225* | 0.723*** | 0.086 | -0.080 | -0.241 |
| | (1.72) | (3.41) | (0.51) | (0.53) | (1.52) |
| $R^2$ | 0.14 | 0.20 | 0.13 | 0.01 | 0.08 |
| Panel C. Fama-French-Carhart Four-Factor Model | | | | | |
| $\alpha$ | 0.728** | -0.039 | 0.227 | -0.023 | -0.133 |
| | (2.01) | (0.09) | (0.81) | (0.06) | (0.32) |
| $\beta_{MKT}$ | -0.316*** | -0.361*** | -0.316*** | 0.065 | -0.229** |
| | (3.49) | (3.41) | (3.78) | (0.66) | (2.37) |
| $\beta_{SMB}$ | 0.616*** | 0.050 | 0.296** | 0.030 | 0.378*** |
| | (5.58) | (0.36) | (2.39) | (0.26) | (2.67) |
| $\beta_{HML}$ | 0.243* | 0.805*** | 0.144 | 0.045 | -0.179 |
| | (1.75) | (3.70) | (0.88) | (0.33) | (1.23) |
| $\beta_{MOM}$ | 0.054 | 0.240** | 0.166** | 0.361*** | 0.176* |
| | (0.66) | (2.11) | (2.13) | (3.14) | (1.86) |
| $R^2$ | 0.15 | 0.22 | 0.15 | 0.10 | 0.10 |

# Appendix A

# Appendix for Chapter 1

**Summary:**

I include the supplementary material for Chapter 1 in this Appendix. Section A.1.1 discusses the DEA method and presents all results using DEA efficiency score as the dependent variable. Section A.1.2 presents the results with TFP estimate of Imrohoroglu and Tuzel (2014) as dependent variable. Section A.1.3 present robustness tests for the evaluation of borrower default risk using Mahalanobis propensity score matching technique. Section A.1.4 presents the robustness test results using Altman's Z-score and Whited-Wu financial constraint index as alternative proxies of default risk. Section A.1.5 shows the results using alternative relationship bank measures. Section A.1.6 presents placebo tests using pseudo relationship bank dummy variable. Section A.1.7 shows the results of possible survivorship bias analysis. Section A.1.8 presents the results excluding top 5 lead lenders in the sample to evaluate possible lender bias.

## A.1 DEA method:

Farrell (1957) introduced a single-input/output efficiency measure for the measurement of productive efficiency, which is based on a production possibility set consisting of the convex hull of input-output vectors. This measure is generalized into a multiple-input/output case by Charnes et al. (1978) and the authors named the method Data Envelopment Analysis (DEA).

A DEA model can be divided into an input-oriented model, which minimizes inputs while satisfying at least the given output levels, and an output-oriented model, which maximizes outputs without requiring more of any observed input values. DEA models can also be divided in terms of returns to scale by adding weight constraints. Charnes et al. (1978) originally proposed the efficiency measurement of the DMUs for constant returns to scale (CRS), where all DMUs are operating at their optimal scale. Later Banker et al. (1984) introduced the variable returns to scale (VRS) efficiency measurement model, allowing the breakdown of efficiency into technical and scale efficiencies in DEA (Ji and Lee, 2010).

The linear programming method of technical efficiency (TE) is stated by Murillo-Zamorano (2004) as:

$$TE_{VRS} = \min_{\mu} \psi \tag{A.A.1}$$

s.t.

$$\sum_{j=1}^{n} \mu_j X_{ij} \leq \psi X_i^0 \tag{A.A.2}$$

$$\sum_{j=1}^{n} \mu_j Y_{rj} \geq Y_r^0 \tag{A.A.3}$$

$$\sum_{j=1}^{n} \mu_j = 1 \tag{A.A.4}$$

where $X_{ij}$ are the inputs, $Y_{rj}$ are the outputs and $\psi$ is the proportion of consumption of inputs. This method allows for flexibility in the weights ($\mu_j$) assigned to each DMU (decision making unit) and calculates the relative efficiency score of a DMU compared to the Pareto-efficient frontier technology as opposed to average efficiency comparisons done by OLS and stochastic frontier analysis. Therefore it is more flexible than OLS and stochastic frontier analysis (Demerjian et al., 2012). I use the input minimization with variable returns to scale option of DEA. The equation (A.1.4) satisfies variable returns to scale condition.

I follow Demerjian et al. (2012)'s measure of firm efficiency and solve the following optimization problem for all firms in each year and industry, using Fama-French 12 industry classification (Fama and French, 1997):

$$\begin{aligned} \min_{\mu} \psi = (Sales) * (&\mu_1 CoGS + \mu_2 SG\&A + \mu_3 PPE \\ &+ \mu_4 OpsLease + \mu_5 R\&D + \mu_6 Goodwill \\ &+ \mu_7 OtherIntan)^{-1} \end{aligned} \tag{A.A.5}$$

in which $\psi \in [0, 1]$ is the efficiency measure. As in SFA model, the output is the revenue of a firm (REVT) in a given year and the inputs are cost of goods sold (COGS) that are the costs of production; selling, general and administrative expenses (SG&A), which are operational costs also known as the costs unrelated to the production process; net property, plant and equipment (PPENT) that accounts for fixed assets; net operating leases (OpsLease) that are included to capture the expenses of the firms that lease the fixed assets rather than purchase; research and development expenses (R&D); purchased goodwill (Goodwill), which is the excess of the purchase price for a business acquisition; and other intangibles (OtherIntan) that include items such as client lists, patent costs, and copyrights. The five stock variables (PPENT, OpsLease, R&D, Goodwill and OtherIntan) are measured at the beginning of year $t$ and the two flow measures (COGS and SG&A) are measured over the year $t$. I follow Ge (2006) to calculate Net Operating Leases as the discounted present value of the next five years of required operating lease payments (MRC1-MRC5 on Compustat). I follow Lev and Sougiannis (1996), who use a five-year capitalization period of R&D expense. Other Intangible Assets item (OtherIntan) is calculated by subtracting Goodwill (GDWL) from the Other Acquired and Capitalized Intangibles (INTAN).

Table A.1 below presents the results of the second stage fractional response regression estimation of equation (1.5) using DEA efficiency as the dependent variable. Column 1 presents all sample results, which exhibit support for *Hypothesis 1*. That is, borrowing firm technical efficiency increases as a result of a new loan from the relationship bank. Particularly, 1% increase in the likelihood of existence of relationship bank increases DEA efficiency by 0.7 percentage points at 5% significance level . These results are identical to the SFA results provided in Table 5.

Similar to SFA estimations, I test *Hypothesis 2* for the subsamples of low vs. elevated default risk firms defined by the first and fourth quartile of Jarrow Merton default probabilities. Columns 2 and 3 in Table A.1 present the second stage DEA results of the estimation of equation (1.5) for subsamples of low vs. elevated default risk firms, respectively. The results provide proof for *Hypothesis 2* that relationship banks concentrate on producing private information to improve the efficiency of those firms with elevated risk of default. Specifically, 1% increase in the likelihood of existence of relationship banking increases the efficiency of high PD subsample firms by 1.9 percentage points, whereas the efficiency of low PD subsample firms remain unchanged.

To test *Hypothesis 3*, I define the subsamples according to below and above median baseline DEA efficiency scores. The results in columns 4 and 5 of Table A.1 indicate that low baseline efficiency firms experience 1.8 percentage points increase in their efficiency as a result of 1% increase in the likelihood of existence of relationship bank, while a similar increase in the likelihood of relationship bank decreases the efficiency of high baseline efficiency firms by 0.6 percentage points at 10% significance level. Therefore these results present further evidence for *Hypothesis 3* that relationship banks concentrate on producing private information to improve the efficiency of those firms with low baseline efficiency.

**Table A.1:** Second Stage Results using DEA Efficiency

The table shows the semi-elasticities ($dy/ex$) of the second stage results of two-stage model using fractional response regression and DEA efficiency as dependent variable for the whole sample as well as subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) (columns (2) and (3)) and below and above median baseline DEA efficiency scores (columns (4) and (5)). The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| Dependent variable: DEA efficiency | All sample | Low PD subsample | High PD subsample | Low Efficiency subsample | High Efficiency subsample |
|---|---|---|---|---|---|
| *Rel_dummy*$_t$ *(instrumented)* | 0.007** | 0.002 | 0.019*** | 0.018*** | -0.006* |
| | (2.06) | (0.34) | (3.48) | (5.29) | (1.89) |
| *ROA* | 0.010*** | 0.002 | 0.002 | 0.010*** | -0.006** |
| | (4.82) | (0.31) | (0.86) | (4.73) | (2.04) |
| *Efficiency* | 0.418*** | 0.443*** | 0.363*** | 0.209*** | 0.305*** |
| | (44.04) | (31.04) | (20.67) | (22.64) | (27.46) |
| *Size* | -0.260*** | -0.317*** | -0.373*** | 0.079*** | -0.309*** |
| | (10.47) | (5.88) | (8.40) | (2.78) | (12.61) |
| *Size*$^2$ | 0.180*** | 0.217*** | 0.205*** | -0.014 | 0.184*** |
| | (13.67) | (7.66) | (9.38) | (1.01) | (13.99) |
| *Cash/TA* | 0.007*** | 0.010*** | 0.006** | 0.001 | 0.004*** |
| | (4.49) | (4.35) | (2.49) | (0.66) | (3.36) |
| *M/B* | 0.008*** | 0.015*** | -0.011** | -0.004 | 0.012*** |
| | (2.96) | (3.18) | (2.50) | (1.30) | (4.68) |
| *JM prob. of default* | 0.002*** | 0.002*** | 0.002 | -0.000 | 0.000 |
| | (2.71) | (3.35) | (1.07) | (0.42) | (0.45) |
| *Tangibility* | 0.007** | -0.002 | 0.007 | 0.002 | 0.001 |
| | (2.55) | (0.42) | (1.43) | (0.50) | (0.36) |
| *Interest coverage* | 0.000 | 0.000 | -0.001 | 0.000 | 0.000 |
| | (0.48) | (0.46) | (0.81) | (0.60) | (0.43) |
| *Capex/TA* | -0.003 | 0.012*** | -0.008* | -0.007*** | 0.006*** |
| | (1.16) | (2.96) | (1.90) | (2.65) | (2.76) |
| *Leverage* | -0.004* | 0.000 | 0.012*** | -0.001 | -0.000 |
| | (1.81) | (0.14) | (2.63) | (0.39) | (0.12) |
| *Firm age* | -0.002 | -0.000 | -0.002 | 0.001 | -0.004*** |
| | (0.97) | (0.02) | (0.63) | (0.37) | (2.75) |
| *Rating dummy* | -0.001 | -0.002 | 0.001 | 0.000 | 0.001 |
| | (1.11) | (0.98) | (0.29) | (0.32) | (1.22) |
| *Lambda* | 0.025 | 0.004 | 0.141*** | 0.112*** | -0.031** |
| | (1.39) | (0.18) | (3.33) | (4.84) | (2.22) |
| *N* | 23,711 | 6,864 | 5,081 | 11,510 | 12,201 |

Table A.2 below reports the second stage DEA results of the estimation of equation (1.5). 1% increase in the likelihood of existence of bank relationship increases the efficiency of low efficiency firms that have an elevated probability of default (column 3) by 1.3 percentage points at 5% statistical significance level. A similar increase does not have a statistically significant effect on the efficiency of high baseline efficiency firms that have an elevated probability of default (column 4). Similarly, while firms with high baseline efficiency and low default risk (column 2) do not experience significant change in their efficiencies as a result of relationship bank borrowing, firms with low baseline efficiency with low default risk (column 1) experience 2 percentage points increase in their efficiency when the likelihood of relationship banking increases by 1%. These results show that among the firms with elevated risk of default increases in efficiency in the presence of relationship bank loans are highest for firms that have low baseline levels of operational efficiency. In addition, these results show additional evidence for *Hypothesis 3* that relationship banks concentrate on producing private information to improve the efficiency of those firms with low baseline efficiency.

**Table A.2:** Second stage of low vs. high DEA efficiency and low vs. high PD subsamples

The table shows the semi-elasticities ($dy/ex$) of the second stage results of two-stage model using fractional response regression and DEA efficiency as dependent variable for the subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) and below and above median baseline DEA efficiency scores. The subsample in column (1) is low PD - low efficiency, (2) is low PD - high efficiency, (3) is high PD - low efficiency, and (4) is high PD - high efficiency. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Low PD | | High PD | |
|---|---|---|---|---|
| Dependent variable: DEA Efficiency | Low Efficiency | High Efficiency | Low Efficiency | High Efficiency |
| *Rel_dummy$_t$ (instrumented)* | 0.020*** | -0.008 | 0.013** | 0.013 |
| | (2.87) | (1.35) | (2.54) | (1.58) |
| *ROA* | 0.001 | -0.007 | 0.005** | -0.013*** |
| | (0.18) | (1.49) | (2.19) | (3.00) |
| *Efficiency* | 0.209*** | 0.305*** | 0.190*** | 0.297*** |
| | (14.28) | (19.87) | (12.06) | (12.20) |
| *Size* | 0.186*** | -0.390*** | -0.042 | -0.401*** |
| | (2.87) | (7.92) | (0.87) | (10.10) |
| *Size$^2$* | -0.059* | 0.230*** | 0.033 | 0.211*** |
| | (1.80) | (9.15) | (1.44) | (10.43) |
| *Cash/TA* | 0.006* | 0.006*** | 0.000 | 0.003 |
| | (1.81) | (3.23) | (0.14) | (1.36) |
| *M/B* | 0.006 | 0.010*** | -0.010** | 0.005 |
| | (0.98) | (2.59) | (2.11) | (1.00) |
| *JM prob. of default* | 0.001 | 0.001** | -0.001 | 0.000 |
| | (1.06) | (2.50) | (0.39) | (0.08) |
| *Tangibility* | -0.014** | 0.004 | 0.000 | -0.007 |
| | (2.50) | (1.17) | (0.04) | (1.48) |
| *Interest coverage* | -0.000 | 0.000 | -0.000 | -0.000 |
| | (0.31) | (0.20) | (0.68) | (0.66) |
| *Capex/TA* | 0.004 | 0.007** | -0.009** | 0.007* |
| | (0.92) | (2.47) | (2.06) | (1.88) |
| *Leverage* | 0.003 | -0.002 | 0.013*** | 0.006 |
| | (0.97) | (0.66) | (2.92) | (1.40) |
| *Firm age* | 0.003 | -0.004* | 0.004 | -0.004 |
| | (0.88) | (1.80) | (1.46) | (1.29) |
| *Rating dummy* | -0.002 | 0.002 | 0.004** | -0.000 |
| | (0.92) | (1.01) | (2.20) | (0.19) |
| *Lambda* | 0.086** | -0.032 | 0.113** | 0.062 |
| | (2.54) | (1.49) | (2.40) | (1.51) |
| *N* | 2,581 | 4,283 | 3,203 | 1,878 |

As in SFA estimations, I test the persistence of this impact using 5-year window around the year a new loan from a relationship lender is granted. Particularly, I estimate equation (1.5) for two years before and after the new relationship borrowing takes place as well as for the year of borrowing for subsamples of low DEA efficiency firms substantially above the default threshold and low DEA efficiency firms that have an elevated probability of default. Table A.3 shows that both low PD and high PD firms experience statistically significant increases in technical efficiency (at the 1% and 5% levels, respectively) in the year of a new relationship bank loan. However, the efficiency improving effect of the relationship bank loan becomes negative two years after the loan origination for firms with low probability of default whereas it is positive but statistically insignificant for firms with elevated probability of default after the year of loan origination.

Table A.4 shows the 5-year window results for high baseline DEA efficiency firms. The results show that neither the firms with low risk of default, nor those with elevated risk of default experience changes in their efficiencies as a result of existence of relationship banking. Therefore, as in SFA results, the findings in Tables A.3 suggest that the benefits of relationship bank information production in generating efficiency improvements offer diminishing returns over time.

**Table A.3:** Regression results for low DEA subsample of firms

The table shows the semi-elasticities ($dy/ex$) of the second stage results of two-stage model using fractional response regression and DEA efficiency as dependent variable for the subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) and below median baseline DEA efficiency scores. In the period $t-2$ *Rel_dummy* is lagged for two-period and in $t-1$ analysis *Rel_dummy* is lagged for one-period. In $t+1$ analysis one-period forward dependent variable is used and in $t+2$ analysis two-period forward dependent variable is used. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Low PD | | | | | High PD | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *t-2* | *t-1* | *t* | *t+1* | *t+2* | *t-2* | *t-1* | *t* | *t+1* | *t+2* |
| *Rel_dummy$_{t-2}$ (instrumented)* | -0.000 | | | | | 0.001 | | | | |
| | (0.03) | | | | | (0.39) | | | | |
| *Rel_dummy$_{t-1}$ (instrumented)* | | 0.005 | | | | | 0.005 | | | |
| | | (1.24) | | | | | (1.22) | | | |
| *Rel_dummy$_t$ (instrumented)* | | | 0.020*** | -0.001 | -0.037** | | | 0.013** | 0.010 | 0.008 |
| | | | (2.87) | (0.13) | (2.40) | | | (2.54) | (1.40) | (0.98) |
| *ROA* | 0.002 | 0.002 | 0.001 | -0.017** | -0.027** | 0.006*** | 0.006** | 0.005** | 0.004 | 0.005 |
| | (0.34) | (0.34) | (0.18) | (2.04) | (2.33) | (2.58) | (2.57) | (2.19) | (1.14) | (1.40) |
| *Efficiency* | 0.211*** | 0.211*** | 0.209*** | 0.290*** | 0.260*** | 0.192*** | 0.192*** | 0.190*** | 0.229*** | 0.253*** |
| | (14.36) | (14.43) | (14.28) | (12.82) | (9.00) | (12.14) | (12.14) | (12.06) | (10.46) | (9.72) |
| *Size* | 0.225*** | 0.223*** | 0.186*** | 0.242*** | 0.434*** | -0.006 | -0.009 | -0.042 | -0.047 | -0.139* |
| | (3.48) | (3.46) | (2.87) | (2.61) | (3.46) | (0.14) | (0.21) | (0.87) | (0.71) | (1.65) |
| *Size$^2$* | -0.068** | -0.070** | -0.059* | -0.082* | -0.157** | 0.024 | 0.023 | 0.033 | 0.033 | 0.086** |
| | (2.04) | (2.15) | (1.80) | (1.68) | (2.37) | (1.07) | (1.02) | (1.44) | (1.07) | (2.18) |
| *Cash/TA* | 0.002 | 0.003 | 0.006* | 0.001 | -0.011 | -0.002 | -0.001 | 0.000 | 0.005 | 0.009** |
| | (0.64) | (1.10) | (1.81) | (0.15) | (1.64) | (0.72) | (0.42) | (0.14) | (1.29) | (1.98) |
| *M/B* | 0.008 | 0.007 | 0.006 | 0.011 | 0.025** | -0.010* | -0.010** | -0.010** | -0.011* | -0.007 |
| | (1.27) | (1.14) | (0.98) | (1.28) | (2.15) | (1.93) | (2.03) | (2.11) | (1.71) | (0.88) |
| *JM prob. of default* | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | -0.001 | -0.001 | -0.001 | 0.004 | 0.008*** |
| | (0.92) | (1.07) | (1.06) | (0.50) | (0.62) | (0.78) | (0.49) | (0.39) | (1.33) | (2.66) |
| *Tangibility* | -0.016*** | -0.015*** | -0.014** | -0.012 | -0.025** | -0.001 | -0.000 | 0.000 | 0.012 | 0.019** |
| | (2.89) | (2.71) | (2.50) | (1.52) | (2.39) | (0.26) | (0.09) | (0.04) | (1.62) | (2.21) |
| *Interest coverage* | -0.001 | -0.001 | -0.000 | -0.001 | 0.000 | -0.001 | -0.001 | -0.000 | -0.001 | -0.001 |
| | (0.97) | (0.87) | (0.31) | (0.72) | (0.06) | (0.88) | (0.86) | (0.68) | (0.66) | (1.11) |
| *Capex/TA* | 0.005 | 0.005 | 0.004 | -0.004 | -0.003 | -0.008* | -0.008* | -0.009** | -0.009 | -0.003 |
| | (1.15) | (1.05) | (0.92) | (0.59) | (0.33) | (1.84) | (1.96) | (2.06) | (1.51) | (0.42) |
| *Leverage* | 0.004 | 0.003 | 0.003 | -0.005 | -0.010 | 0.013*** | 0.013*** | 0.013*** | 0.012* | 0.011 |
| | (1.11) | (1.02) | (0.97) | (1.04) | (1.27) | (2.92) | (2.85) | (2.92) | (1.88) | (1.31) |
| *Firm age* | 0.002 | 0.002 | 0.003 | -0.001 | 0.004 | 0.004 | 0.004 | 0.004 | 0.001 | -0.005 |
| | (0.68) | (0.68) | (0.88) | (0.15) | (0.72) | (1.29) | (1.30) | (1.46) | (0.18) | (1.05) |
| *Rating dummy* | 0.000 | -0.000 | -0.002 | 0.006* | 0.014*** | 0.006*** | 0.005*** | 0.004** | 0.004 | 0.005 |
| | (0.14) | (0.23) | (0.92) | (1.88) | (3.23) | (3.20) | (2.99) | (2.20) | (1.56) | (1.46) |
| *Lambda* | -0.009 | -0.008 | 0.086** | -0.016 | -0.170** | -0.005 | -0.004 | 0.113** | 0.090 | 0.060 |
| | (1.20) | (1.06) | (2.54) | (0.31) | (2.30) | (0.47) | (0.43) | (2.40) | (1.36) | (0.76) |
| *N* | 2,581 | 2,581 | 2,581 | 2,068 | 1,645 | 3,203 | 3,203 | 3,203 | 2,579 | 2,168 |

**Table A.4:** Regression results for high DEA subsample of firms

The table shows the semi-elasticities ($dy/ex$) of the second stage results of two-stage model using fractional response regression and DEA efficiency as dependent variable for the subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) and above median baseline DEA efficiency scores. In the period $t-2$ *Rel_dummy* is lagged for two-period and in $t-1$ analysis *Rel_dummy* is lagged for one-period. In $t+1$ analysis one-period forward dependent variable is used and in $t+2$ analysis two-period forward dependent variable is used. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Low PD | | | | | High PD | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *t-2* | *t-1* | *t* | *t+1* | *t+2* | *t-2* | *t-1* | *t* | *t+1* | *t+2* |
| $Rel\_dummy_{t\text{-}2}$ *(instrumented)* | -0.005 | | | | | 0.002 | | | | |
| | (1.49) | | | | | (0.38) | | | | |
| $Rel\_dummy_{t\text{-}1}$ *(instrumented)* | | -0.004 | | | | | 0.003 | | | |
| | | (1.11) | | | | | (0.64) | | | |
| $Rel\_dummy_{t}$ *(instrumented)* | | | -0.008 | -0.002 | -0.005 | | | 0.013 | 0.010 | -0.010 |
| | | | (1.35) | (0.21) | (0.50) | | | (1.58) | (0.76) | (0.80) |
| *ROA* | -0.008 | -0.008 | -0.007 | -0.001 | 0.006 | -0.012*** | -0.012*** | -0.013*** | -0.002 | 0.006 |
| | (1.61) | (1.61) | (1.49) | (0.14) | (0.59) | (2.81) | (2.83) | (3.00) | (0.29) | (0.84) |
| *Efficiency* | 0.305*** | 0.305*** | 0.305*** | 0.335*** | 0.322*** | 0.297*** | 0.297*** | 0.297*** | 0.321*** | 0.304*** |
| | (19.88) | (19.83) | (19.87) | (15.69) | (11.21) | (12.10) | (12.14) | (12.20) | (8.81) | (8.21) |
| *Size* | -0.403*** | -0.401*** | -0.390*** | -0.384*** | -0.301*** | -0.376*** | -0.378*** | -0.401*** | -0.348*** | -0.285*** |
| | (8.43) | (8.35) | (7.92) | (5.07) | (2.92) | (10.08) | (10.08) | (10.10) | (5.15) | (4.18) |
| $Size^2$ | 0.237*** | 0.235*** | 0.230*** | 0.260*** | 0.223*** | 0.204*** | 0.204*** | 0.211*** | 0.217*** | 0.198*** |
| | (9.48) | (9.41) | (9.15) | (6.76) | (4.60) | (9.93) | (10.01) | (10.43) | (6.48) | (5.69) |
| *Cash/TA* | 0.006*** | 0.006*** | 0.006*** | 0.006** | 0.004 | 0.002 | 0.002 | 0.003 | 0.008** | 0.005 |
| | (3.55) | (3.58) | (3.23) | (2.47) | (1.26) | (0.81) | (0.93) | (1.36) | (2.07) | (1.36) |
| *M/B* | 0.010*** | 0.010** | 0.010*** | 0.018*** | 0.018** | 0.006 | 0.006 | 0.005 | 0.009 | 0.001 |
| | (2.64) | (2.57) | (2.59) | (3.17) | (2.21) | (1.17) | (1.14) | (1.00) | (1.11) | (0.13) |
| *JM prob. of default* | 0.001** | 0.001** | 0.001** | 0.002** | 0.001 | -0.000 | 0.000 | 0.000 | 0.001 | 0.001 |
| | (2.49) | (2.48) | (2.50) | (2.38) | (0.55) | (0.03) | (0.08) | (0.08) | (0.56) | (0.23) |
| *Tangibility* | 0.004 | 0.005 | 0.004 | -0.001 | 0.001 | -0.008* | -0.007 | -0.007 | 0.004 | -0.000 |
| | (1.17) | (1.23) | (1.17) | (0.09) | (0.17) | (1.67) | (1.63) | (1.48) | (0.46) | (0.00) |
| *Interest coverage* | 0.000 | 0.000 | 0.000 | 0.001 | -0.000 | -0.000 | -0.000 | -0.000 | -0.001 | -0.002 |
| | (0.29) | (0.38) | (0.20) | (0.76) | (0.19) | (0.68) | (0.69) | (0.66) | (0.62) | (1.39) |
| *Capex/TA* | 0.008** | 0.007** | 0.007** | 0.006 | 0.001 | 0.007* | 0.007* | 0.007* | 0.005 | 0.009 |
| | (2.53) | (2.48) | (2.47) | (1.09) | (0.09) | (1.95) | (1.94) | (1.88) | (0.74) | (1.11) |
| *Leverage* | -0.001 | -0.002 | -0.002 | -0.002 | -0.000 | 0.006 | 0.006 | 0.006 | 0.021*** | 0.014* |
| | (0.57) | (0.65) | (0.66) | (0.52) | (0.10) | (1.30) | (1.32) | (1.40) | (2.80) | (1.69) |
| *Firm age* | -0.004* | -0.004* | -0.004* | -0.007** | -0.006* | -0.004 | -0.004 | -0.004 | -0.009** | -0.007* |
| | (1.78) | (1.72) | (1.80) | (2.08) | (1.66) | (1.31) | (1.32) | (1.29) | (2.02) | (1.65) |
| *Rating dummy* | 0.002 | 0.001 | 0.002 | -0.002 | 0.000 | 0.001 | 0.001 | -0.000 | -0.004 | -0.002 |
| | (0.89) | (0.78) | (1.01) | (0.67) | (0.11) | (0.59) | (0.42) | (0.19) | (1.10) | (0.58) |
| *Lambda* | -0.004 | -0.003 | -0.032 | -0.004 | -0.009 | -0.002 | -0.003 | 0.062 | 0.043 | -0.056 |
| | (1.20) | (0.85) | (1.49) | (0.12) | (0.25) | (0.37) | (0.44) | (1.51) | (0.61) | (0.83) |
| *N* | 4,283 | 4,283 | 4,283 | 3,623 | 3,007 | 1,878 | 1,878 | 1,878 | 1,609 | 1,426 |

## A.2 Results using TFP estimates:

Table A.5 below presents the results of the second stage 2SLS regression estimation of equation (1.5) using TFP estimate of Imrohoroglu and Tuzel (2014) as the dependent variable. Column 1 presents all sample results, which exhibit additional support for *Hypothesis 1*. Particularly, one standard deviation increase in the likelihood of existence of relationship bank increases TFP by 0.05 points (0.136*0.372)[1] at 1% significance level. These results are similar to the SFA results in Table 1.5 and DEA results in Table A.1.

Similar to SFA and DEA estimations, I test *Hypothesis 2* for the subsamples of low vs. elevated default risk firms defined by the first and fourth quartile of Jarrow Merton default probabilities. Columns 2 and 3 in Table A.5 present the second stage TFP results of the estimation of equation (1.5) for subsamples of low vs. elevated default risk firms, respectively. The results provide proof for *Hypothesis 2* that relationship banks concentrate on producing private information to improve the efficiency of those firms with elevated risk of default. Specifically, one standard deviation increase in the likelihood of existence of relationship banking increases the efficiency of high PD subsample firms by 0.177 points (0.542*0.328), whereas the efficiency of low PD subsample firms remain unchanged[2].

To test *Hypothesis 3*, I define the subsamples according to below and above median baseline TFP estimates. The results in columns 4 and 5 of Table A.5 indicate that low baseline efficiency firms experience 0.049 points increase (0.147*0.340) in their efficiency as a result of one standard deviation increase in the likelihood of existence of relationship bank, while a similar increase in the likelihood of relationship bank increases the efficiency of high baseline efficiency firms by 0.031 points (0.076*0.419) at 10% significance level[3]. Therefore these results present further evidence for *Hypothesis 3* that relationship banks concentrate

[1] The standard deviation of *Rel_dummy* for the whole sample is 0.372.

[2] For high PD firms, the standard deviation of *Rel_dummy* is 0.328

[3] For low efficiency firms the standard deviation of *Rel_dummy* is 0.340 and for high baseline efficiency firms it is 0.419.

on producing private information to improve the efficiency of those firms with low baseline efficiency.

**Table A.5:** Second Stage Results of TFP Estimate

The table shows the second stage results of 2SLS. TFP estimate as dependent variable for the whole sample as well as subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) (columns (2) and (3)) and below and above median baseline TFP estimate (columns (4) and (5)). The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| Dependent variable: TFP | All sample | Low PD subsample | High PD subsample | Low TFP subsample | High TFP subsample |
|---|---|---|---|---|---|
| *Rel_dummy$_t$ (instrumented)* | 0.136*** | 0.002 | 0.542*** | 0.147** | 0.076* |
| | (3.30) | (0.03) | (3.39) | (2.37) | (1.78) |
| *ROA* | -0.071 | -0.358*** | -0.220 | 0.603*** | -0.451*** |
| | (1.01) | (3.52) | (1.07) | (4.86) | (4.71) |
| *Efficiency* | 0.788*** | 0.848*** | 0.716*** | 0.323*** | 0.630*** |
| | (46.81) | (39.72) | (11.66) | (8.16) | (30.05) |
| *Size* | -0.008 | -0.048*** | -0.094*** | 0.036** | -0.092*** |
| | (0.73) | (3.19) | (3.65) | (2.12) | (8.07) |
| *Size$^2$* | 0.001* | 0.003*** | 0.007*** | -0.002 | 0.006*** |
| | (1.92) | (3.43) | (3.94) | (1.45) | (7.66) |
| *Cash/TA* | 0.094** | 0.165*** | 0.006 | -0.106 | 0.269*** |
| | (2.05) | (2.66) | (0.04) | (1.64) | (6.02) |
| *M/B* | 0.038*** | 0.047*** | -0.014 | -0.032*** | 0.039*** |
| | (5.55) | (5.92) | (0.72) | (2.74) | (5.50) |
| *JM prob. of default* | -0.002 | 0.023*** | -0.001 | -0.004 | 0.004* |
| | (1.03) | (3.93) | (0.43) | (1.51) | (1.73) |
| *Tangibility* | 0.024 | -0.041 | 0.005 | 0.050 | 0.017 |
| | (1.13) | (1.36) | (0.08) | (1.41) | (0.63) |
| *Interest coverage* | -0.000* | -0.000*** | 0.000 | 0.000 | -0.000*** |
| | (1.95) | (3.35) | (0.58) | (1.25) | (3.69) |
| *Capex/TA* | -0.183* | 0.120 | -0.046 | -0.294* | 0.129 |
| | (1.78) | (0.80) | (0.18) | (1.78) | (1.23) |
| *Leverage* | -0.002 | -0.003 | 0.269*** | 0.031 | 0.003 |
| | (0.12) | (0.08) | (4.72) | (1.09) | (0.12) |
| *Firm age* | 0.000 | -0.000* | 0.000 | 0.000 | 0.000 |
| | (0.02) | (1.86) | (0.22) | (1.05) | (0.15) |
| *Rating dummy* | 0.006 | 0.020** | 0.017 | 0.001 | 0.004 |
| | (0.72) | (2.03) | (0.66) | (0.07) | (0.43) |
| *Lambda* | 0.174*** | -0.007 | 0.659*** | 0.199** | 0.098* |
| | (3.34) | (0.11) | (3.34) | (2.47) | (1.87) |
| *Constant* | -0.305*** | 0.138* | -0.686*** | -0.785*** | 0.276*** |
| | (5.67) | (1.90) | (3.70) | (8.21) | (4.64) |
| $R^2$ | 0.53 | 0.69 | 0.26 | 0.16 | 0.55 |
| *N* | 16,328 | 5,281 | 2,908 | 8,259 | 8,069 |

Table A.6 below reports the second stage TFP results of the estimation of equation (1.5). According to these results, regardless of their default probabilities at the time of relationship bank borrowing, low PD firms do not experience increase in their efficiencies as a result of relationship bank borrowing. Among the firms with elevated probability of default, one standard deviation increase in the likelihood of existence of bank relationship increases the efficiency of low efficiency firms (column 3) by 0.127 points (0.410*0.314) at 5% statistical significance level[4]. A similar increase increases the efficiency of high baseline efficiency firms that have an elevated probability of default (column 4) by 0.197 (0.486*0.406). Although high baseline TFP firms with elevated probability of default seem to experience a higher increase in efficiency than low baseline TFP firms with elevated probability of default, the former subsample has 780 observations, which are less than half of the subsamples in SFA and DEA results due to missing values in TFP estimate (This is due to the missing values in the variables used for the TFP estimation by Imrohoroglu and Tuzel (2014).). Therefore, these results show further evidence that those firms with elevated risks of default experience increases in their efficiencies in the presence of new loans from relationship banks.

[4]The standard deviation of *Rel_dummy* for low baseline TFP firms with elevated default risk is 0.314. The standard deviation of *Rel_dummy* for high baseline efficiency firms with elevated default risk is 0.406.

**Table A.6:** Second stage of low vs. high TFP and low vs. high PD subsamples

The table shows the second stage results of 2SLS. TFP estimate as dependent variable for the subsample of firms defined according to first and fourth quartile of Jarrow- Merton default probabilities (PD) and below and above median baseline TFP. The subsample in column (1) is low PD - low TFP, (2) is low PD - high TFP, (3) is high PD - low TFP, and (4) is high PD - high TFP. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Low PD | | High PD | |
|---|---|---|---|---|
| Dependent variable: TFP | Low TFP | High TFP | Low TFP | High TFP |
| *Rel_dummy$_t$ (instrumented)* | -0.088 | 0.013 | 0.410** | 0.486*** |
| | (1.51) | (0.21) | (2.09) | (3.28) |
| *ROA* | -0.039 | -0.354*** | 0.292 | -0.742*** |
| | (0.30) | (2.98) | (1.14) | (3.09) |
| *Efficiency* | 0.399*** | 0.729*** | 0.452*** | 0.484*** |
| | (9.00) | (28.90) | (5.34) | (8.30) |
| *Size* | 0.052** | -0.089*** | -0.081** | -0.100*** |
| | (2.32) | (5.01) | (2.53) | (3.22) |
| *Size$^2$* | -0.003* | 0.006*** | 0.006** | 0.005** |
| | (1.86) | (4.98) | (2.45) | (2.47) |
| *Cash/TA* | -0.164* | 0.283*** | -0.113 | 0.473*** |
| | (1.86) | (4.19) | (0.64) | (3.62) |
| *M/B* | 0.017 | 0.034*** | -0.054** | 0.026 |
| | (1.25) | (3.83) | (2.27) | (1.48) |
| *JM prob. of default* | 0.008 | 0.016** | -0.000 | -0.000 |
| | (1.50) | (2.52) | (0.01) | (0.08) |
| *Tangibility* | -0.048 | 0.015 | 0.126 | -0.135** |
| | (1.25) | (0.40) | (1.56) | (2.09) |
| *Interest coverage* | -0.000 | -0.000*** | 0.000 | 0.000 |
| | (0.71) | (3.29) | (0.58) | (0.45) |
| *Capex/TA* | -0.035 | 0.069 | -0.382 | 0.528** |
| | (0.16) | (0.42) | (1.19) | (2.20) |
| *Leverage* | -0.047 | 0.030 | 0.236*** | 0.203*** |
| | (1.29) | (0.69) | (3.60) | (2.63) |
| *Firm age* | 0.000 | -0.000* | 0.001 | -0.000 |
| | (0.70) | (1.75) | (1.09) | (0.21) |
| *Rating dummy* | 0.007 | 0.012 | -0.003 | -0.017 |
| | (0.63) | (0.98) | (0.08) | (0.73) |
| *Lambda* | -0.145* | 0.019 | 0.515** | 0.550*** |
| | (1.82) | (0.24) | (2.13) | (3.03) |
| *Constant* | -0.361*** | 0.360*** | -0.779*** | -0.200 |
| | (3.20) | (4.14) | (3.38) | (1.25) |
| $R^2$ | 0.27 | 0.63 | 0.12 | 0.12 |
| *N* | 1,734 | 3,547 | 2,128 | 780 |

As in SFA and DEA estimations, I test the persistence of the impact of relationship banking oversight using 5-year window around the year the new borrowing from a relationship lender takes place. Particularly, I estimate equation (1.5) for two years before and after the relationship borrowing takes place as well as for the year of borrowing for subsamples of low TFP firms substantially above the default threshold and low TFP firms that have an elevated probability of default. Table A.7 shows that only high PD firms experience statistically significant increase in TFP (at the 5% levels) in the year of a new relationship bank loan. However, the efficiency improving effect of the relationship bank loan disappears in the year after the loan origination.

Table A.8 shows the 5-year window results for high baseline TFP firms. The results show that low default risk firms do not experience statistically significant change in their TFP, whereas those with elevated risk of default experience increases in their efficiencies only in the year of relationship bank borrowing. Therefore, the findings in Tables A.7 and A.8 also show that the benefits of relationship bank information production in generating efficiency improvements offer diminishing returns over time.

**Table A.7:** Regression results for low TFP subsample of firms

The table shows the second stage results of 2SLS. TFP estimate as dependent variable for the subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) and below median baseline TFP. In the period $t-2$ *Rel_dummy* is lagged for two-period and in $t-1$ analysis *Rel_dummy* is lagged for one-period. In $t+1$ analysis one-period forward dependent variable is used and in $t+2$ analysis two-period forward dependent variable is used. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Low PD | | | | | High PD | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *t-2* | *t-1* | *t* | *t+1* | *t+2* | *t-2* | *t-1* | *t* | *t+1* | *t+2* |
| $Rel\_dummy_{t\text{-}2}$ *(instrumented)* | -0.034 | | | | | -0.038 | | | | |
| | (0.65) | | | | | (0.26) | | | | |
| $Rel\_dummy_{t\text{-}1}$ *(instrumented)* | | -0.099** | | | | | 0.079 | | | |
| | | (2.18) | | | | | (0.64) | | | |
| $Rel\_dummy_{t}$ *(instrumented)* | | | -0.088 | 0.004 | -0.027 | | | 0.410** | 0.204 | 0.124 |
| | | | (1.51) | (0.03) | (0.22) | | | (2.09) | (1.06) | (0.59) |
| *ROA* | -0.048 | -0.046 | -0.039 | -0.156 | -0.426* | 0.363 | 0.335 | 0.292 | -0.077 | -0.749* |
| | (0.38) | (0.37) | (0.30) | (0.89) | (1.74) | (1.43) | (1.33) | (1.14) | (0.26) | (1.76) |
| *Efficiency* | 0.395*** | 0.401*** | 0.399*** | 0.417*** | 0.397*** | 0.451*** | 0.455*** | 0.452*** | 0.430*** | 0.523*** |
| | (9.15) | (9.07) | (9.00) | (7.78) | (6.05) | (5.58) | (5.60) | (5.34) | (6.24) | (4.94) |
| *Size* | 0.049** | 0.049** | 0.052** | 0.043 | 0.023 | -0.062** | -0.067** | -0.081** | -0.038 | -0.000 |
| | (2.22) | (2.17) | (2.32) | (1.56) | (0.49) | (2.07) | (2.20) | (2.53) | (1.17) | (0.01) |
| $Size^2$ | -0.003* | -0.003 | -0.003* | -0.003 | -0.001 | 0.006*** | 0.005** | 0.006** | 0.003 | 0.001 |
| | (1.83) | (1.56) | (1.86) | (1.29) | (0.20) | (2.72) | (2.51) | (2.45) | (1.44) | (0.23) |
| *Cash/TA* | -0.145* | -0.173* | -0.164* | 0.100 | 0.098 | -0.277* | -0.219 | -0.113 | 0.057 | 0.048 |
| | (1.71) | (1.96) | (1.86) | (0.81) | (0.68) | (1.66) | (1.30) | (0.64) | (0.35) | (0.27) |
| *M/B* | 0.017 | 0.018 | 0.017 | 0.027* | 0.034 | -0.051** | -0.051** | -0.054** | -0.029 | 0.045* |
| | (1.27) | (1.32) | (1.25) | (1.69) | (1.37) | (2.12) | (2.12) | (2.27) | (0.94) | (1.89) |
| *JM prob. of default* | 0.009 | 0.009 | 0.008 | 0.015* | 0.007 | -0.002 | -0.001 | -0.000 | -0.001 | 0.000 |
| | (1.50) | (1.37) | (1.50) | (1.93) | (0.39) | (0.45) | (0.36) | (0.01) | (0.14) | (0.01) |
| *Tangibility* | -0.044 | -0.049 | -0.048 | -0.028 | -0.032 | 0.107 | 0.113 | 0.126 | 0.121* | 0.187** |
| | (1.15) | (1.24) | (1.25) | (0.47) | (0.49) | (1.39) | (1.49) | (1.56) | (1.78) | (2.33) |
| *Interest coverage* | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | 0.000 | 0.000 | 0.000 | -0.000 | -0.000 |
| | (0.66) | (0.57) | (0.71) | (1.15) | (0.91) | (0.19) | (0.34) | (0.58) | (0.36) | (0.72) |
| *Capex/TA* | -0.030 | -0.029 | -0.035 | 0.078 | -0.361 | -0.348 | -0.376 | -0.382 | -0.290 | -0.678* |
| | (0.14) | (0.13) | (0.16) | (0.27) | (0.93) | (1.15) | (1.23) | (1.19) | (0.97) | (1.75) |
| *Leverage* | -0.051 | -0.039 | -0.047 | -0.024 | -0.078 | 0.217*** | 0.228*** | 0.236*** | 0.168*** | 0.115 |
| | (1.40) | (1.01) | (1.29) | (0.46) | (1.03) | (3.60) | (3.63) | (3.60) | (2.75) | (1.63) |
| *Firm age* | 0.000 | 0.000 | 0.000 | -0.000 | -0.000 | 0.001 | 0.001 | 0.001 | -0.000 | -0.000 |
| | (0.92) | (0.88) | (0.70) | (0.02) | (0.66) | (1.03) | (1.09) | (1.09) | (0.19) | (0.00) |
| *Rating dummy* | 0.006 | 0.007 | 0.007 | 0.016 | 0.015 | 0.023 | 0.014 | -0.003 | 0.018 | 0.005 |
| | (0.56) | (0.60) | (0.63) | (1.00) | (0.57) | (0.84) | (0.50) | (0.08) | (0.67) | (0.16) |
| *Lambda* | -0.030* | -0.035** | -0.145* | 0.015 | -0.035 | 0.026 | 0.037 | 0.515** | 0.212 | 0.095 |
| | (1.74) | (2.10) | (1.82) | (0.09) | (0.22) | (0.55) | (0.78) | (2.13) | (0.96) | (0.35) |
| *Constant* | -0.449*** | -0.429*** | -0.361*** | -0.511*** | -0.359 | -0.468*** | -0.469*** | -0.779*** | -0.486** | -0.562** |
| | (4.71) | (4.37) | (3.20) | (2.61) | (1.55) | (3.15) | (3.10) | (3.38) | (2.04) | (2.54) |
| $R^2$ | 0.28 | 0.25 | 0.27 | 0.23 | 0.22 | 0.19 | 0.19 | 0.12 | 0.15 | 0.15 |
| *N* | 1,734 | 1,734 | 1,734 | 1,382 | 1,038 | 2,128 | 2,128 | 2,128 | 1,683 | 1,428 |

**Table A.8:** Regression results for high TFP subsample of firms

The table shows the second stage results of 2SLS. TFP estimate as dependent variable for the subsample of firms defined according to first and fourth quartile of Jarrow-Merton default probabilities (PD) and above median baseline TFP. In the period $t-2$ *Rel_dummy* is lagged for two-period and in $t-1$ analysis *Rel_dummy* is lagged for one-period. In $t+1$ analysis one-period forward dependent variable is used and in $t+2$ analysis two-period forward dependent variable is used. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Low pd | | | | | High pd | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *t-2* | *t-1* | *t* | *t+1* | *t+2* | *t-2* | *t-1* | *t* | *t+1* | *t+2* |
| $Rel\_dummy_{t\text{-}2}$ *(instrumented)* | -0.053 | | | | | -0.076 | | | | |
| | (1.60) | | | | | (1.06) | | | | |
| $Rel\_dummy_{t\text{-}1}$ *(instrumented)* | | -0.040 | | | | | 0.032 | | | |
| | | (1.18) | | | | | (0.42) | | | |
| $Rel\_dummy_{t}$ *(instrumented)* | | | 0.013 | 0.002 | -0.003 | | | 0.486*** | 0.231 | 0.238 |
| | | | (0.21) | (0.02) | (0.03) | | | (3.28) | (1.31) | (1.33) |
| *ROA* | -0.327*** | -0.342*** | -0.354*** | -0.458*** | -0.482** | -0.727*** | -0.686*** | -0.742*** | -0.285 | -0.250 |
| | (2.73) | (2.88) | (2.98) | (2.59) | (2.21) | (3.19) | (3.02) | (3.09) | (1.11) | (0.95) |
| *Efficiency* | 0.724*** | 0.728*** | 0.729*** | 0.698*** | 0.680*** | 0.498*** | 0.490*** | 0.484*** | 0.489*** | 0.453*** |
| | (28.17) | (28.68) | (28.90) | (19.76) | (15.77) | (8.08) | (8.30) | (8.30) | (6.26) | (6.80) |
| *Size* | -0.084*** | -0.085*** | -0.089*** | -0.094*** | -0.099*** | -0.071** | -0.075*** | -0.100*** | -0.099*** | -0.082* |
| | (4.97) | (5.02) | (5.01) | (3.96) | (3.65) | (2.56) | (2.75) | (3.22) | (2.69) | (1.80) |
| $Size^2$ | 0.005*** | 0.005*** | 0.006*** | 0.006*** | 0.007*** | 0.004** | 0.004** | 0.005** | 0.006** | 0.006* |
| | (4.95) | (4.96) | (4.98) | (4.18) | (3.70) | (2.33) | (2.42) | (2.47) | (2.29) | (1.91) |
| *Cash/TA* | 0.262*** | 0.265*** | 0.283*** | 0.146 | -0.028 | 0.217** | 0.232** | 0.473*** | 0.452** | 0.421** |
| | (4.23) | (4.25) | (4.19) | (1.61) | (0.26) | (2.16) | (2.46) | (3.62) | (2.56) | (2.17) |
| *M/B* | 0.034*** | 0.034*** | 0.034*** | 0.050*** | 0.064*** | 0.040** | 0.032** | 0.026 | 0.029 | 0.027 |
| | (3.78) | (3.80) | (3.83) | (4.10) | (4.45) | (2.36) | (2.04) | (1.48) | (1.28) | (1.37) |
| *JM prob. of default* | 0.016** | 0.016** | 0.016** | 0.022** | 0.021* | -0.002 | -0.001 | -0.000 | -0.014** | 0.002 |
| | (2.48) | (2.50) | (2.52) | (2.51) | (1.89) | (0.56) | (0.14) | (0.08) | (2.08) | (0.41) |
| *Tangibility* | 0.004 | 0.006 | 0.015 | -0.009 | -0.041 | -0.131** | -0.128** | -0.135** | -0.181* | -0.146* |
| | (0.10) | (0.16) | (0.40) | (0.16) | (0.59) | (2.18) | (2.25) | (2.09) | (1.84) | (1.76) |
| *Interest coverage* | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000 | -0.000 | 0.000 | -0.001** | -0.001*** |
| | (3.42) | (3.37) | (3.29) | (2.80) | (3.49) | (0.48) | (0.25) | (0.45) | (2.00) | (3.39) |
| *Capex/TA* | 0.094 | 0.101 | 0.069 | 0.171 | 0.243 | 0.610*** | 0.559*** | 0.528** | 0.145 | 0.130 |
| | (0.58) | (0.61) | (0.42) | (0.72) | (0.70) | (2.77) | (2.62) | (2.20) | (0.48) | (0.38) |
| *Leverage* | 0.049 | 0.044 | 0.030 | 0.011 | -0.035 | 0.106* | 0.089* | 0.203*** | 0.231*** | 0.124 |
| | (1.04) | (0.95) | (0.69) | (0.17) | (0.43) | (1.86) | (1.65) | (2.63) | (2.65) | (1.55) |
| *Firm age* | -0.000* | -0.000* | -0.000* | -0.001* | -0.001 | 0.000 | 0.000 | -0.000 | 0.000 | -0.000 |
| | (1.70) | (1.65) | (1.75) | (1.89) | (1.33) | (0.55) | (0.32) | (0.21) | (0.30) | (0.63) |
| *Rating dummy* | 0.016 | 0.017 | 0.012 | 0.026 | 0.038* | 0.024 | 0.014 | -0.017 | 0.013 | -0.002 |
| | (1.39) | (1.45) | (0.98) | (1.53) | (1.70) | (1.41) | (0.76) | (0.73) | (0.41) | (0.06) |
| *Lambda* | -0.005 | -0.003 | 0.019 | -0.025 | -0.060 | -0.050** | -0.042* | 0.550*** | 0.232 | 0.283 |
| | (0.37) | (0.21) | (0.24) | (0.24) | (0.49) | (2.18) | (1.79) | (3.03) | (1.07) | (1.22) |
| *Constant* | 0.355*** | 0.369*** | 0.360*** | 0.386*** | 0.379** | 0.161 | 0.189* | -0.200 | -0.623** | -0.153 |
| | (4.58) | (4.83) | (4.14) | (3.14) | (2.57) | (1.42) | (1.90) | (1.25) | (2.33) | (0.56) |
| $R^2$ | 0.63 | 0.63 | 0.63 | 0.51 | 0.42 | 0.36 | 0.39 | 0.12 | 0.26 | 0.28 |
| *N* | 3,547 | 3,547 | 3,547 | 2,950 | 2,472 | 780 | 780 | 780 | 685 | 604 |

## A.3 Examining the Impact on Default Risk

As a robustness check, I examine *Hypothesis 4* by estimating the propensity score using Mahalanobis matching and compare the year-to-year difference in the probability of default of firms that have relationship banking with those of matched control firms that have public debt. I match the firms according to their propensity score (using 0.1 as the maximum distance criteria), estimated as the probability of having a relationship banking one period before the borrowing took place. I estimate equation (1.4) using logistic regression, where the dependent variable is equal to one for the firms that have relationship banking during the sample period (treatment group) and zero for the firms, which do not have relationship banks during the sample period but have issued public debt (control group). Following Rosenbaum and Rubin (1985) I check the standardized percentage bias for the matched treated and non-treated groups' covariates before and after the matching. The bias after matching is reduced to below 25%, which is the accepted limit. After matching I define the difference of default probabilities between year *0* and *-1*, where *0* is the year of borrowing and *-1* is the prior year. Similarly I check the difference of default probabilities between year *1* and *-1* and year *2* and *-1*.

Similar to the results in Table 1.10, Panel A of Table A.9 show a reduction in default risk over years *1* and *2* (as compared to year *-1*) only for the high default risk borrowers with bank relationships. That is, default risk declined by 0.78% both one year and two years after the origination of a relationship bank loan. These measures are all statistically significant at the 1% and 5% levels, respectively. In contrast, Panel B of Table A.9 shows that default risk actually increases for both relationship bank borrowers (treatment group) and public debt issuers (control group) that are far from the default threshold.

The quasi diff-in-diff estimations in boldface in Panel A of Table A.9 show that relationship bank borrowers experience significant decreases in default risk as compared to bond issuers in the year of new debt issuance as compared to the year before. The differences are not significant for the low default risk subsample shown in Panel B. These results provide support for *Hypothesis 4* that the probability of default decreases for firms with elevated risk of default in the years following a new loan from a relationship bank.

**Table A.9:** Propensity Score Matching Estimations of Default Probabilities

The matching is done on the year before the relationship borrowing takes place ($year = -1$) using mahalanobis matching technique. The matching the probabilities are estimated in equation (1.4) using the dummy variable defined as one for the treatment group firms ($PD_t$), which have only relationship bank borrowing and zero for the control group firms ($PD_c$), which have only public debt borrowing. Panel A shows results for firms in the fourth quartile of Jarrow-Merton default probabilities. Panel B includes firms that are in the first quartile of Jarrow-Merton default probabilities. The results in bold are quasi diff-in-diff estimations of differences in default probabilities of treatment and control groups for the year of borrowing and one year and two years after the borrowing takes place. The period of analysis is between 1991-2011. *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| High Probability of Default Firms | | | | |
|---|---|---|---|---|
| | Obs. | Mean | St.Error | T-Stat |
| $\Delta PD_{t,0} = \bar{PD}_{bank\_relationship,0}$ - $\bar{PD}_{bank\_relationship,\text{-}1}$ | 1,221 | 0.0125 | 0.2777 | 0.04 |
| $\Delta PD_{c,0} = \bar{PD}_{public\_debt,0}$ - $\bar{PD}_{public\_debt,\text{-}1}$ | 1,221 | 0.1621 | 0.1577 | 1.02 |
| $\Delta PD_{t,0}$ - $\Delta PD_{c,0}$ | 1,221 | -0.1495 | 0.3159 | -0.47 |
| $\Delta PD_{t,1} = \bar{PD}_{bank\_relationship,1}$ - $\bar{PD}_{bank\_relationship,\text{-}1}$ | 1,044 | -0.7892 | 0.2996 | -2.63*** |
| $\Delta PD_{c,1} = \bar{PD}_{public\_debt,1}$ - $\bar{PD}_{public\_debt,\text{-}1}$ | 1,044 | 0.3651 | 0.1751 | 2.08** |
| $\Delta PD_{t,1}$ - $\Delta PD_{c,1}$ | 1,044 | -1.1544 | 0.3331 | -3.46*** |
| $\Delta PD_{t,2} = \bar{PD}_{bank\_relationship,2}$ - $\bar{PD}_{bank\_relationship,\text{-}1}$ | 882 | -0.7868 | 0.3302 | -2.38** |
| $\Delta PD_{c,2} = \bar{PD}_{public\_debt,2}$ - $\bar{PD}_{public\_debt,\text{-}1}$ | 882 | 0.4337 | 0.2046 | 2.11** |
| $\Delta PD_{t,2}$ - $\Delta PD_{c,2}$ | 882 | -1.2205 | 0.3643 | -3.35*** |
| Low Probability of Default Firms | | | | |
| | Obs. | Mean | St.Error | T-Stat |
| $\Delta PD_{t,0} = \bar{PD}_{bank\_relationship,0}$ - $\bar{PD}_{bank\_relationship,\text{-}1}$ | 2,304 | 0.1008 | 0.0107 | 9.34*** |
| $\Delta PD_{c,0} = \bar{PD}_{public\_debt,0}$ - $\bar{PD}_{public\_debt,\text{-}1}$ | 2,304 | 0.1621 | 0.0707 | 2.29** |
| $\Delta PD_{t,0}$ - $\Delta PD_{c,0}$ | 2,304 | -0.0613 | 0.0709 | -0.86 |
| $\Delta PD_{t,1} = \bar{PD}_{bank\_relationship,1}$ - $\bar{PD}_{bank\_relationship,\text{-}1}$ | 1,848 | 0.2881 | 0.0407 | 7.06*** |
| $\Delta PD_{c,1} = \bar{PD}_{public\_debt,1}$ - $\bar{PD}_{public\_debt,\text{-}1}$ | 1,848 | 0.4798 | 0.0902 | 5.31*** |
| $\Delta PD_{t,1}$ - $\Delta PD_{c,1}$ | 1,848 | -0.1917 | 0.0981 | -1.95* |
| $\Delta PD_{t,2} = \bar{PD}_{bank\_relationship,2}$ - $\bar{PD}_{bank\_relationship,\text{-}1}$ | 1,683 | 0.5236 | 0.0731 | 7.15*** |
| $\Delta PD_{c,2} = \bar{PD}_{public\_debt,2}$ - $\bar{PD}_{public\_debt,\text{-}1}$ | 1,683 | 0.5785 | 0.0983 | 5.88*** |
| $\Delta PD_{t,2}$ - $\Delta PD_{c,2}$ | 1,683 | -0.0549 | 0.1221 | -0.44 |

## A.4 Robustness tests with alternative default risk measures:

As robustness checks, I use Altman's Z–score (Altman, 1968; Denis and Mihov, 2003) and Whited and Wu (2006)'s financial constraint index instead of Jarrow-Merton default probabilities. Altman's Z–score uses multiple discriminant analysis to predict bankruptcies. The calculation is:

$$\begin{aligned} Altman's\ z\text{–}score_{it} = 1.2 * WC/TA_{it} + 1.4 * RE/TA_{it} + 3.3 * EBIT/TA_{it} \\ +0.6 * M/B_{it} + 0.999 * NS/TA_{it} \end{aligned} \tag{A.A.6}$$

in which *WC/TA* (Working Capital/Total Assets) is the liquidity measure; *RE/TA* (Retained Earnings/Total Assets) is the cumulative profitability; *EBIT/TA* (Earnings Before Interest and Taxes/Total Assets) is the true productivity of a firm; *M/B* (Market Value of Equity/Book Value of Liabilities) measures insolvency; and *NS/TA* (Net Sales/Total Assets) is the capital turnover ratio, which measures the revenue generating ability of the assets. According to this construction, firms with higher z-score are in safety zone (>2.99) and firms with low z score are in distress (<1.81). Since the first and fourth quartiles of Altman's z–score in Table 1.1 are within the range of distressed firms (1.20) and safety zone (2.81), respectively, in terms of predicted bankruptcies, the sample is representative of both types of firms.

**Table A.10:** Second Stage Results Using Altman's Z–score

The table shows the second stage results of SFA and DEA efficiencies and TFP as dependent variable for the subsample of firms defined according to fourth (low PD) and first quartile (high PD) of Altman's Z–score (PD) and below and above median baseline SFA efficiency, DEA efficiency and TFP, respectively. The estimation is done by fractional response regression model with probit for SFA and DEA efficiency scores and semi-elasticities ($dy/ex$) are reported. TFP estimations are done by 2SLS. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Low PD | High PD | Low Eff | High Eff |
|---|---|---|---|---|
| Panel A: SFA Efficiency | | | | |
| *Rel_dummy (instrumented)* | 0.003*** | 0.018*** | 0.012*** | 0.001** |
| | (2.91) | (4.34) | (6.51) | (2.08) |
| *Lambda* | 0.022*** | 0.113*** | 0.086*** | 0.004* |
| | (2.72) | (3.75) | (5.93) | (1.74) |
| *Other controls* | YES | YES | YES | YES |
| *N* | 6,626 | 4,182 | 11,510 | 12,201 |
| Panel B: DEA Efficiency | | | | |
| *Rel_dummy (instrumented)* | -0.002 | 0.031*** | 0.018*** | -0.006* |
| | (0.43) | (3.62) | (5.50) | (1.88) |
| *Lambda* | -0.019 | 0.169*** | 0.116*** | -0.031** |
| | (0.71) | (3.07) | (5.04) | (2.21) |
| *Other controls* | YES | YES | YES | YES |
| *N* | 6,626 | 4,182 | 11,679 | 12,032 |
| Panel C: TFP | | | | |
| *Rel_dummy (instrumented)* | 0.089 | 0.366** | 0.142** | 0.071* |
| | (1.33) | (2.38) | (2.30) | (1.66) |
| *Lambda* | 0.110 | 0.394** | 0.193** | 0.093* |
| | (1.37) | (2.00) | (2.40) | (1.76) |
| *Other controls* | YES | YES | YES | YES |
| *N* | 5,014 | 1,955 | 8,259 | 8,069 |

As a second robustness check I use Whited and Wu (2006)'s financial constraint index constructed via generalized method of moments estimation of an investment Euler equation. The calculated parameters are as follows:

$$\begin{aligned} Financial\ Constraint_{it} = &-0.091 * CF_{it} - 0.062 * DIVPOS_{it} + 0.021 * TLTD_{it} \\ &-0.044 * LNTA_{it} + 0.102 * ISG_{it} - 0.035 * SG_{it} \end{aligned} \tag{A.A.7}$$

in which *CF* is the ratio of cash flow to total assets; *DIVPOS* is an indicator that takes the value of one if the firm pays cash dividends; *TLTD* is the ratio of the long-term debt to total assets; *LNTA* is the natural log of total assets, *ISG* is the firm's industry sales growth; *SG* is firm sales growth. Firms with higher scores in this index are more financially constrained.

**Table A.11:** Second Stage Results Using Whited–Wu Financial Constraint Index

The table shows the second stage results of SFA and DEA efficiencies and TFP as dependent variable for the subsample of firms defined according to first (low PD) and fourth quartile (high PD) of Whited-Wu financial constraint index (PD) and below and above median baseline SFA efficiency, DEA efficiency and TFP, respectively. The estimation is done by fractional response regression model with probit for SFA and DEA efficiency scores and semi-elasticities ($dy/ex$) are reported. TFP estimations are done by 2SLS. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | Low PD | High PD | Low Eff | High Eff |
|---|---|---|---|---|
| Panel A: SFA Efficiency | | | | |
| *Rel_dummy (instrumented)* | 0.004* | 0.006*** | 0.012*** | 0.001** |
| | (1.90) | (4.19) | (6.42) | (2.12) |
| *Lambda* | 0.010* | 0.186*** | 0.085*** | 0.004* |
| | (1.65) | (4.04) | (5.84) | (1.77) |
| *Other controls* | YES | YES | YES | YES |
| *N* | 8,842 | 3,134 | 11,679 | 12,032 |
| Panel B: DEA Efficiency | | | | |
| *Rel_dummy (instrumented)* | 0.015** | 0.001 | 0.018*** | -0.006* |
| | (2.32) | (0.54) | (5.36) | (1.90) |
| *Lambda* | 0.033* | 0.068 | 0.112*** | -0.031** |
| | (1.65) | (0.85) | (4.91) | (2.23) |
| *Other controls* | YES | YES | YES | YES |
| *N* | 8,842 | 3,134 | 11,510 | 12,201 |
| Panel C: TFP | | | | |
| *Rel_dummy (instrumented)* | 0.162*** | 0.669* | 0.147** | 0.073* |
| | (3.26) | (1.71) | (2.38) | (1.70) |
| *Lambda* | 0.222*** | 0.590 | 0.198** | 0.096* |
| | (3.45) | (1.64) | (2.46) | (1.81) |
| *Other controls* | YES | YES | YES | YES |
| *N* | 6,919 | 1,418 | 8,259 | 8,069 |

## A.5 Robustness tests with alternative relationship bank measures:

As robustness tests, I use alternative relationship bank measures and estimate the whole sample results using all three efficiency measures. I replace *Rel_dummy* variable in the previous estimations with *Rel_intensity* and *Rel_number* as alternative relationship bank definitions. Following Bharath et al. (2011) I define *Rel_intensity* as the amount of loans by bank $m$ to borrower $i$ in the last 5 years scaled by the total amount of loans by borrower $i$ in the last 5 years and *Rel_number* as the number of loans by bank $m$ to borrower $i$ in the last 5 years scaled by the total number of loans by borrower $i$ in the last 5 years. The results in Table A.12 below present evidence that alternative measures also have positive and statistically significant effect on borrower efficiency.

**Table A.12:** Second Stage Results using Alternative Relationship Banking Definitions

The table shows the second stage results of SFA and DEA efficiencies and TFP using *Rel_intensity* and *Rel_number* as alternative relationship bank definitions. *Rel_intensity* is defined as the amount of loans by bank $m$ to borrower $i$ in the last 5 years scaled by the total amount of loans by borrower $i$ in the last 5 years. *Rel_number* is defined as the number of loans by bank $m$ to borrower $i$ in the last 5 years scaled by the total number of loans by borrower $i$ in the last 5 years. The estimation is done by fractional response regression model with probit for SFA and DEA efficiency scores and semi-elasticities ($dy/ex$) are reported. TFP estimations are done by 2SLS. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | (1) | (2) |
|---|---|---|
| Panel A: SFA Efficiency | | |
| *Rel_intensity (instrumented)* | 0.007** | |
| | (2.01) | |
| *Rel_number (instrumented)* | | 0.007** |
| | | (1.99) |
| *Lambda* | 0.024 | 0.025 |
| | (1.34) | (1.35) |
| *Other controls* | YES | YES |
| *N* | 23,711 | 23,711 |
| Panel B: DEA Efficiency | | |
| *Rel_intensity (instrumented)* | 0.007*** | |
| | (6.42) | |
| *Rel_number (instrumented)* | | 0.007*** |
| | | (6.33) |
| *Lambda* | 0.040*** | 0.041*** |
| | (5.68) | (5.62) |
| *Other controls* | YES | YES |
| *N* | 23,711 | 23,711 |
| Panel C: TFP | | |
| *Rel_intensity (instrumented)* | 0.164*** | |
| | (3.10) | |
| *Rel_number (instrumented)* | | 0.181*** |
| | | (3.09) |
| *Lambda* | 0.166*** | 0.173*** |
| | (3.13) | (3.12) |
| *Other controls* | YES | YES |
| *N* | 16,328 | 16,328 |

## A.6 Placebo Tests with Pseudo Relationship dummy variable:

I estimate an additional robustness test, in which I generate a $Pseudo\_Rel$ dummy variable, which includes the same number of relationship bank loans as in *Rel_dummy* but in random ordering. I estimate the first and second stage results using the generated residuals and estimated probabilities from equations (1.3) and (1.4). The results in Table A.13 below show that the instrument in the first stage does not explain the $Pseudo\_Rel$ variable, as expected. In the second stage instrumented $Pseudo\_Rel$ variable has a spurious negative and statistically significant effect on SFA efficiency and statistically insignificant effect on DEA efficiency and TFP.

**Table A.13:** Placebo Regressions with *Pseudo_Rel* dummy variable

The table shows the first and second stage results using *Pseudo_Rel* dummy variable. First three columns are first stage results using the *Pseudo_Rel* as the dependent variable and probabilities estimated in equation (1.4) as the instruments. SFA and DEA efficiencies and TFP are the dependent variables in columns 3, 4 and 5, respectively. The estimation is done by fractional response regression model with probit for SFA and DEA efficiency scores and semi-elasticities ($dy/ex$) are reported. TFP estimations are done by 2SLS. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| | First Stage Results | | | Second Stage Results | | |
|---|---|---|---|---|---|---|
| | Pseudo_Rel | Pseudo_Rel | Pseudo_Rel | SFA Efficiency | DEA Efficiency | TFP |
| *Probability of Rel_dummy (instrument)* | -0.040 | -0.039 | -0.062* | | | |
| | (1.37) | (1.34) | (1.73) | | | |
| *Pseudo_Rel (instrumented)* | | | | -4.904*** | -0.987 | -0.957 |
| | | | | (6.92) | (0.98) | (1.33) |
| *ROA* | -0.064* | -0.046 | -0.012 | 0.085 | 0.242*** | -0.107 |
| | (1.91) | (1.40) | (0.19) | (1.35) | (3.36) | (1.15) |
| *Efficiency* | 0.073 | -0.005 | -0.027* | 1.901*** | 2.144*** | 0.759*** |
| | (1.25) | (0.22) | (1.96) | (21.11) | (44.78) | (28.53) |
| *Size* | -0.003 | 0.001 | -0.001 | 0.082*** | -0.160*** | 0.004 |
| | (0.36) | (0.17) | (0.05) | (8.42) | (12.01) | (0.28) |
| *Size*$^2$ | -0.000 | -0.000 | 0.000 | 0.002*** | 0.018*** | 0.001 |
| | (0.07) | (0.34) | (0.10) | (2.82) | (14.66) | (1.01) |
| *Cash/TA* | -0.057** | -0.056** | -0.065* | -0.277*** | 0.116** | -0.021 |
| | (2.05) | (2.02) | (1.77) | (6.60) | (2.01) | (0.36) |
| *M/B* | 0.002 | 0.002 | 0.005 | 0.034*** | 0.021*** | 0.041*** |
| | (0.54) | (0.41) | (0.89) | (7.34) | (3.41) | (4.40) |
| *JM prob. of default* | 0.001 | 0.001 | -0.000 | -0.002 | 0.006*** | -0.001 |
| | (0.49) | (0.43) | (0.01) | (1.14) | (2.92) | (0.31) |
| *Tangibility* | 0.036* | 0.035* | -0.020 | 0.227*** | 0.122** | -0.001 |
| | (1.94) | (1.91) | (0.81) | (6.55) | (2.47) | (0.04) |
| *Interest coverage* | 0.000 | 0.000 | -0.000 | 0.000*** | -0.000 | -0.000 |
| | (0.18) | (0.22) | (0.47) | (3.41) | (0.39) | (1.40) |
| *Capex/TA* | 0.063 | 0.058 | 0.179* | 0.332*** | -0.109 | 0.041 |
| | (0.81) | (0.74) | (1.68) | (3.30) | (0.80) | (0.20) |
| *Leverage* | -0.022 | -0.021 | -0.015 | -0.132*** | -0.078** | -0.024 |
| | (1.16) | (1.12) | (0.60) | (5.42) | (2.28) | (0.74) |
| *Firm age* | 0.000 | 0.000 | -0.000 | -0.001** | -0.000 | -0.000 |
| | (0.39) | (0.25) | (0.28) | (2.56) | (0.41) | (0.53) |
| *Rating dummy* | 0.019** | 0.019** | 0.025** | 0.120*** | -0.002 | 0.028* |
| | (2.35) | (2.32) | (2.55) | (9.31) | (0.11) | (1.65) |
| *Lambda* | -0.000 | -0.000 | -0.008 | -0.028*** | -0.048*** | -0.008 |
| | (0.02) | (0.01) | (0.58) | (2.77) | (3.40) | (0.43) |
| *N* | 21,527 | 21,527 | 14,520 | 27,337 | 27,337 | 14,203 |

## A.7 Analysis of survivorship bias:

I analyze the effect of existence of relationship banking on efficiency for firms that have gap years or drop out of the sample completely. I define $Dropped\_dummy$ variable equal to 1 if the firm dropped out of the sample for any reason (reported under *dlrsn* variable in Compustat) and 0 otherwise. $Dropped * Rel\_dummy$ is the interaction of first-step estimated probabilities of existence of relationship and $Dropped\_dummy$ variable. The results in Table A.14 below show that firms that dropped out of the sample have 0.018 lower SFA efficiency in the year of borrowing (0.054 lower DEA efficiency and 0.036 lower TFP). Yet, firms that dropped out of the sample did not experience statistically significant differences in their efficiencies as a result of existence of relationship banking ($Dropped * Rel\_dummy$) in the years they existed in the sample period. Therefore these results provide evidence that the results drawn in this study are not driven by survivorship bias.

**Table A.14:** Analysis of survivorship bias

The dependent variable is the SFA efficiency score for the first three columns, DEA Efficiency score for the second three columns and TFP for the last three columns. The estimation is done by fractional response regression model with probit for SFA and DEA efficiency scores and semi-elasticities ($dy/ex$) are reported. TFP estimations is done by 2SLS. Dropped_dummy is equal to 1 if the firm dropped out of the sample within the sample period for any reason (reported under dlrsn variable in Compustat) and 0 if it survived. $Dropped * Rel_dummy$ is the interaction of first-step estimated probabilities of existence of relationship and Dropped_dummy. In the period (t+1) analysis of one-period forward dependent variable is used and in (t+2) analysis two-period forward dependent variable is used. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| Panel A: SFA Efficiency | | | |
|---|---|---|---|
| | *t* | *t+1* | *t+2* |
| $Rel\_dummy_t$ (instrumented) | 0.007*** | 0.004*** | 0.002 |
| | (6.66) | (3.50) | (1.38) |
| $Dropped\_dummy_t$ | -0.001*** | -0.001** | -0.002*** |
| | (2.74) | (2.21) | (2.68) |
| $Dropped * Rel\_dummy_t$ | 0.000 | 0.000 | 0.000 |
| | (1.40) | (0.09) | (0.44) |
| *Lambda* | 0.043*** | 0.025*** | 0.008 |
| | (6.16) | (3.09) | (0.94) |
| *N* | 23,711 | 20,152 | 17,335 |
| Panel B: DEA Efficiency | | | |
| $Rel\_dummy_t$ (instrumented) | 0.006* | 0.005 | 0.001 |
| | (1.92) | (1.15) | (0.11) |
| $Dropped\_dummy_t$ | -0.006*** | -0.007*** | -0.007*** |
| | (6.11) | (5.20) | (4.84) |
| $Dropped * Rel\_dummy_t$ | 0.001** | 0.000 | -0.000 |
| | (2.27) | (0.35) | (0.00) |
| *Lambda* | 0.028 | 0.022 | -0.004 |
| | (1.57) | (1.02) | (0.17) |
| *N* | 23,711 | 20,152 | 17,335 |
| Panel C: TFP | | | |
| $Rel\_dummy_t$ (instrumented) | 0.135*** | 0.089* | 0.070 |
| | (3.30) | (1.80) | (1.17) |
| $Dropped\_dummy_t$ | -0.036*** | -0.042*** | -0.046*** |
| | (5.15) | (4.47) | (4.09) |
| $Dropped * Rel\_dummy_t$ | 0.020 | 0.004 | -0.007 |
| | (1.32) | (0.20) | (0.32) |
| *Lambda* | 0.180*** | 0.094 | 0.062 |
| | (3.50) | (1.51) | (0.82) |
| *N* | 16,328 | 13,808 | 11,793 |
| $R^2$ | 0.53 | 0.46 | 0.43 |

## A.8 Breakdown of loans by the top 20 lead lenders:

One possible concern about the existence of relationship banking on firm efficiency can be that several big lead lenders might be the lenders of the majority of the loans in the sample. In order to address this concern, I look at the breakdown of the percentage of loans lent by the top 20 lead lenders in the sample. Table A.15 shows that Bank of America lends 17.51% of the relationship loans and top 5 banks lend 33.41% of the relationship loans. Table A.16 below presents results for second stage analysis excluding the top 5 lead lenders from the sample. The results are robust, which suggest that they are not driven by a few, big lead lenders.

**Table A.15:** Breakdown of Loans by Lead Lenders

| Lender | Number of relationship loans | Percent | Cumulative |
|---|---|---|---|
| Bank of America | 1,473 | 17.51 | 17.51 |
| Citibank | 440 | 5.23 | 22.74 |
| SunTrust Bank | 321 | 3.82 | 26.56 |
| Chase Manhattan Bank | 289 | 3.44 | 30.00 |
| JP Morgan Chase Bank NA | 287 | 3.41 | 33.41 |
| Bank of Nova Scotia | 205 | 2.44 | 35.85 |
| BNP Paribas SA | 199 | 2.37 | 38.22 |
| JP Morgan | 195 | 2.32 | 40.54 |
| Morgan Guaranty Trust | 152 | 1.81 | 42.35 |
| Wachovia Bank | 148 | 1.76 | 44.11 |
| US Bank NA | 147 | 1.75 | 45.86 |
| Deutsche Bank AG | 139 | 1.65 | 47.51 |
| ABN AMRO Bank NV [RBS] | 138 | 1.64 | 49.15 |
| Bank of New York | 137 | 1.63 | 50.78 |
| BANK ONE Corp | 123 | 1.46 | 52.24 |
| PNC Bank | 120 | 1.43 | 53.67 |
| General Electric Capital Corp | 113 | 1.34 | 55.01 |
| Credit Suisse First Boston | 101 | 1.2 | 56.21 |
| Wells Fargo Bank | 95 | 1.13 | 57.34 |
| Barclays Bank Plc | 90 | 1.07 | 58.41 |

## **Table A.16:** Second Stage Results Excluding Top 5 Lead Lenders

The table shows the semi-elasticities ($dy/ex$) of the second stage results of two-stage model using fractional response regression and SFA efficiency as dependent variable in Panel A and DEA efficiency as dependent variable in Panel B. Panel C shows the second stage results of 2SLS using TFP estimate as dependent variable. The period of analysis is between 1991-2011. The control variables are the average values of previous 5 years. All regressions include industry and year fixed effects. The standard errors are bootstrapped and clustered at the firm level. T-stats are in parenthesis and *, **, *** denote 10%, 5% and 1% significance levels, respectively.

| Panel A: SFA Efficiency | | | | | |
|---|---|---|---|---|---|
| | All sample | Low PD subsample | High PD subsample | Low Efficiency subsample | High Efficiency subsample |
| $Rel\_dummy_t$ (instrumented) | 0.006*** | 0.005*** | 0.009*** | 0.009*** | 0.001** |
| | (6.41) | (3.89) | (4.48) | (6.03) | (2.16) |
| *Lambda* | 0.042*** | 0.027*** | 0.097*** | 0.081*** | 0.005* |
| | (5.49) | (3.45) | (4.03) | (5.30) | (1.82) |
| $N$ | 21,697 | 6,076 | 4,750 | 11,104 | 10,593 |
| **Panel B: DEA Efficiency** | | | | | |
| | All sample | Low PD subsample | High PD subsample | Low Efficiency subsample | High Efficiency subsample |
| $Rel\_dummy_t$ (instrumented) | 0.152** | 0.034 | 0.548*** | 0.296*** | -0.145* |
| | (2.31) | (0.30) | (4.11) | (4.84) | (1.66) |
| *Lambda* | 0.143* | 0.025 | 0.652*** | 0.352*** | -0.208* |
| | (1.76) | (0.18) | (3.93) | (4.55) | (1.93) |
| $N$ | 21,697 | 6,076 | 4,750 | 10,868 | 10,829 |
| **Panel C: TFP** | | | | | |
| | All sample | Low PD subsample | High PD subsample | Low TFP subsample | High TFP subsample |
| $Rel\_dummy_t$ (instrumented) | 0.119*** | -0.012 | 0.567*** | 0.128** | 0.053 |
| | (2.73) | (0.20) | (3.42) | (2.00) | (1.15) |
| *Lambda* | 0.130*** | -0.021 | 0.545*** | 0.144** | 0.063 |
| | (2.75) | (0.32) | (3.32) | (2.01) | (1.29) |
| $R^2$ | 0.53 | 0.68 | 0.27 | 0.18 | 0.55 |
| $N$ | 14,797 | 4,661 | 2,670 | 7,730 | 7,067 |

# Appendix B

# Appendix for Chapter 2

**Table B.1:** Tobin's Q regressions on components of OC (with $\delta = 0$)

The dependent variable in all regressions is Tobin's Q, defined as the market value of equity plus the book values of debt and preferred equity, all divided by the book value of assets. We calculate HC_OC with no depreciation of human capital ($\delta = 0$). Regression in columns (1) is OLS estimation with industry and year fixed effects. Other estimations include firm and year fixed effects. Column (3) includes lagged dependent variable as a control. All independent variables are one period lagged. In all estimations the standard errors are clustered at the firm level. The sample period is 1992 to 2015. *, ** and *** indicate 10%, 5% and 1% significance levels, respectively.

| Dependent variable: M/B | (1) | (2) | (3) |
|---|---|---|---|
| $HC\_OC_{t-1}$ | 5.761*** | 7.521*** | 4.158*** |
| | (4.79) | (4.37) | (4.17) |
| $Residual\_OC_{t-1}$ | 0.018 | 0.090 | 0.106* |
| | (0.36) | (1.00) | (1.83) |
| $M/B_{t-1}$ | | | 0.540*** |
| | | | (17.89) |
| $Institutional\,Ownership_{t-1}$ | -0.013 | -0.157 | -0.218*** |
| | (0.13) | (1.63) | (2.95) |
| $Managerial\,Ownership_{t-1}$ | 0.009 | 3.046** | 1.864* |
| | (0.01) | (1.97) | (1.83) |
| $Managerial\,Ownership^2_{t-1}$ | -0.457 | -6.319 | -4.339* |
| | (0.14) | (1.54) | (1.67) |
| $Size_{t-1}(Ind.med.adjusted)$ | -0.004 | -0.285*** | -0.144*** |
| | (0.23) | (2.91) | (2.74) |
| $Tangibility_{t-1}$ | -0.399** | -0.590** | -0.143 |
| | (2.53) | (2.03) | (0.84) |
| $Leverage_{t-1}$ | -1.633*** | -0.947*** | -0.117 |
| | (10.71) | (6.62) | (1.28) |
| $ROA_{t-1}$ | 4.067*** | 2.276*** | 0.461** |
| | (6.55) | (4.01) | (2.25) |
| $Firm\,age_{t-1}$ | -0.003** | -0.008 | -0.006* |
| | (2.36) | (1.55) | (1.71) |
| $Capex/TA_{t-1}$ | 0.989** | 0.352 | -0.403 |
| | (2.28) | (0.90) | (1.40) |
| $Intercept$ | 1.907*** | 1.753*** | 0.867*** |
| | (7.94) | (6.80) | (4.80) |
| $Firm\ Fixed\ Effects$ | NO | YES | YES |
| $Industry\ Fixed\ Effects$ | YES | NO | NO |
| $Year\ Fixed\ Effects$ | YES | YES | YES |
| $R^2$ | 0.38 | 0.19 | 0.43 |
| $N$ | 9,052 | 9,052 | 9,052 |

**Table B.2:** Tobin's Q regressions on components of OC

The dependent variable in all regressions is Tobin's Q, defined as the market value of equity plus the book values of debt and preferred equity, all divided by the book value of assets. Residual_OC2 is the residual of regression of OC on HC_OC. Regression in columns (1) is OLS estimation with industry and year fixed effects. Other estimations include firm and year fixed effects. Column (3) includes lagged dependent variable as a control. All independent variables are one period lagged. In all estimations the standard errors are clustered at the firm level. The sample period is 1992 to 2015. *, ** and *** indicate 10%, 5% and 1% significance levels, respectively.

| Dependent variable: M/B | (1) | (2) | (3) |
|---|---|---|---|
| $HC\_OC_{t-1}$ | 5.875*** | 8.208*** | 4.931*** |
| | (5.25) | (5.54) | (5.72) |
| $Residual\_OC_{t-1}$ | 0.022 | 0.015 | 0.066 |
| | (0.42) | (0.16) | (1.09) |
| $M/B_{t-1}$ | | | 0.540*** |
| | | | (17.88) |
| $Institutional\,Ownership_{t-1}$ | -0.011 | -0.162* | -0.221*** |
| | (0.11) | (1.69) | (3.00) |
| $Managerial\,Ownership_{t-1}$ | 0.005 | 3.037** | 1.840* |
| | (0.00) | (1.97) | (1.82) |
| $Managerial\,Ownership^2_{t-1}$ | -0.435 | -6.264 | -4.256* |
| | (0.13) | (1.54) | (1.65) |
| $Size_{t-1}(Ind.med.adjusted)$ | -0.004 | -0.293*** | -0.148*** |
| | (0.23) | (2.98) | (2.80) |
| $Tangibility_{t-1}$ | -0.401** | -0.558* | -0.127 |
| | (2.53) | (1.93) | (0.75) |
| $Leverage_{t-1}$ | -1.629*** | -0.954*** | -0.119 |
| | (10.59) | (6.69) | (1.31) |
| $ROA_{t-1}$ | 4.068*** | 2.266*** | 0.457** |
| | (6.56) | (4.00) | (2.22) |
| $Firm\,age_{t-1}$ | -0.003** | -0.011** | -0.009*** |
| | (2.36) | (2.38) | (2.93) |
| $Capex/TA_{t-1}$ | 0.994** | 0.361 | -0.399 |
| | (2.29) | (0.92) | (1.38) |
| $Intercept$ | 1.920*** | 1.867*** | 1.006*** |
| | (8.08) | (8.13) | (6.49) |
| $Firm\ Fixed\ Effects$ | NO | YES | YES |
| $Industry\ Fixed\ Effects$ | YES | NO | NO |
| $Year\ Fixed\ Effects$ | YES | YES | YES |
| $R^2$ | 0.38 | 0.19 | 0.43 |
| $N$ | 9,054 | 9,054 | 9,054 |

**Table B.3:** Asset Pricing: Five portfolios sorted on HC_OC (equal-weighted portfolios)

This table shows asset-pricing estimations for five portfolios sorted on HC_OC over book value of assets relative to their industry peers within each year. In Panel A we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio. In Panel B we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and high-minus-low HC_OC factor (HMLHC). In Panel C we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and Fama and French (1993) SMB and HML factors. In Panel D we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio, Fama and French (1993) SMB and HML factors and Carhart (1997) MOM factor. Data on SMB, HML, and MOM are from Kenneth French's website. The sample period is June 1992 to December 2015. All portfolio returns correspond to equal-weighted returns by firm market capitalization.

| Portfolio | Low | 2 | 3 | 4 | High | High-Low |
|---|---|---|---|---|---|---|
| | | | Panel A. CAPM | | | |
| $\alpha$ | 0.165 | 0.181 | 0.213 | 0.310* | 0.406** | 0.241 |
| | (1.25) | (1.18) | (1.34) | (1.91) | (2.38) | (1.37) |
| $\beta_{MKT}$ | 0.953*** | 1.009*** | 1.021*** | 1.016*** | 1.058*** | 0.105** |
| | (24.36) | (20.45) | (21.20) | (21.99) | (24.32) | (2.58) |
| $R^2$ | 0.79 | 0.76 | 0.76 | 0.74 | 0.75 | 0.02 |
| | | | Panel B. two-factor model | | | |
| $\alpha$ | 0.246** | 0.202 | 0.195 | 0.242 | 0.246** | |
| | (2.03) | (1.32) | (1.22) | (1.58) | (2.03) | |
| $\beta_{MKT}$ | 0.988*** | 1.018*** | 1.013*** | 0.986*** | 0.988*** | |
| | (27.71) | (21.13) | (20.98) | (21.66) | (27.71) | |
| $\beta_{HMLHC}$ | -0.337*** | -0.088 | 0.071 | 0.284*** | 0.663*** | |
| | (5.70) | (1.17) | (0.93) | (3.58) | (11.21) | |
| $R^2$ | 0.84 | 0.77 | 0.76 | 0.77 | 0.87 | |
| | | | Panel C. three-factor model | | | |
| $\alpha$ | 0.058 | 0.034 | 0.074 | 0.179 | 0.304** | 0.246** |
| | (0.52) | (0.27) | (0.57) | (1.47) | (2.47) | (2.00) |
| $\beta_{MKT}$ | 1.015*** | 1.043*** | 1.027*** | 0.980*** | 0.988*** | -0.027 |
| | (33.23) | (29.41) | (25.86) | (28.84) | (27.22) | (0.89) |
| $\beta_{SMB}$ | 0.018 | 0.266*** | 0.365*** | 0.532*** | 0.606*** | 0.588*** |
| | (0.36) | (4.74) | (5.35) | (8.87) | (8.62) | (10.15) |
| $\beta_{HML}$ | 0.397*** | 0.494*** | 0.438*** | 0.372*** | 0.249*** | -0.148*** |
| | (7.30) | (7.27) | (6.86) | (5.70) | (3.80) | (2.60) |
| $R^2$ | 0.86 | 0.85 | 0.85 | 0.86 | 0.87 | 0.54 |
| | | | Panel D. four-factor model | | | |
| $\alpha$ | 0.150 | 0.143 | 0.160 | 0.284** | 0.340*** | 0.190 |
| | (1.40) | (1.20) | (1.24) | (2.40) | (2.68) | (1.49) |
| $\beta_{MKT}$ | 0.969*** | 0.988*** | 0.984*** | 0.928*** | 0.970*** | 0.001 |
| | (31.41) | (28.78) | (24.42) | (28.07) | (24.98) | (0.03) |
| $\beta_{SMB}$ | 0.034 | 0.285*** | 0.380*** | 0.550*** | 0.612*** | 0.578*** |
| | (0.84) | (6.42) | (6.33) | (11.28) | (9.17) | (9.93) |
| $\beta_{HML}$ | 0.357*** | 0.446*** | 0.401*** | 0.326*** | 0.233*** | -0.124** |
| | (6.61) | (6.89) | (6.61) | (5.89) | (3.49) | (2.18) |
| $\beta_{MOM}$ | -0.116*** | -0.138*** | -0.108*** | -0.132*** | -0.046 | 0.071** |
| | (4.04) | (4.41) | (3.63) | (4.19) | (1.45) | (2.18) |
| $R^2$ | 0.87 | 0.87 | 0.86 | 0.87 | 0.87 | 0.55 |

**Table B.4:** Asset Pricing: Five portfolios sorted on Residual_OC (equal-weighted portfolios)

This table shows asset-pricing estimations for five portfolios sorted on Residual_OC over book value of assets relative to their industry peers within each year. In Panel A we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio. In Panel B we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and high-minus-low Residual_OC factor (HMLRes). In Panel C we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and Fama and French (1993) SMB and HML factors. In Panel D we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio, Fama and French (1993) SMB and HML factors and Carhart (1997) MOM factor. Data on SMB, HML, and MOM are from Kenneth French's website. The sample period is June 1992 to December 2015. All portfolio returns correspond to equal-weighted returns by firm market capitalization.

| Portfolio | Low | 2 | 3 | 4 | High | High-Low |
|---|---|---|---|---|---|---|
| | | | Panel A: CAPM | | | |
| $\alpha$ | 0.033 | 0.102 | 0.282** | 0.436*** | 0.431*** | 0.399*** |
| | (0.20) | (0.67) | (2.02) | (3.36) | (2.84) | (3.17) |
| $\beta_{MKT}$ | 1.077*** | 1.021*** | 1.021*** | 0.967*** | 0.949*** | -0.127*** |
| | (21.22) | (22.86) | (24.60) | (26.13) | (21.52) | (3.95) |
| $R^2$ | 0.75 | 0.77 | 0.81 | 0.81 | 0.75 | 0.07 |
| | | | Panel B: two-factor model | | | |
| $\alpha$ | 0.297** | 0.227 | 0.350** | 0.437*** | 0.297** | |
| | (2.04) | (1.53) | (2.54) | (3.30) | (2.04) | |
| $\beta_{MKT}$ | 0.992*** | 0.981*** | 1.000*** | 0.967*** | 0.992*** | |
| | (22.05) | (22.01) | (23.89) | (25.53) | (22.05) | |
| $\beta_{HMLRES}$ | -0.663*** | -0.314*** | -0.171** | -0.002 | 0.337*** | |
| | (8.27) | (3.41) | (2.34) | (0.03) | (4.21) | |
| $R^2$ | 0.82 | 0.79 | 0.81 | 0.81 | 0.77 | |
| | | | Panel C: three-factor model | | | |
| $\alpha$ | -0.106 | -0.025 | 0.171 | 0.326*** | 0.294*** | 0.401*** |
| | (0.74) | (0.19) | (1.49) | (3.17) | (2.68) | (3.22) |
| $\beta_{MKT}$ | 1.093*** | 1.034*** | 1.019*** | 0.958*** | 0.933*** | -0.160*** |
| | (25.45) | (28.18) | (30.64) | (33.19) | (29.12) | (4.69) |
| $\beta_{SMB}$ | 0.321*** | 0.302*** | 0.326*** | 0.353*** | 0.465*** | 0.144*** |
| | (4.85) | (4.38) | (5.56) | (7.38) | (8.52) | (3.06) |
| $\beta_{HML}$ | 0.450*** | 0.407*** | 0.341*** | 0.333*** | 0.411*** | -0.040 |
| | (6.42) | (5.89) | (5.77) | (6.31) | (7.24) | (0.86) |
| $R^2$ | 0.83 | 0.84 | 0.87 | 0.88 | 0.87 | 0.13 |
| | | | Panel D: four-factor model | | | |
| $\alpha$ | 0.001 | 0.078 | 0.254** | 0.396*** | 0.356*** | 0.355*** |
| | (0.01) | (0.62) | (2.28) | (3.79) | (3.16) | (2.80) |
| $\beta_{MKT}$ | 1.039*** | 0.983*** | 0.977*** | 0.923*** | 0.902*** | -0.137*** |
| | (23.81) | (26.72) | (29.03) | (30.66) | (27.87) | (3.93) |
| $\beta_{SMB}$ | 0.340*** | 0.320*** | 0.341*** | 0.365*** | 0.476*** | 0.136*** |
| | (5.91) | (5.51) | (6.85) | (8.59) | (9.94) | (2.86) |
| $\beta_{HML}$ | 0.404*** | 0.363*** | 0.306*** | 0.303*** | 0.384*** | -0.020 |
| | (6.08) | (5.41) | (5.38) | (5.78) | (7.22) | (0.43) |
| $\beta_{MOM}$ | -0.135*** | -0.129*** | -0.104*** | -0.087*** | -0.077*** | 0.058** |
| | (4.09) | (3.85) | (3.92) | (3.29) | (2.97) | (2.07) |
| $R^2$ | 0.84 | 0.85 | 0.88 | 0.89 | 0.87 | 0.14 |

**Table B.5:** Asset Pricing: Q-factor and five-factor results for portfolios sorted on HC_OC

This table shows asset-pricing estimations for five portfolios sorted on HC_OC over book value of assets relative to their industry peers within each year. In Panel A we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and Hou et al. (2015) SMB, RMW and CMA factors. In Panel B we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio, Fama and French (2015) SMB, HML, RMW and CMA factors. Data on SMB, HML, RMW and CMA are from Kenneth French's website. The sample period is June 1992 to December 2015. All portfolio returns correspond to value-weighted returns.

| Portfolio | Low | 2 | 3 | 4 | High | High-Low |
|---|---|---|---|---|---|---|
| | | | Panel A: Q-factor model | | | |
| $\alpha$ | 0.161 | 0.109 | -0.044 | 0.058 | 0.218 | 0.056 |
| | (1.42) | (0.82) | (0.29) | (0.35) | (1.00) | (0.23) |
| $\beta_{MKT}$ | 0.979*** | 0.995*** | 1.053*** | 1.009*** | 1.054*** | 0.075 |
| | (32.07) | (24.81) | (20.66) | (21.12) | (17.98) | (1.19) |
| $\beta_{SMB}$ | -0.243*** | -0.040 | 0.240*** | 0.381*** | 0.431*** | 0.674*** |
| | (5.57) | (0.60) | (4.90) | (5.38) | (5.23) | (8.32) |
| $\beta_{RMW}$ | 0.121 | 0.292*** | 0.339*** | 0.166* | -0.090 | -0.212 |
| | (1.62) | (3.99) | (5.18) | (1.90) | (0.63) | (1.37) |
| $\beta_{CMA}$ | -0.020 | 0.167* | -0.036 | -0.112 | -0.597*** | -0.577*** |
| | (0.22) | (1.96) | (0.48) | (1.11) | (4.63) | (3.66) |
| $R^2$ | 0.86 | 0.79 | 0.80 | 0.77 | 0.80 | 0.50 |
| | | | Panel B: five-factor model | | | |
| $\alpha$ | 0.133 | 0.092 | -0.014 | 0.077 | 0.202 | 0.069 |
| | (1.16) | (0.72) | (0.09) | (0.46) | (0.97) | (0.29) |
| $\beta_{MKT}$ | 0.992*** | 1.004*** | 1.039*** | 0.999*** | 1.061*** | 0.069 |
| | (32.49) | (26.16) | (21.13) | (21.92) | (18.12) | (1.12) |
| $\beta_{SMB}$ | -0.248*** | -0.043 | 0.245*** | 0.384*** | 0.429*** | 0.676*** |
| | (5.57) | (0.65) | (5.08) | (5.43) | (5.24) | (8.46) |
| $\beta_{HML}$ | -0.095* | -0.058 | 0.100 | 0.065 | -0.051 | 0.043 |
| | (1.81) | (0.78) | (1.27) | (0.70) | (0.50) | (0.38) |
| $\beta_{RMW}$ | 0.164** | 0.318*** | 0.295*** | 0.136* | -0.067 | -0.231 |
| | (2.33) | (4.49) | (4.22) | (1.67) | (0.50) | (1.55) |
| $\beta_{CMA}$ | 0.066 | 0.219** | -0.126 | -0.171 | -0.550*** | -0.616*** |
| | (0.69) | (2.26) | (1.29) | (1.38) | (3.67) | (3.66) |
| $R^2$ | 0.86 | 0.79 | 0.81 | 0.77 | 0.80 | 0.50 |

**Table B.6:** Asset Pricing: Q-factor and five-factor results for portfolios sorted on Residual_OC

This table shows asset-pricing estimations for five portfolios sorted on Residual_OC over book value of assets relative to their industry peers within each year. In Panel A we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and Hou et al. (2015) SMB, RMW and CMA factors. In Panel B we report portfolio alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio, Fama and French (2015) SMB, HML, RMW and CMA factors. Data on SMB, HML, RMW and CMA are from Kenneth French's website. The sample period is June 1992 to December 2015. All portfolio returns correspond to value-weighted returns.

| Portfolio | Low | 2 | 3 | 4 | High | High-Low |
|---|---|---|---|---|---|---|
| | | | Panel A: Q-factor model | | | |
| $\alpha$ | -0.223 | 0.288** | 0.045 | 0.096 | 0.120 | 0.343* |
| | (1.53) | (2.05) | (0.41) | (0.79) | (0.86) | (1.87) |
| $\beta_{MKT}$ | 1.120*** | 0.945*** | 0.970*** | 0.924*** | 0.812*** | -0.309*** |
| | (25.56) | (27.57) | (36.00) | (26.89) | (20.86) | (5.31) |
| $\beta_{SMB}$ | -0.129** | -0.196*** | 0.019 | -0.155*** | 0.018 | 0.147* |
| | (2.28) | (3.59) | (0.42) | (2.99) | (0.34) | (1.82) |
| $\beta_{RMW}$ | 0.098 | 0.009 | 0.254*** | 0.222*** | 0.346*** | 0.248** |
| | (1.06) | (0.11) | (4.77) | (3.03) | (4.88) | (2.25) |
| $\beta_{CMA}$ | -0.015 | -0.081 | 0.192*** | 0.123* | 0.251*** | 0.267** |
| | (0.15) | (0.84) | (3.14) | (1.73) | (3.44) | (2.05) |
| $R^2$ | 0.81 | 0.81 | 0.83 | 0.80 | 0.67 | 0.29 |
| | | | Panel B: five-factor model | | | |
| $\alpha$ | -0.230 | 0.261* | 0.035 | 0.058 | 0.087 | 0.317* |
| | (1.56) | (1.78) | (0.32) | (0.49) | (0.61) | (1.68) |
| $\beta_{MKT}$ | 1.123*** | 0.958*** | 0.975*** | 0.942*** | 0.827*** | -0.296*** |
| | (25.07) | (25.52) | (34.67) | (27.77) | (23.36) | (5.34) |
| $\beta_{SMB}$ | -0.131** | -0.200*** | 0.018 | -0.161*** | 0.012 | 0.143* |
| | (2.26) | (3.61) | (0.39) | (3.18) | (0.23) | (1.74) |
| $\beta_{HML}$ | -0.022 | -0.090 | -0.032 | -0.129** | -0.111 | -0.089 |
| | (0.28) | (1.36) | (0.59) | (2.23) | (1.33) | (0.84) |
| $\beta_{RMW}$ | 0.107 | 0.049 | 0.268*** | 0.279*** | 0.395*** | 0.288*** |
| | (1.16) | (0.62) | (5.09) | (3.70) | (5.51) | (2.67) |
| $\beta_{CMA}$ | 0.004 | -0.001 | 0.221*** | 0.239*** | 0.351*** | 0.347** |
| | (0.03) | (0.00) | (2.89) | (2.85) | (3.41) | (2.15) |
| $R^2$ | 0.81 | 0.81 | 0.83 | 0.81 | 0.67 | 0.29 |

**Table B.7:** Asset Pricing: Five portfolios sorted on institutional ownership (IO) and HC_OC (equal-weighted portfolios)

This table shows asset-pricing estimations for five portfolios sorted on institutional ownership (IO) and HC_OC over book value of assets relative to their industry peers within each year. In Panel A we report high-minus-low HC_OC portfolios (sorted on IO) alphas and betas of the regressions of excess portfolio returns on excess returns of the market portfolio. In Panel B we report high-minus-low HC_OC portfolios (sorted on IO) alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and Fama and French (1993) SMB and HML factors. In Panel C we report high-minus-low HC_OC portfolios (sorted on IO) alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio, Fama and French (1993) SMB and HML factors and Carhart (1997) MOM factor. Data on SMB, HML, and MOM are from Kenneth French's website. The sample period is June 1992 to December 2015. All portfolio returns correspond to equal-weighted returns by firm market capitalization.

| Portfolio | IO=low | IO=2 | IO=3 | IO=4 | IO=high |
|---|---|---|---|---|---|
| | | | Panel A: CAPM | | |
| $\alpha$ | 0.671** | 0.239 | 0.131 | -0.021 | -0.438 |
| | (2.03) | (0.68) | (0.41) | (0.06) | (1.09) |
| $\beta_{MKT}$ | 0.219** | 0.054 | -0.076 | 0.097 | 0.132 |
| | (2.47) | (0.59) | (0.98) | (0.95) | (1.29) |
| $R^2$ | 0.03 | 0.00 | 0.00 | 0.01 | 0.01 |
| | | | Panel B: three-factor model | | |
| $\alpha$ | 0.716** | 0.253 | 0.144 | 0.071 | -0.289 |
| | (2.38) | (0.76) | (0.50) | (0.22) | (0.77) |
| $\beta_{MKT}$ | 0.052 | -0.057 | -0.206*** | -0.069 | -0.037 |
| | (0.74) | (0.67) | (2.75) | (0.76) | (0.38) |
| $\beta_{SMB}$ | 0.633*** | 0.464*** | 0.546*** | 0.468*** | 0.342** |
| | (4.29) | (4.22) | (4.34) | (3.48) | (2.50) |
| $\beta_{HML}$ | -0.307** | -0.153 | -0.175 | -0.512*** | -0.634*** |
| | (2.23) | (0.99) | (1.40) | (3.30) | (4.27) |
| $R^2$ | 0.24 | 0.10 | 0.16 | 0.14 | 0.16 |
| | | | Panel C: four-factor model | | |
| $\alpha$ | 0.661** | 0.080 | 0.053 | -0.141 | -0.559 |
| | (2.15) | (0.25) | (0.17) | (0.42) | (1.48) |
| $\beta_{MKT}$ | 0.079 | 0.029 | -0.162** | 0.028 | 0.098 |
| | (0.97) | (0.33) | (2.23) | (0.31) | (0.95) |
| $\beta_{SMB}$ | 0.623*** | 0.433*** | 0.530*** | 0.470*** | 0.294** |
| | (4.19) | (4.21) | (4.10) | (3.73) | (2.39) |
| $\beta_{HML}$ | -0.283** | -0.078 | -0.136 | -0.445*** | -0.517*** |
| | (2.10) | (0.52) | (1.14) | (3.10) | (3.58) |
| $\beta_{MOM}$ | 0.069 | 0.217*** | 0.111 | 0.255*** | 0.339*** |
| | (0.80) | (2.64) | (1.30) | (3.05) | (4.60) |
| $R^2$ | 0.24 | 0.13 | 0.17 | 0.18 | 0.22 |

**Table B.8:** Asset Pricing: Five portfolios sorted on institutional ownership (IO) and Residual_OC (equal-weighted portfolios)

This table shows asset-pricing estimations for five portfolios sorted on institutional ownership (IO) and Residual_OC over book value of assets relative to their industry peers within each year. In Panel A we report high-minus-low Residual_OC portfolios (sorted on IO) alphas and betas of the regressions of excess portfolio returns on excess returns of the market portfolio. In Panel B we report high-minus-low Residual_OC portfolios (sorted on IO) alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio and Fama and French (1993) SMB and HML factors. In Panel C we report high-minus-low Residual_OC portfolios (sorted on IO) alphas and betas of a regression of excess portfolio returns on excess returns of the market portfolio, Fama and French (1993) SMB and HML factors and Carhart (1997) MOM factor. Data on SMB, HML, and MOM are from Kenneth French's website. The sample period is June 1992 to December 2015. All portfolio returns correspond to equal-weighted returns by firm market capitalization.

| Portfolio | IO=low | IO=2 | IO=3 | IO=4 | IO=high |
|---|---|---|---|---|---|
| | | | Panel A: CAPM | | |
| $\alpha$ | 0.698** | 0.278 | 0.241 | 0.240 | 0.061 |
| | (2.52) | (1.04) | (0.96) | (0.82) | (0.19) |
| $\beta_{MKT}$ | -0.201*** | -0.144** | -0.161*** | -0.022 | -0.261*** |
| | (3.09) | (2.04) | (2.77) | (0.30) | (3.34) |
| $R^2$ | 0.04 | 0.02 | 0.03 | 0.00 | 0.04 |
| | | | Panel B: three-factor model | | |
| $\alpha$ | 0.677*** | 0.220 | 0.251 | 0.281 | 0.100 |
| | (2.60) | (0.82) | (1.01) | (0.97) | (0.31) |
| $\beta_{MKT}$ | -0.292*** | -0.165** | -0.214*** | -0.066 | -0.370*** |
| | (4.62) | (2.43) | (3.53) | (0.89) | (4.95) |
| $\beta_{SMB}$ | 0.474*** | 0.262*** | 0.208** | 0.080 | 0.373*** |
| | (4.59) | (2.66) | (2.56) | (0.81) | (3.37) |
| $\beta_{HML}$ | -0.026 | 0.162* | -0.086 | -0.175 | -0.232** |
| | (0.25) | (1.74) | (0.92) | (1.42) | (1.98) |
| $R^2$ | 0.15 | 0.06 | 0.07 | 0.02 | 0.12 |
| | | | Panel C: four-factor model | | |
| $\alpha$ | 0.687*** | 0.197 | 0.155 | 0.201 | -0.087 |
| | (2.67) | (0.73) | (0.64) | (0.66) | (0.28) |
| $\beta_{MKT}$ | -0.297*** | -0.154** | -0.167*** | -0.027 | -0.279*** |
| | (4.26) | (2.14) | (2.86) | (0.37) | (3.77) |
| $\beta_{SMB}$ | 0.476*** | 0.258** | 0.192** | 0.066 | 0.341*** |
| | (4.50) | (2.55) | (2.40) | (0.65) | (3.29) |
| $\beta_{HML}$ | -0.030 | 0.172** | -0.046 | -0.142 | -0.153 |
| | (0.29) | (1.99) | (0.52) | (1.12) | (1.51) |
| $\beta_{MOM}$ | -0.013 | 0.029 | 0.116* | 0.097 | 0.226*** |
| | (0.22) | (0.35) | (1.78) | (1.05) | (3.24) |
| $R^2$ | 0.15 | 0.06 | 0.08 | 0.03 | 0.16 |

# Bibliography


Acharya, V., Almeida, H., Ippolito, F., and Perez, A. (2014). Bank lines of credit as contingent liquidity: a study of covenant violations and their implications. Ecb working paper series, 1702.

Adams, R., Almeida, H., and Ferreira, D. (2009). Understanding the relationship between founder ceos and firm performance. *Journal of empirical Finance*, 16(1):136–150.

Aigner, D. J., Lovell, C. A. K., and Schmidt, P. J. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6.

Allen, L., Guo, H., and Weintrop, J. (2008). The information content of quarterly earnings in syndicated bank loan prices. *Asia-Pacific Journal of Accounting and Economics*, 15:91–122.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4):589–609.

Arrazola, M. and Hevia, J. D. (2004). More on the estimation of the human capital depreciation rate. *Applied Economics Letters*, 11(3):145–148.

Atkeson, A. and Kehoe, P. (2005). Modeling and measuring organization capital. *Journal of Political Economy*, 113(5):1026–1053.

Baik, B., Chae, J., Choi, S., and Farber, D. B. (2013). Changes in operational efficiency and firm performance: a frontier analysis approach. *Contemporary Accounting Research*, 3:3.

Baltagi, B. (2008). *Econometric analysis of panel data*. John Wiley & Sons.

Banker, R. D., Charnes, A., and Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30:9.

Banker, R. D., Huang, R., and Natarajan, R. (2011). Equity incentives and long-term value created by sg&a expenditure. *Contemporary Accounting Research*, 28(3):794–830.

Battese, G. and Corra, G. (1977). Estimation of a production frontier model with application to the pastoral zone of easter australia. *Australian Journal of Agricultural Economics*, 21:3.

Bebchuk, L. and Grinstein, Y. (2005). The growth of executive pay. *Oxford review of economic policy*, 21(2):283–303.

Bebchuk, L. A., Cremers, K. J. M., and Peyer, U. C. (2011). The ceo pay slice. *Journal of Financial Economics*, 102(1):199–221.

Bebchuk, L. A. and Fried, J. M. (2003). Executive compensation as an agency problem. *Journal of economic perspectives*, 17(3):71–92.

Bebchuk, L. A., Fried, J. M., and Walker, D. I. (2002). Managerial power and rent extraction in the design of executive compensation. *National Bureau of Economic Research*, (w9068).

Benmelech, E. and Bergman, N. (2017). Debt, information and illiquidity. Working paper.

Berger, P. G., Ofek, E., and Yermack, D. L. (1997). Managerial entrenchment and capital structure decisions. *The journal of finance*, 52(4):1411–1438.

Berk, J., Binsbergen, J., and Liu, B. (2016). Matching capital and labor. Working paper.

Bertrand, M. and Mullainathan, S. (2003). Enjoying the quiet life? corporate governance and managerial preferences. *Journal of political Economy*, 111(5):1043–1075.

Bertrand, M. and Schoar, A. (2003). Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics*, 118(4):1169–1208.

Bethel, J. E., Liebeskind, J. P., and Opler, T. (1998). Block share purchases and corporate performance. *The Journal of Finance*, 53(2):605–634.

Bharath, S. T., Dahiya, S., Saunders, A., and Srinivasan, A. (2007). So what do i get? the bank's view of lending relationships. *Journal of Financial Economics*, 85:368–419.

Bharath, S. T., Dahiya, S., Saunders, A., and Srinivasan, A. (2011). Lending relationships and loan contract terms. *Review of Financial Studies*, 24(4):1141–1203.

Bharath, S. T. and Hertzel, M. G. (2016). External governance and debt structure. Working paper.

Bhattacharaya, S. and Chiesa, G. (1995). Proprietary information, financial intermediation, and research incentives. *Journal of Financial Intermediation*, 4.

Bloom, N. and Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *The Quarterly Journal of Economics*, 122(4):1351–1408.

Bogetoft, P. and Otto, L. (2011). *Benchmarking with DEA, SFA and R*, volume 157. Springer.

Boguth, O., Newton, D., and Simutin, M. (2016). The fragility of organization capital. Technical report. Working Paper.

Boot, A. W. A. (2000). Relationship banking: what do we know? *Journal of Financial Intermediation*, 9.

Boot, A. W. A. and Thakor, A. V. (1994). Moral hazard and secured lending in an infinitely repeated credit market game. *International Economic Review*, pages 899–920.

Boot, A. W. A. and Thakor, A. V. (2000). Can relationship banking survive competition? *Journal of Finance*, 55:2.

Boyd, J. H. and Prescott, E. C. (1986). Financial intermediary-coalitions. *Journal of Economic Theory*, 38:2.

Browning, M., Hansen, L. P., and Heckman, J. J. (1999). Micro data and general equilibrium models. *Handbook of macroeconomics*, 1:543–633.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52:57–82.

Carlin, B. I., Chowdhry, B., and Garmaise, M. J. (2012). Investment in organization capital. *Journal of Financial Intermediation*, 21(2):268–286.

Chang, Y. Y., Dasgupta, S., and Hilary, G. (2010). Ceo ability, pay, and firm performance. *Management Science*, 56(10):1633–1652.

Charnes, A., Cooper, W., and E.Rhodes (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research*, 2.

Chava, S. and Roberts, M. R. (2008). How does financing impact investment? the role of debt covenants. *Journal of Finance*, 63.

Chen, C. X., Lu, H., and Sougiannis, T. (2012). The agency problem, corporate governance, and the asymmetrical behavior of selling, general, and administrative costs. *Contemporary Accounting Research*, 29(1):252–282.

Coles, J. L., Lemmon, M. L., and Meschke, J. F. (2012). Structural models and endogeneity in corporate finance: The link between managerial ownership and corporate performance. *Journal of Financial Economics*, 103(1):149–168.

Corrado, C., Hulten, C., and Sichel, D. (2009). Intangible capital and us economic growth. *Review of income and wealth*, 55(3):661–685.

Cummins, J. D., Grace, M. F., Leverty, J. T., and Phillips, R. D. (2008). The missing link: Is book value efficiency recognized by the market. Working Paper, University of Iowa.

Dang, T. V., Gorton, G., Holmstrom, B., and Ordonez, G. (2017). Banks as secret keepers. *The American Economic Review*, 107(4):1005–1029.

Dass, N. and Massa, M. (2011). The impact of a strong bank-firm relationship on the borrowing firm. *The Review of Financial Studies*, 24:4.

Datta, D. K., Guthrie, J. P., Basuil, D., and Pandey, A. (2010). Causes and effects of employee downsizing: A review and synthesis. *Journal of Management*, 36(1):281–348.

Demerjian, P., Lev, B., and McVay, S. (2012). Quantifying managerial ability: a new measure and validity tests. *Management Science*, 58(3).

Denis, D. J. and Mihov, V. T. (2003). The choice among bank debt, non-bank private debt, and public debt: evidence from new corporate borrowings. *Journal of Financial Economics*, 70.

Dennis, S. A. and Mullineaux, D. J. (2000). Syndicated loans. *Journal of Financial Intermediation*, 9.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies*, 51(3).

Diamond, D. W. (1991). Monitoring and reputation: the choice between bank loans and directly placed debt. *Journal of Political Economy*, 99(4).

Donangelo, A. (2014). Labor mobility: Implications for asset pricing. *The Journal of Finance*, 69(3):1321–1346.

Eisfeldt, A. L. and Papanikolaou, D. (2013). Organization capital and the cross-section of expected returns. *Journal of Finance*, 68(4):1365–1406.

Eisfeldt, A. L. and Papanikolaou, D. (2014). The value and ownership of intangible capital. *American Economic Review Papers and Proceedings*, 104(5):189–194.

Eisfeldt, A. L. and Rampini, A. A. (2008). Managerial incentives, capital reallocation and the business cycle. *Journal of Financial Economics*, 87:177–199.

Elsas, R. (2005). Empirical determinants of relationship lending. *Journal of Financial Intermediation*, 14.

Evenson, R. E. and Westphal, L. E. (1995). Technological change and technology strategy. *Handbook of development economics*, 3:2209–2299.

Fahlenbrach, R. and Stulz, R. M. (2009). Managerial ownership dynamics and firm value. *Journal of Financial Economics*, 92(3):342–361.

Faleye, O. (2007). Classified boards, firm value, and managerial entrenchment. *Journal of Financial Economics*, 83(2):501–529.

Fama, E. F. (1985). What's different about banks? *Journal of monetary economics*, 15(1):29–39.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33:3–56.

Fama, E. F. and French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics*, 43(2):153–193.

Fama, E. F. and French, K. R. (2015). A five-factor asset-pricing model. *Journal of Financial Economics*, 116:1–22.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, 120.

Ferrier, G. D. and Lovell, C. A. K. (1990). Measuring cost efficiency in banking: Econometric and linear programming evidence. *Journal of Econometrics*, 46.

Francis, B. B., Mani, S. B., and Wu., Q. (2015). The impact of organization capital on firm innovation. Working paper.

Frijns, B., Margaritis, D., and Psillaki, M. (2012). Firm efficiency and stock returns. *Journal of Productivity Analysis*, 37.

Frydman, C. and Saks, R. E. (2010). Executive compensation: A new view from a long-term perspective. *Review of Financial Studies*, 120:1936–2005.

Garleanu, N. and Zwiebel, J. (2008). Design and renegotiation of debt covenants. *The Review of Financial Studies*, 22(2):749–781.

Ge, W. (2006). Off-balance sheet activities, earnings persistence and stock prices: evidence from operating leases. working paper, University of Washington, Seattle.

Gustafson, M., Ivanov, I., and Meisenzahl, R. R. (2017). Bank monitoring: Evidence from syndicated loans. Working paper.

Hale, G. and Santos, J. A. (2009). Do banks price their informational monopoly? *Journal of Financial Economics*, 93(2):185–206.

Hope, O.-K. and Thomas, W. B. (2008). Managerial empire building and firm disclosure. *Journal of Accounting Research*, 46(3):591–626.

Hou, K., Xue, C., and Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3):650–705.

Imrohoroglu, A. and Tuzel, S. (2014). Firm-level productivity, risk and return. *Management Science*, 60(8):2073–2090.

Jaimovich, N. and Siu, H. (2012). The trend is the cycle: Job polarization and jobless recoveries. Working Paper 18334, NBER.

James, C. (1987). Some evidence on the uniqueness of bank loans. *Journal of Financial Economics*, 19(2):217–235.

Jensen, M. C. (1986). Agency cost of free cash flow, corporate finance, and takeovers. *American Economic Review*, 76(2).

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics*, 3(4):305–360.

Ji, Y.-b. and Lee, C. (2010). Data envelopment analysis. *The Stata Journal*, 10:2.

KRIS (2011). Kamakura corporation risk information services: Kamakura public firm models. 5.

Leland, H. and Pyle, D. H. (1977). Informational asymmetries, financial structure, and financial intermediation. *Journal of Finance*, 32:2.

Leung, W. S., Mazouz, K., and Chen, J. (2016). Organization capital, labor market flexibility and stock returns around the world. Working paper.

Lev, B. and Radhakrishnan, S. (2005). The valuation of organization capital. In *Measuring capital in the new economy*, pages 73–110. University of Chicago Press.

Lev, B., Radhakrishnan, S., and Zhang, W. (2009). Organization capital. *ABACUS*, 45(3).

Lev, B. and Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of r&d. *Journal of Accounting and Economics*, 21(1).

Leverty, J. and Qian, Y. (2011). Do acquisitions create more value when good management replaces bad management? Working paper, University of Iowa, Iowa City.

Leverty, J. T. and Grace, M. F. (2010). The robustness of output measures in property-liability insurance efficiency studies. *Journal of Banking and Finance*, 34(7):1510–1524.

Leverty, T. and Grace, M. (2012). Dupes or incompetents? an examination of management's impact on firm distress. *Journal of Risk and Insurance*, 79(3):751–783.

Li, C. and Ongena, S. (2015). Bank loan announcements and borrower stock returns before and during the recent financial crisis. *Journal of Financial Stability*, 21:1–12.

Ludwig, A., Schelkle, T., and Vogel, E. (2012). Demographic change, human capital and welfare. *Review of Economic Dynamics*, 15(1):94–107.

Lustig, H., Syverson, C., and Van Nieuwerburgh, S. (2011). Technological change and the growing inequality in managerial compensation. *Journal of Financial Economics*, 99(3):601–627.

Malmendier, U. and Tate, G. (2008). *Superstar ceos*, volume w14140. National Bureau of Economic Research.

Martín-Oliver, A. and Salas-Fumás, V. (2012). It assets, organization capital and market power: Contributions to business value. *Decision Support Systems*, 52(3):612–623.

Masulis, R. W., Wang, C., and Xie, F. (2007). Corporate governance and acquirer returns. *The Journal of Finance*, 62(4):1851–1889.

McConnell, J. J. and Servaes, H. (1990). Additional evidence on equity ownership and corporate value. *Journal of Financial economics*, 27(2):595–612.

McConnell, J. J., Servaes, H., and Lins, K. V. (2008). Changes in insider ownership and changes in the market value of the firm. *Journal of Corporate Finance*, 14(2):92–106.

Meeusen, W. and van den Broeck, J. (1977). Efficiency estimation from cobb-douglas production functions with composed error. *International Economic Review*, 18.

Mehran, H. (1995). Executive compensation structure, ownership, and firm performance. *Journal of financial economics*, 38(2):163–184.

Morck, R., Shleifer, A., and Vishny, R. W. (1988). Management ownership and market valuation: An empirical analysis. *Journal of financial economics*, 20:293–315.

Murillo-Zamorano, L. R. (2004). Economic efficiency and frontier techniques. *Journal of Economic Surveys*, 18(1).

Ongena, S. and Smith, D. C. (1998). *Bank Relationships: A Review in The Performance of Financial Institutions*. Cambridge University Press.

Oshima, A., Ravikumar, B., and Riezman, R. (2009). Entrepreneurship, organization capital and the evolution of the firm. Working Paper 2242, CESifo.

Papke, L. E. and Wooldridge, J. (1993). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. Technical Working Paper 147, NBER.

Petersen, M. A. and Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *Journal of Finance*, 49(1).

Phelan, G. (2017). *Correlated Default and Financial Intermediation*. The Journal of Finance.

Preece, D. and Mullineaux, D. J. (1996). Monitoring, loan renegotiability, and firm value: The role of lending syndicates. *Journal of Banking & Finance*, 20(3):577–593.

Prescott, E. C. and Visscher, M. (1980). Organization capital. *Journal of Political Economy*, 88(3):446–461.

Rajan, R. and Winton, A. (1995). Covenants and collateral as incentives to monitor. *The Journal of Finance*, 50(4):1113–1146.

Ramalho, E. A., Ramalho, J. J., and Henriques, P. D. (2010). Fractional regression models for second stage dea efficiency analyses. *Journal of Productivity Analysis*, 34(3):239–255.

Ramalho, E. A., Ramalho, J. J., and Murteira, J. M. (2011). Alternative estimating and testing empirical strategies for fractional regression models. *Journal of Economic Surveys*, 25(1):19–68.

Roberts, M. R. (2015). The role of dynamic renegotiation and asymmetric information in financial contracting. *Journal of Financial Economics*, 116(1):61–81.

Rosenbaum, P. R. and Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 39(1):33–38.

Sanderson, E. and Windmeijer, F. (2016). A weak instrument f-test in linear iv models with multiple endogenous variables. *Journal of Econometrics*, 190(2):212–221.

Shleifer, A. and Vishny, R. W. (1986a). Large shareholders and corporate control. *Journal of political economy*, 94(3, Part 1):461–488.

Shleifer, A. and Vishny, R. W. (1986b). Large shareholders and corporate control. *Journal of political economy*, 94(3, Part 1):461–488.

Shue, K. and Townsend, R. R. (2017). Growth through rigidity: An explanation for the rise in ceo pay. *Journal of Financial Economics*, 123:1–21.

Spyridopoulos, I. (2017). Tough love: The causal effects of debt covenants on firm performance. Working paper.

Stulz, R. (1990). Managerial discretion and optimal financing policies. *Journal of financial Economics*, 26(1):3–27.

Sufi, A. (2007). Information asymmetry and financing arrangements: evidence from syndicated loans. *Journal of Finance*, 62(2).

Venieris, G., Naoum, V. C., and Vlismas, O. (2015). Organization capital and sticky behaviour of selling, general and administrative expenses. *Management Accounting Research*, 26:54–82.

Whited, T. M. and Wu, G. (2006). Financial constraints risk. *Review of Financial Studies*, 19(2):531–559.

Williamson, O. E. (1963). Managerial discretion and business behavior. *The American Economic Review*, pages 1032–1057.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Yermack, D. (1996). Higher market valuation of companies with a small board of directors. *Journal of financial economics*, 40(2):185–211.

Yosha, O. (1995). Information disclosure costs and the choice of financing source. *Journal of Financial intermediation*, 4(1):3–20.