# Investment Bank Governance and Client Relationships*

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**Abstract**

The relational contract at the heart of an investment banking relationship is valuable because it engenders and requires mutual trust in a setting where conflicts of interest are significant and are not easily resolved through formal contract. But a bank's ability to commit to a relational contract depends on internal governance mechanisms that align the interests of individual bankers with those of the bank. We argue that increasing complexity in investment banks weakens internal governance and estimate a causal model that indicates that the likelihood of a relationship being broken is increasing in bank complexity.

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Investment banking is not what it used to be. Investment banks were once partnerships whose employees formed close-knit social communities (Pak, 2013). Partners had long tenure, seldom moved between banks, and maintained long-lived relationships with their clients. They appeared to be more concerned with their reputational than their financial capital. In contrast, modern investment banking is dominated by very large, complex, publicly-owned firms that increasingly struggle to address internal conflicts of interest. Labor mobility is high among today's senior bankers, and bank-client relationships have weakened steadily for almost a half century.[1] Many observers have expressed concerns that behavioral standards have declined in financial firms. The spirit of these concerns was captured in a 2013 speech by William Dudley, the president of the Federal Reserve Bank of New York. President Dudley identified "deep-seated cultural and ethical failures" in the banking sector, as well as an "apparent lack of respect for law, regulation, and public trust." But he also noted that it is hard to determine whether these failures are a consequence of "size and complexity, bad incentives or some other issues."[2]

In their intermediary role, investment bankers are naturally exposed to conflicts of interest[3] and, because clients are less informed than their bankers on market conditions and the technicalities of deal-making, it is very hard for them consistently to monitor banker behavior. It follows that clients cannot rely upon formal contract to prevent bankers from abusing their superior knowledge. Inevitably, investment banking business frequently rests upon trust between banker and client. This argument suggests that we can better understand changes to cultural and ethical standards in investment banking if we study the institutional features that enable trust. We claim that trust upon which investment banking rests is both engendered by, and also serves as the foundation of, close investment bank-client relationships. In this paper, we therefore examine the effect that the increasing scale and complexity of investment banks has had upon their relationships with securities

[1] See Morrison and Wilhelm (2008) on banks' incentives to go public and Morrison, Thegeya, Schenone, and Wilhelm (2018) on long-term patterns in banker tenure and relationship exclusivity.

[2] "Ending Too Big to Fail," Remarks at the Global Economic Policy Forum, New York City, November 7, 2013. https://www.newyorkfed.org/newsevents/speeches/2013/dud131107.htm

[3] Kang and Lowery (2014), Reuter (2006), Nimalendran, Ritter, and Zhang (2007) study conflicts between banks and securities issuers that stem from institutional brokerage relationships. Asker and Ljungqvist (2010) provide evidence that issuers avoid banks that may be conflicted by serving multiple clients within a product market. Bodnaruk, Massa, and Simonov (2009), Griffin, Shu, and Topaloglu (2012), and Jegadeesh and Tang (2010) provide evidence of banks' ability to exploit information gained from advising M&A clients. Mehran and Stulz (2007) for a broad review of the literature on conflicts of interest in financial institutions.

issuers.

At the heart of our analysis is a trade-off between the costs and benefits of relationship maintenance. A trust-based relationship can address agency problems within banks, but it exposes both parties to opportunity costs. Issuers that maintain a relationship forgo competitive bidding for their underwriting mandates, while banks may be forced to decline profitable business that could threaten client relationships. Both parties to the relationship sacrifice opportunities to match with a counterparty whose characteristics are more complementary to their requirements or capabilities (Fernando, Gatchev, and Spindt, 2005).

The theoretical discussion of Section 1 examines the effect that an investment bank's internal governance has upon the cost-benefit tradeoff for client relationships. We argue that, if a bank's internal governance weakens, it becomes less able to control employee opportunism. This makes it harder for the bank to honor the promises that underpin its long-term relationships, and, hence, reduces the value of those relationships. It follows that anything that weakens an investment bank's internal governance should increase the likelihood that its clients switch to a different bank. In particular, we argue that it is harder to govern a more complex bank, so that increases to a bank's complexity should weaken its client relationships.

We test this hypothesis using a sample of debt and equity issues that were brought to market between January 1960 and December 1998 by issuers who had a prior relationship with one of 30 sample banks. We estimate models in which securities issuers condition their decision to break or to continue a relationship on three measures of bank complexity that are intended to proxy for the unobservable underlying agency problem: those proxies are bank capital, the number of bank partners or comparable senior officers, and discrete changes in organizational structure. It is worth noting that banks that are more complex judged by these measures are often able to offer a wider range of services and can draw from a larger pool of human resources for their delivery. As a consequence, evidence in favor of our hypothesis indicates that any positive relationship effects associated with greater scale and scope of operations are dominated by the associated costs of complexity.

Our sample period witnessed unprecedented technological and organizational change in investment banking. Our analysis is complicated by the fact that organizational change was not exogenous: Morrison and Wilhelm (2008) argue that it was often driven by technological advances in both information technology and financial economic theory that increased the efficient scale of investment banks and contributed to increasing conflicts of interest within investment banks.[4] We therefore construct two instruments that link bank complexity to the incentives that individual bankers have to adopt technological advances in their own institutions.

The construction of our instruments reflects theoretical work on the ways that early career experience affects human capital formation (for example Jovanovic (1979) and Greenwood and Jovanovic (1999)) and empirical work that links early life or career experience to future behavior.[5] They rest on our ability to identify on an annual basis the relationship bank's partners and place them in cohort years according to their first year of service in that capacity.[6]

The first instrument is an annual index for each bank that reflects the average of the state of technology during a window immediately before each partner's entry to the partnership. The instrument varies in the cross-section of banks with differences in their partner cohort structures in a given year. We assume that banks that are dominated by partners who entered the partnership when information technology was relatively primitive will be less inclined to adopt new technologies, because those technologies are less likely to complement their human capital, and may even undermine it. In contrast, banks that are dominated by partners of more recent vintage should be closer to the technological cutting edge. Bank cohort structures change as old partners retire and are replaced by younger ones; these changes serve to change the bank's receptivity to new technology adoption. The second instrument is constructed similarly, but uses a measure of credit

[4]Philippon and Reshef (2012) provide evidence that technological change and deregulation placed a premium on highly skilled workers during the second half of our sample period. See Chen, Morrison, and Wilhelm (2014) for a model of agency problems that stem from individual bankers facing strong incentives to build their personal reputation at the expense of their clients and their bank's reputation. Chen, Morrison, and Wilhelm (2015) present a model in which client trust is undermined by conflicts of interest between divisions of full-service investment banks.

[5]Bertrand and Schoar (2003) show that older CEOs are more conservative, Oyer (2008) demonstrates that career outcomes for MBAs entering investment banking are influenced by the state of the stock market at the outset of their careers, Malmendier and Nagel (2011) demonstrate a lower willingness to assume financial risk among people who have experienced lower stock-market returns, Malmendier, Tate, and Yan (2011) present evidence that CEOs who grew up during the Great Depression are averse to debt and lean excessively on internal finance, and Schoar and Zuo (2017) finds that managers who began their careers during recessions are more conservative.

[6]We are indebted to Steve Karolyi for conversations that motivated the use of partner cohorts in the construction of our instruments.

market conditions in place of technology at the time of a partner's accession to the partnership. In this case, we conjecture that early career exposure to difficult credit market conditions will promote conservatism later in life.

First-stage regressions are consistent with our theory: bank complexity increases with greater receptivity to technology adoption, as measured by our instruments. In the second-stage regressions, switching propensity is increasing in our measures of bank complexity and the marginal effect is statistically significant in both linear probability and probit model specifications. We also show that bank complexity weakens the tendency for issuers with strong existing relationships to continue their relationship. At high levels of complexity, the presence of a strong banking relationship does little to deter an issuer from breaking its relationship. Finally, we show that relationships involving poorly "matched" banks and issuers are more likely to be broken. But, when we interact our measure of the mismatch between the issuer and its relationship bank with proxies for bank complexity, the apparent preference for positive assortative matching is amplified. This result is consistent with the existence of the tradeoff between the costs and benefits of a relationship described above.

Our work contributes to the broad literature on the securities issuance process and, specifically, on the influence that investment-banking relationships have upon the assignment of underwriting mandates.[7] The switching model is similar in spirit to those used by Krigman, Shaw, and Womack (2001), Fernando, Gatchev, and Spindt (2005), and Ljungqvist and Wilhelm (2005) to examine why firms switch banks between their initial public offering of equity (IPO) and first subsequent equity offering. However, we do not restrict our attention to IPOs. Our work is most closely related to work by Yasuda (2005; 2007), Ljungqvist, Marston, and Wilhelm (2006; 2009), and Asker and Ljungqvist (2010). Just as we do, these papers find that issuers favor banks with whom they have a relationship and that the effect is increasing in the degree of relationship exclusivity.[8] Morrison, Thegeya, Schenone, and Wilhelm (2018) show that many relationships were exclusive, or nearly so, prior to the 1970s but that relationship exclusivity and the influence of the state of the relationship on issuer decisions weakened substantially thereafter. Our theory suggests that, to the extent that

[7]See Ljungqvist (2007) and Eckbo, Masulis, and Norli (2007) for reviews of the literature on equity offerings.

[8]Also see Schenone (2004) for the benefits to IPO issuers that select a bank with which they have a lending relationship.

strong relationships sustain trust between banks and their clients, greater organizational complexity in modern investment banks contributed to a decline in trust by undermining bank governance. Our empirical analysis provides support for this interpretation.

## 1. Theoretical Framework and Identification

Kahn and Whited (2018, p. 3) argue that identification is always based on a verbal or mathematical theory and, hence, that identification depends upon the plausibility of the assumptions underlying the theory. We therefore begin by presenting our theory and the assumptions upon which it rests. We then discuss our identification strategy.

First, note that most firms access the capital markets infrequently. We therefore assume that investment banks have better information than their clients about market conditions and about the best way to meet their clients' needs.[9] Indeed, this knowledge is one of the most important things that the investment bank has to sell to its clients. But the knowledge is complex and nuanced and, hence, the quality of the advice tendered by an investment bank is seldom verifiable. This problem gives rise to conflicts of interest, because an investment banker has incentives to sell advice or products that are sub-optimal from the perspective of its clients, but that generate benefits for the banker. Those benefits could be earned by favoring clients' counterparties or competitors or by bundling high-margin products with advice; more subtly, they could be earned if the banker succumbs to the temptation to build her reputation at the expense of her clients by performing excessively complex deals. Ely and Välimäki (2003) demonstrate that this type of "bad reputation" concern can arise whenever technically able advisers are better informed than their clients.[10]

Securities issuance is only possible if a solution can be found to the bank-client agency problems outlined above. Formal contract does not provide a solution, because so much of investment banking

[9] This assumption is in contrast to the relationship lending literature, which usually stresses the relative informational advantage that borrowers have over their banks. Skilled lenders address the associated agency problems by screening their borrowers ex ante, and monitoring their performance after loans have been extended. See, for example, Boot (2000). The type of knowledge studied in this literature concerns the nature of the borrower, rather than the congruence between the borrower and the products it receives from its investment bank. Like commercial banks, investment banks are better able to check client quality than other investors and, hence, can have a certification role, as in studies by Booth and Smith (1986), Titman and Trueman (1986), Carter and Manaster (1990), and Chemmanur and Fulghieri (1994).

[10] See also Morris (2001), Ely, Fudenberg, and Levine (2008), Bolton, Freixas, and Shapiro (2007) and Chen, Morrison, and Wilhelm (2014), (2015).

relies on promises and tacit understandings that are hard-to-codify and probably impossible-to-verify. Investment banks and their clients need an alternative way to address their agency problems. Our second assumption is that bank-client relationships evolved for this purpose.

Relationships underpin the tacit promises that banks make to their clients. Within such a relationship, the bank and its client can establish a clear understanding of the meaning of the bank's promises to its client over such complex matters as the quality of advice and the way in which conflicts will be resolved. A close dealing relationship also increases the likelihood that the client will discover any breach of those promises. If a client believes that these relationship properties result in a higher-quality service, then it is willing to pay a premium to its relationship banker. The relationship therefore generates future rents for the relationship banker: provided breach is observed with sufficient likelihood, a patient banker therefore keeps its promises so as to maintain the relationship and the associated rents.[11] Eccles and Crane (1988) show that, in the early part of our sample period, client relationships encompassed a wide range of businesses, so that routine advisory work was provided in the expectation of future compensation from underwriting mandates.

An issuer's decision to maintain a banking relationship reflects a trade-off. On the one hand, a strong banking relationship addresses bank-client agency problems. On the other hand, maintaining an existing relationship prevents the issuer from realizing any benefits from seeking competitive bids for its underwriting mandate. We argue below that those benefits could include lower issuance fees and a closer match between bank skill and issuer requirements, but our analysis hinges upon the existence of a tradeoff, and not upon the specific nature of the benefits of relationship banking.

Our third assumption is that, while the close client relationships may maximize the investment bank's profits, they need not maximize an individual banker's utility. It follows immediately that relational contracts between investment banks and their clients are only possible if corporate governance systems in the investment bank incentivize individual bankers to maintain the bank's relationships. That is, bank-client relationships are effective, and therefore survive, only if the bank's internal governance systems are effective.

Managing client relationships, brokering complex deals, and giving advice are difficult skills.

[11] See, for example, Levin (2003, Theorem 6).

Morrison and Wilhelm (2004) argue that they have a substantial tacit component and that they are learned on-the-job through close mentoring relationships with senior staff. This adds an additional layer of complexity to the bank-client relationship: the relationship relies upon the successful transfer of human capital in a mentoring relationship, but that transfer is not contractible. Absent a contractual commitment, it is hard for junior staff to be sure that they will receive adequate mentoring and for senior staff to be sure both that they will be compensated for providing it and that their peers will not free-rider on others' mentoring effort. Morrison and Wilhelm show that partnership organizations, like the investment banking partnerships that were common through the first part of our sample period, can resolve these problems. Key to their analysis is the relative opacity of the partnership, and the illiquidity of partnership stakes. These factors serve to limit labour mobility among junior and senior staff, respectively. Senior staff therefore mentor to ensure the future value of their long-term partnership stake, while junior staff pay for their mentoring by sticking around to contribute to the long-term success of their organization.

Morrison and Wilhelm (2008) demonstrate that the free-rider problem among partners places an upper bound on the size of the partnership. This limits the partnership's investment opportunities because large capital investments are spread across a suboptimal number of partners. The firm must therefore choose between the governance advantages afforded by the partnership form, and the potential efficiency gains that could be achieved through large-scale capital investment. Morrison and Wilhelm argue that banking partnerships went public when the efficiency effect outweighed the governance advantages. Chen, Morrison, and Wilhelm (2014; 2015) extend this argument to show how governance problems associated with "bad reputation" concerns are aggravated at greater scale and scope of operations.

Our analysis identifies a complex hierarchy of governance problems. Bank-client relationships resolve agency problems deriving from superior bank information and the non-codifiability of the bank's services. Those relationships rely upon the expertise of the bank's officers and upon the alignment of their personal well-being with the success of their firms. The internal governance arrangements that support mentoring and mitigate conflicts between personal and corporate interests are therefore essential foundations for bank-client relationships. It follows that any change to the internal governance of investment banks that weakens their ability to control internal agency problems must also weaken their ability to commit to relationships and, hence, undermine their value. We therefore hypothesize that clients respond to weaker internal bank governance by breaking their banking relationships.

Our hypothesis requires a proxy for the ease with which an investment bank can be governed. The final building block in our theory is that it is harder to govern a complex institution. We therefore estimate equations of the following form:

$$\mathbb{P}\left[\text{Relationship breaks}\right] = \beta_1 \mathit{Complexity} + \mathbf{x}\beta, \tag{1}$$

where $\mathbf{x}$ is a matrix of exogenous covariates. Our theory predicts that complexity weakens governance and so causes relationship breaks. We should therefore find that $\beta_1 > 0$.

We experiment with three measures of *Complexity* that follow directly from the analysis of Morrison and Wilhelm (2008). *Capital* measures the scale of capital investment. During the last half of our sample period, it is also directly related to a bank's capacity for risk-taking activities, such as over-the-counter derivatives trading, hostile takeovers, and mergers and acquisitions arbitrage, that often caused internal conflicts and so threatened client relationships. A second proxy, *Partners*, is the number of bank partners or senior officers. *Partners* is a measure of the number of people who are responsible for mentoring and maintaining governance standards in a bank. Other things equal, we expect free-riding, and thus governance failures, to be increasing in *Partners*. Finally, *Public* is a discrete variable that indicates whether a bank has gone public. Morrison and Wilhelm (2008) argue that a bank's decision to go public reflects a decision to sacrifice good governance in favor of investment efficiency. *Public* should therefore capture weaker governance standards. We describe the data used to measure each proxy in Section 2.

Our proxies assign higher values of *Complexity* to banks that offer a wider range of services and can draw from a larger pool of human resources for their delivery. Such banks experience hard-to-manage conflicts of interest. Our theory therefore predicts that the promises made by full-service investment banks are less credible to their clients and, hence, that those banks will be unable to sustain long-term client relationships. Elite merger and acquisition bankers frequently drew attention to this effect in the latter part of our period, claiming that conflicts of interest between the divisions of large, full-service, investment banks posed a serious threat to client relationships. But large complex banks are also able to realize efficiencies of scale and scope. They can therefore undercut their smaller competitors and, hence, should be able to attract more customers. The emergence of full-service investment banks therefore pits our theory against the alternative story that relationships are strengthened when banks are more efficient. If our theory is borne out by the data, then the governance effects of full-service banking upon bank relationships outweigh any strengthening effect of efficiency.[12]

Equation (1) does not identify the effect of governance problems within investment banks on client decisions to continue a banking relationship. Although our complexity measures are tightly bound to the theoretical motivation for our analysis, as proxies for the state of bank governance they suffer from measurement error. If the measurement error is uncorrelated with the state of bank governance, then the OLS coefficient for the complexity proxy exhibits attenuation bias, which increases in the error variance from a linear projection of the (unobserved) state of bank governance on the covariates in equation (1) relative to the variance of the measure of *Complexity* (Roberts and Whited, 2013). We find evidence of this bias in the OLS results reported in Section 3. We address the endogeneity problem by constructing instruments that seek to measure incentives for technology adoption and, hence, the complexity of the adopting bank, but has no direct effect upon the issuer's decision to continue its investment banking relationship.

The size of banking partnerships, their per-partner capitalization and their number of employees started to increase in the 1960s. Morrison and Wilhelm (2008, p. 314) hypothesize that these changes were precipitated by advances in information technology and financial economic theory that enabled more arm's-length contracting and that increased the efficient operating scale for some investment banking businesses. We assume that the decision to adopt new technologies at a given bank is partly reflective of the preferences of senior bankers. It follows that, if preferences vary

[12]Chen, Morrison, and Wilhelm (2015) explicitly model the tension between a bank's ability to make tacit commitments and to provide services efficiently. They show that elite bankers respond to the tension by leaving leave full-service banks to found narrow "boutique" advisory banks. The first prominent example occurred in 1988 when Bruce Wasserstein and Joseph Parella left First Boston to start Wassserstein Parella.

across the cross-section of banks, rates of technological adoption should also vary. One reason to believe that preferences may be heterogenous is advanced by Greenwood and Jovanovic (1999), who suggest that actors may resist the adoption of technologies that would devalue human capital that was formed during an earlier technological regime. It follows that, if decision-taking powers in a bank are mostly held by partners whose human capital is of less recent vintage, then that bank is less likely to adopt new technology.

Our first instrument reflects this reasoning. *Technology Exposure* is a measure of the average levels of early career technology exposure among a bank's partnership. If the propensity to adopt new technology is higher among people whose human capital was formed recently, then our measures of bank complexity should be increasing in *Technology Exposure*. Our calculation of *Technology Exposure* begins with an annual measure of the natural log of the *minimum* cost to date per million computations per second (in 2006 constant dollars) based on data compiled by Nordhaus (2007).[13] We compute an annual technology state variable by averaging this measure over the three years prior to every year in our sample.[14] Each partner is assigned the value of the state variable for the cohort year that he was admitted to the partnership. We then calculate the average partner state variable; *Technology Exposure* is obtained by reversing the sign of this quantity. *Technology Exposure* is an average of the technology state variable in which each year's state variable is weighted by the size of that year's partnership cohort; the sign change ensures that higher values of *Technology Exposure* correspond to lower computational costs and to banks with relatively young partnership cohort structures.

Our second instrument, *Default Exposure*, measures early career exposure to borrower default among a bank's partnership. It is calculated in a similar way to *Technology Exposure*, using a three-year moving average of Moody's annual measure of speculative grade borrower default as the

[13]The raw data underlying the series are summarized in Figure 3 in Nordhaus (2007) and were downloaded from http://www.econ.yale.edu/ nordhaus/Computers/Appendix.xls where the data series appears as "Cost per million computations (2006 $)" in the "Data" page of Appendix.xls. It is worth noting that over the 1966-2006 period our *minimum cost* time series has a correlation of 0.92 with the natural log of the Bureau of Economic Analysis' chain-type quantity index of the net capital stock of mainframes and PCs held by firms in the Securities, Commodity Contracts, and Investments sector (BEA Code 5230).

[14]We have experimented with one-, two-, and three-year windows on either side of the partner cohort year. Our results are not sensitive to these alternative specifications in the case of *Technology Exposure*. In the case of *Default Exposure*, statistical signficance is weaker when using one- or two-year windows.

state variable[15] in place of the computation cost measure of the previous paragraph. The literature on the effects of early career experience suggests that exposure to difficult market conditions promotes conservatism later in life.[16] Assuming that bank risk policies reflect the preferences of their partners and senior officers, banks with higher *Default Exposure* values should therefore be more conservative. This conservatism could manifest itself in two ways. First, it might lead to complete risk avoidance. This would rule out a number of business lines, so rendering banks less complex and, hence, causing a negative partial correlation between bank complexity and *Default Exposure*. Second, if risk-taking is inevitable, the partners of banks with higher *Default Exposure* values should be relatively more willing to expend resources to mitigate its effects. This could be accomplished in several ways: the bank could increase its equity capital and, hence, its ability to absorb negative shocks; it could admit more partners or senior officers with equity compensation so as to share risk more effectively, or it could expand the range of businesses in which it operates so as to diversify its exposure. Each of these actions is associated with higher bank complexity. Hence, if conservatism is manifested in risk mitigation measures, we should see a positive partial correlation between bank complexity and *Default Exposure*. In practice, both effects are likely at work, so that our regression coefficient reflects a net effect.

Figure 1 shows the annual equally-weighted average of bank *Technology Exposure* from 1960 to 1998. The time trend is dominated by the declining cost of computation. The one-standard-deviation bands around the average show that cross-sectional variation in the instrument is declining over time. In large part, this is a consequence of a declining number of banks in the sample (see Section 2.2). Figure 2 shows the annual equally-weighted average of bank *Default Exposure*. As one would expect, the time trend exhibits more variation than we observe in *Technology Exposure*.

Each of our instruments is an average of an annual state variable, weighted by a bank's annual cohort size. The bank's cohort structure determines the average tenure of its partners in a given year. The annual average of each bank's average partner tenure is illustrated in Figure 3. Average partner

[15]See *Moody's Global Credit Policy*, February 2009, p. 29, Exhibit 36.

[16]See, for example, Schoar and Zuo (2017), Malmendier and Nagel (2011), and Malmendier and Tate (2005). In addition to the Moody's default measure, we have experimented with recession years by aggregating data from the NBER business cycle dating database and an annualized measure of volatility for the S&P 500 index. In each case, the first-stage partial correlation with the proxy for bank complexity was positive. However, judged by the Cragg-Donald F-statistic, each was a "weak" instrument.

tenure declines until the early 1970s and then begins a steady increase.[17] As was clear in Figure 1, variation across banks generally declined over time.[18]

Figure 1 shows the annual equally-weighted average of bank *Technology Exposure* from 1960 to 1998. The time trend is dominated by the declining cost of computation (for which we reversed the sign). The one-standard-deviation bands around the average show that cross-sectional variation in the instrument is declining over time. In large part, this is a consequence of a declining number of banks in the sample for reasons described in Section 2.2. Figure 2 shows the annual equally-weighted average of bank *Default Exposure*. As one would expect, the time trend exhibits more variation than we observe in *Technology Exposure*. Each instrument is obtained by combining the bank's partnership cohort structure with a state variable. The cohort structure is easily translated into the average tenure of a bank's partners in a given year. The average across banks is shown in Figure 3. Average partner tenure declines until the early 1970s and then begins a steady increase.[19] As was clear in Figure 1, variation across banks generally declined over time.[20]

We show in Section 3.1 that each instrument satisfies the relevance condition for instrument validity. Satisfying the exclusion restriction for instrument validity requires that *Technology Exposure* and *Default Exposure* be uncorrelated with the error term in regressions taking the form of Equation 1. Our primary concern lies with whether the bank complexity measures are good proxies for the state of bank governance and the nature of the residual (measurement error) embodied in the error term. The strength of our instruments coupled with the signs of the second-stage coefficient estimates for the complexity measures gives us some confidence that they are good proxies for the state of bank governance. With respect to the latter, we have no plausible alternative interpretation of the results.

[17]The decline in tenure during the 1960s reflected both the retirement of a generation of partners of long standing and the necessity of replacing them with new hires because relatively few successors were groomed during the post-Second World War era. See Hayes (1971) for further details.

[18]Experiments with banks' annual average partner tenure as an instrument in first-stage regressions produces results that are quite similar to those described later in Tables V and A.II with one exception. Parameter estimates for log(*Capital*) are smaller than those reported in Table V and are only marginally statistically different from zero.

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As discussed above, our complexity measures are imperfect measures of the state of bank governance, and, hence, may introduce an attenuation bias into our results. But any residual effects of the state of bank governance that are not captured by our complexity measures are unlikely to be highly correlated with the instruments. We include time fixed effects that absorb any time trend in the measurement error, or in the error term generally, that might otherwise correlate with the time series behavior of *Technology Exposure* and *Default Exposure*. Irrespective of the state of technology and the quality of governance systems, bad actors will always find ways to subvert the formal and informal rules that should govern their actions. But we contend that their actions are idiosyncratic and local, so that the measurement error that they introduce has little relationship to the broad time patterns and conditions captured by the instruments.

As a practical matter, we are concerned with the informativeness of inference when the exclusion restriction is relaxed. It is well known that the 2SLS estimator is less sensitive to violations of the exclusion restriction when the instruments are strong.[21] We show in Section 3.1 that our instruments are quite strong judged by the relevant Stock and Yogo (2005) criterion. In Section 4.3 we use a Bayesian approach to relaxing the exclusion restriction suggested by Conley, Hansen, and Rossi (2012) to shed further light on the insensitivity of inference from our models.

## 2. Data and Variable Construction

Our unit of observation is a securities transaction for which the issuer engaged one or more of 30 banks described below to manage its *previous transaction*. At the time of the transaction, we define the issuer's "relationship bank(s)" to be the bank(s) that managed its previous transaction; we estimate the issuer's propensity to switch away from its relationship bank. In the remainder of this section, we describe the bank and transaction sample and we describe our measures of bank complexity, the "state" of bank-client relationships, and a battery of control variables.

[21] See Angrist and Krueger (1994) and Bound, Jaeger, and Baker (1995)

2.1 *Transaction Sample*

The transaction sample includes public and private underwritten common equity and debt offerings by U.S. issuers between January 1960 and December 1998. Additionally, we draw on transaction data from 1933–1959 to construct several variables described below. Transaction data from 1970 forward are collected from the Thomson Reuters SDC database. Pre-1970 data are collected from Issuer Summaries (1933-1949) prepared by counsel for several defendants in *United States v. Henry S. Morgan, et al* and Investment Dealers' Digest, Corporate Financing (1950-1960 and 1960-1969).[22]

The 1975–2003 sample period studied by Asker and Ljungqvist (2010) is the closest comparable to ours. To enable comparison, we follow Asker and Ljunqvist and screen out financial and governmental issues. As reported in Panel 1 of Table I, this screening criterion yields 52,883 transactions between 1960 and 1998 with total proceeds of $5.1 trillion (all dollar values are in 1996 GDP-deflated constant dollars).[23] All annual market share measures that we use in the paper are calculated relative to this "full sample". By comparison, Asker and Ljungqvist (2010) report 50,128 deals over the 1975-2003 period with proceeds of about $4.7 trillion. Equity offerings account for 44% of transactions and 23% of proceeds in our sample versus 39% of transactions and 26% of proceeds in the Asker and Ljungqvist (2010) sample.

Panel 2 of Table I reports characteristics of the sample used to estimate the switching model. For a transaction to be included in the "estimation sample" the issuer must have had at least two transactions after January 1, 1930 and its *last transaction* must have been led by at least one of the 30 sample banks described below. Compustat coverage is less comprehensive during the early part of our sample period, which limits our ability to measure issuer characteristics consistently. We do not exclude issuers for lack of Compustat coverage, but instead impose the weaker requirement that the issuer's 2-digit SIC code be available. We then use an industry fixed effect to complement observable characteristics of the issuer's transaction to control for issuer characteristics.

These requirements yield an estimation sample of 16,280 transactions that raised $2.2 trillion

[22] See Morrison, Thegeya, Schenone, and Wilhelm (2018) for details.

[23] When the issuer carries out more than one transaction on the same day, we treat the bundle of transactions as a single transaction. Such cases are unusual.

in proceeds. Public and private equity issues account for 28% of transactions and 19%, or about $415 billion, of proceeds. Among the equity transactions, 206 were initial public equity offerings that accounted for 1% of total proceeds. Public and private debt (including preferred equity) issues raised about $1.8 trillion. Private offerings (both debt and equity) account for 24% of transactions and 15% of proceeds. The mean (median) number of transactions per year in the estimation sample is 426 (371). The maximum of 948 occurred in 1986 and the estimation sample includes only 155 transactions in 1998. The reason for the small number of sample transactions from 1998 will be clear when we describe the bank sample in the next section.

Finally, on average 45% of issuers in the estimation sample switched away from their relationship bank in a given year; the minimum switching frequency was 21% in 1970, and the maximum was 60% in 1988. Figure 4 shows that the 3-year moving average of switching frequency increased over the sample period; it was less than 40% prior to 1973 and remained above 49% from 1985 forward. Fernando, Gatchev, and Spindt (2005) find a similar pattern from 1970-2000 in issuers' first seasoned equity offering following their IPO. The increase in switching frequency is consistent with the long-run decline in relationship exclusivity documented by Morrison, Thegeya, Schenone, and Wilhelm (2018, Figure 1).

### 2.2 *Bank Sample*

Table II reports the 30 sample banks ranked by the number of deals they led in the estimation sample of 16,280 transactions reported in panel 2 of Table I. There are 344 transactions for which two sample banks served as lead underwriter and 3 transactions for which three sample banks were identified as a lead underwriter. Our estimation sample therefore yields a total of 16,630 bank-transaction pairs.

With one exception, all of the sample banks were New York Stock Exchange (NYSE) member firms prior to 1970, when the NYSE first allowed member firms to be listed.[24] The sample covers a representative sample of firms that includes large, full-service banks with relatively large retail brokerage operations (e.g., Merrill Lynch), large, full-service banks with a predominantly

[24] First Boston had long been publicly listed and became a member firm in 1971.

institutional focus (e.g., Goldman Sachs), and smaller, more specialized banks dealing with both large and middle market clients (e.g., Lazard, William Blair).[25]

The mean (median) bank led 554 (279) transactions worth \$76 (\$31) billion. The mean (median) client switching frequency is 43% (44%). Among the ten banks that remained in the sample for at least 35 years, the average switching frequency is slightly higher at 45%. Among these ten banks, William Blair's clients had the lowest switching frequency (31%) while Salomon Brothers' clients had the highest (59%). The issuer switches away from its relationship bank in 8,315 (49%) of the 16,630 bank-transaction pairs in our sample. In 80% of those cases, the issues switches to one of our 30 sample banks. About 52% of switching issuers move to a more complex bank when $\log(\textit{Capital})$ is used as the complexity measure; 46% switch to a more complex bank when *Partners* is the complexity measure.

The number of years that a bank appears in the sample from 1960 through 1998 ranges from 7 to 39 with a mean (median) of 26 (29) years. The variation occurs for several reasons. Banks enter the sample in the first year for which we have the partner cohort data needed to construct the instruments described in Section 1: we need the identity of the partners and also the year in which they entered the partnership. This data was available in 1960 for 23 of our 30 banks.[26]

Banks leave the sample before 1998 for two reasons. Some were acquired by another sample bank. For example, Merrill Lynch acquired Goodbody in 1970 and White Weld in 1978.[27] Banks also leave the sample if we are unable consistently to identify their partners or senior officers. Reporting standards were consistent from year to year in partnership banks. After 1970, most of the sample banks either went public (e.g., Merrill Lynch), continued to operate under the same name following acquisition by a publicly-listed entity (e.g., Salomon Brothers), or acquired a

[25]Although both U.S. and non-domestic universal banks were active in securities underwriting during the 1990s, they do not appear in our sample because we could find no source that would enable us to track the career histories of senior officers with status similar to that of invetment-banking partners. It is worth noting, however, that U.S. commercial banks played only a modest role prior to 1992. U.S. commercial banks collectively accounted for less than 10% of debt proceeds through 1994 and less than 17% in 1997. As late as 1997, they accounted for less than 4% of equity issues. We discuss the frequency with which issuers in our sample switched to commercial banks in Section 4.4

[26]Data on bank partners or their post-partner analog was collected from the NYSE's annual Member Firm Directories, annual issues of Standard & Poors' Securities Dealers of North America, and through historical news searches. The earliest partner cohorts date to the first decade of the 20th century. The longest standing partner in our sample at 1960 was B.H. Griswold, Jr., who joined the Alex. Brown partnership in 1904.

[27]In such cases, the acquired bank's partner (and client) histories are merged into those of the acquiring sample bank.

substantial private equity infusion (e.g., Goldman Sachs):[28] these are the criteria for the coding *Public* $= 1$, reported in the last column of Table II, that we use as a proxy for complexity in Section 4.1. Going public or being acquired by a publicly-listed firm typically led, at some point, to a change in reporting standards for the bank's senior officers. At one extreme, Merrill Lynch went public in 1971 but maintained relatively consistent reporting standards through 1988 (its last year in the sample). In contrast, Morgan Stanley began identifying a much smaller number of senior bankers immediately following its public offering in 1986 (its last year in the bank sample).

Six banks did not meet one of the criteria for coding *Public* $= 1$. William Blair, Cowen, Goodbody, and Lazard remained private partnerships and did not raise substantial external equity throughout their time of inclusion in the sample. Hayden Stone was dropped from the sample before being merged into Shearson in 1975. First Boston merged with Credit Suisse in 1988, but each bank was already quite large, heavily capitalized, and offered a wide range of services to its clients. Thus we do not believe that this organizational change was comparable to others in the sample and, hence, we exclude First Boston from the estimation sample used in Section 4.

### 2.3 *Explanatory Variables*

Table III provides summary statistics for variables included in the model of client switching propensity as well as for the instruments described in Section 1. As discussed at the start of this Section, our unit of observation is a securities transactions whose issuer engaged one or more of our 30 sample banks to manage its previous transaction. For clarity, we refer to each unit of observation as an "analyzed transaction." Recall that the relationship bank for an analyzed transaction is the bank that managed the issuer's previous transaction. Statistics for "bank" and "bank-client" characteristics are therefore calculated using characteristics of banks and bank-client pairs measured at the time of each analyzed transaction in the estimation sample described in Table I.

[28]Goldman accepted a $500 million private equity investment from Sumitomo Bank and raised additional private capital from a Hawaiian education trust and a group of private insurers at a time when the partners' capital was around $1 billion (See Endlich (2000, pp. 9-15)). Also see Ljungqvist, Marston, and Wilhelm (2006, p. 310, Figure 1), Morrison and Wilhelm (2007, p. 298, Figure 1), and Morrison and Wilhelm (2008, p. 327, Table I) for further details of the timing and nature of organizational change among investment banks.

### *2.3.1 Bank Characteristics*

The first panel of Table III presents summary statistics for characteristics of each issuer's relationship bank. For each analyzed transaction, *Capital* is the relationship bank's equity plus long-term debt in 1996 dollars measured during the year of the transaction.[29] The wide spread between the mean ($3,063.10m) and median ($702.88m) capitalization reflects substantial cross-sectional variation among the sample banks as well as the large, general increase in the scale and scope of bank operations over the long sample period.

For each analyzed transaction, *Partners* is the number of partners or senior officers reported by the issuer's relationship bank during the year of the transaction. Although the difference in the mean (161.52) and median (127) is not as large as for *Capital*, the substantial difference between the minimum and maximum values again reflects the long sample period as well as cross-sectional variation among banks.

For each analyzed transaction, we also measure the relationship bank's debt and equity market share during the year preceding the transaction. The mean market share for debt and equity is 7% as is the median. Market share is often interpreted as a measure of a bank's market-wide reputation. To the extent that these measures are correlated with a bank's bilateral reputation within a client relationship, we expect them to be negatively correlated with switching propensity.[30]

### *2.3.2 Bank-Client Characteristics*

The second panel in Table III reports summary statistics for two measures of the state of bank-client relationships. For each analyzed transaction, we define *RelationshipStrength* to be the relationship bank's share (scaled 0–1) of the dollar value of the securities sold by the issuer during the 7 years prior to the transaction.[31] *RelationshipStrength* is therefore a measure of the strength of an issuer's

[29]Capital data were collected from annual capitalization rankings published by Finance magazine (prior to 1978) and the Securities Industry Association (from 1978 forward). It is worth noting that the NYSE imposed new net capital rules on member firms effective August 1, 1971 requiring at least $1 of capital for each $10 (as opposed to $15) of aggregate debt. For details see Finance, March 1972 and Seligman (1982, p.458).

[30]See Krigman, Shaw, and Womack (2001) for evidence that issuers prefer more prestigious banks.

[31]When multiple banks manage a transaction, each bank is assigned full credit for measurement purposes. We have also experimented with assigning relationship credit to any bank that served on either of the client's last two transactions and measuring *RelationshipStrength* over the preceding 10 years. Our results are insensitive to both changes.

association with its relationship bank when, at the time of an analyzed transaction, the issuer decides whether or not to break the relationship. In the event that one sample bank is acquired by another, the surviving bank inherits the relationships of the acquired bank.[32] The sample mean (median) value of *RelationshipStrength* is 0.48 (0.43).[33] The literature that uses this measure suggests that a strong existing relationship moderates any incentive an issuer may have to break its banking relationship. In some specifications of the switching model we also interact *RelationshipStrength* with *Capital* or *Partners* to estimate the extent to which this moderating force is undermined by increasing complexity within the relationship bank.

For each analyzed transaction, *SIC Share* is equal to the issuer's share of the total proceeds (inclusive of the issuer's proceeds) raised by the relationship bank for firms in the issuer's 2-digit SIC code industry during the preceding seven years. *SIC Share* is scaled from 0–1 and has a mean (median) value of 0.23 (0.08). *SIC Share* is intended to control for the tension between the potential benefits derived from a bank's industry expertise (Morrison, Thegeya, Schenone, and Wilhelm, 2018) and the potential costs of conflicts of interest stemming from strong ties to the client's competitors (Asker and Ljungqvist, 2010). In light of this tradeoff, the expected net effect of *SIC Share* on switching propensity is ambiguous.

The final bank-client characteristic, *Mismatch*, measures the "quality" mismatch between the issuer and the relationship bank in an analyzed transaction. This measure was proposed by Fernando, Gatchev, and Spindt (2005); we give a more detailed description of the construction of the measure and its motivation in Section 3.3. *Mismatch* is scaled from 0–1 and has mean (median) value of 0.23 (0.19). Fernando *et al.* show that switching propensity is increasing in *Mismatch* and they interpret this result as evidence of positive assortative matching.

[32]See Ljungqvist, Marston, and Wilhelm (2006; 2009), Asker and Ljungqvist (2010), and Morrison, Thegeya, Schenone, and Wilhelm (2018) for details.

[33]About 25% (4,155) of the 16,630 observations in the estimation sample are cases where the issuer did not do a deal with its "relationship bank" during the preceding 7 years but did at least one deal with the bank after January 1, 1930. In these cases, *RelationshipStrength* is set to its minimum value of zero. Among these cases, 43% (1,790/4,155) switched from the bank that underwrote its last transactions. There is no obvious time pattern in switching frequency among these transactions.

*2.3.3 Transaction and Client Characteristics*

A final set of variables control for transaction and client characteristics. Each transaction's *Proceeds* is the dollar amount of securities sold, measured in 1996 constant dollars. The mean value ($137m) of *Proceeds* is much larger than the median amount ($75m). Once again, this difference reflects both the wide range of issuers in our sample and the fact that their scale increases over time. If large issuers are of higher quality then we would expect them to be better able to switch banks and, hence, to have more bargaining power; at the margin, this could weaken existing relationships.

For each analyzed transaction, *Last Deal* measures the number of years since the client's last transaction. Although the median value of *Last Deal* is 1, it ranges from 0 to 40 years; *Last Deal* is 0 when the issuer's previous deal was in the same year. *Last Deal* is intended to control for two things. First, we expect clients that dealt with a bank more recently to have more confidence in the bank's commitment to the relationship, because the rent streams that motivate the bank are higher when dealing is more frequent. Second, *RelationshipStrength* is likely to give a less meaningful signal of the strength of a bank relationship when *Last Deal* is higher. Both of these factors lead to the conclusion that switching propensity should be increasing in *Last Deal*.[34]

The *Client Deal Experience* for each analyzed transaction is the number of transactions performed by the issuer with any bank from 1930 to the present transaction. It is intended to control for the possibility that more experienced issuers are less dependent on their relationship bank. It is also likely to be correlated with firm age, which we are unable to measure for a number of the issuers in our sample. The number of prior transactions ranges from 1 to 157, with mean (median) of 17.07 (9.00).

Finally, *Equity*, *Public Offering*, and *IPO* are binary variables intended to control for differences between the types of analyzed transactions. Each variable identifies transactions that are subject to more severe informational transactions than their complements. Preserving a relationship in these cases might improve certification, but it is also possible, particularly for IPOs, that the issuer will seek certification from a bank with a stronger market reputation than its relationship bank.[35]

[34] See Fernando, Gatchev, and Spindt (2005) for related evidence.

[35] One might argue for estimating separate models for debt and equity transactions under the assumption that there exists a degree of independence among business units within the bank. However, our motivation for bank-client

## 3. The Effects of Bank Complexity on Client Relationships

### 3.1 *Linear Probability Model First-Stage Regressions*

Table IV reports three sets of first-stage regression models in which log(*Capital*) is the (endogenous) measure of bank complexity. The first set (columns 1-3) reports results using *Technology Exposure* as the instrument for log(*Capital*). Columns 4-6 reports result using *Default Exposure* as the instrument for log(*Capital*). The final three columns report results using both instruments. In each set of regressions the first corresponds with the case where there is no interaction between log(*Capital*) and *RelationshipStrength* in the second-stage regression. We also estimate second-stage specifications in which log(*Capital*) is interacted with *RelationshipStrength*. In this case, both log(*Capital*) and the interaction term are endogenous and are separately instrumented. The second and third columns in each set of models reports the corresponding first stage regressions: the second column reports the regression of log(*Capital*) on the instruments(s), and the third reports the regression of log(*Capital*) interacted with *RelationshipStrength* on the instrument(s).[36]

The signs, magnitudes, and statistical signficance of the coefficients associated with the instruments are relatively insensitive to the model specification and, in each case, they conform with the theoretical framework outlined in Section 1. Recall that *Technology Exposure* measures the partner's early career exposure to technology and, hence, their willingness to adopt new technology. This leads us to interpret the positive coefficient estimates for *Technology Exposure* as indicating that bank complexity is increasing in the partners' propensity to adopt technologies. We argue above that *Default Exposure* measures the conservatism of bank partners. The positive coefficient estimates for *Default Exposure* therefore suggest that the net effect of partner conservatism is an attempt to improve the the bank's ability to absorb risk by increasing its capital base. Finally, note that in each case, log(*Capital*) is increasing in *RelationshipStrength* but that this effect is not statistically significant if *RelationshipStrength* is not interacted with one or both instruments.

Table A.I in the appendix reports analogous results for first-stage regressions in which *Partners* is

relationships is that agency problems within the bank at large undermine its ability to commit to a client relationship.

[36]Failing to instrument for the second-stage interaction of log(*Capital*) and *RelationshipStrength* is equivalent to incorrectly assuming that the linear projection of the interaction is equivalent to the interaction of the linear projections of each variable. See Wooldridge (2010, pp. 236-7) for discussion of this "forbidden regression" problem.

the endogenous measure of bank complexity. The results conform with the economic interpretation of the results for log(*Capital*). Moreover, with the exception of the coefficient estimates for *Technology Exposure*, which decline by half when *Default Exposure* is included in the model, coefficients for the instruments are relatively insensitive to the model specification.

*Technology Exposure* is highly correlated with both log(*Capital*) (0.76) and *Partners* (0.57). Similarly, the correlation between *Default Exposure* and log(*Capital*) is 0.75 and the correlation between *Default Exposure* and *Partners* is 0.39. Partial correlations between each complexity measure and the instruments are statistically different from zero at the 1% level. Cragg-Donald F-statistics for the first-stage regressions range from a low of 21.02 in Table IV to 254.41 Table A.I. Judged by the relevant Stock and Yogo (2005) criterion both *Technology Exposure* and *Default Exposure* are strong instruments for our bank complexity measures.

### 3.2 *Second-Stage Switching Regressions*

Table V reports coefficients and robust standard errors (in parentheses) for ordinary least squares (OLS) and second-stage linear probability models (LPMs) of client switching in which log(*Capital*) is the endogenous complexity measure.[37] Each regression includes bank, year, and 2-digit SIC fixed effects.

With the exception of the lagged value of relationship bank market share and *Last Deal*, coefficients for control variables are all statistically significant, and their signs are consistent with intuitions based on prior work. Large (lagged) equity and debt market shares are often interpreted as proxies for a strong market-wide reputation Megginson and Weiss (1991); using these measures, issuers whose relationship banks have strong reputations are less likely to switch banks. Asker and Ljungqvist (2010) argue that clients are disinclined to share a bank with their primary competitors

[37]We note in the discussion of Table II that some of the explanatory variables have relatively wide value ranges. In such cases, there is a greater likelihood that predicted probabilities from the LPM specifications will lie outside the unit interval and, potentially, lead to poor estimates of marginal effects averaged across the distribution of the explanatory variables (Wooldridge, 2010, p. 563). Although we do not report the results below, we have experimented with maximum likelihood estimation of instrumental variables (IV) probit specifications (Wooldridge, 2010, p. 591). The marginal effects from the probit models are not meaningfully different from those reported below for the LPM specifications. It is also worth noting that maximum likelihood estimation of the IV probit model enables a Wald test of the exogeneity of log(*Capital*) or *Partners*. The *p*-values for these tests provide strong evidence that neither log(*Capital*) nor *Partners* should be treated as exogenous.

and, consistent with this result, Table V shows that issuers are less likely to break with their relationship bank when *SIC Share* is high, so that the issuer's business accounts for a large share of their relationship bank's business in their 2-digit SIC industry code.

Issuers also are less likely to break their relationship when undertaking (non-IPO) equity offerings (*Equity* $= 1$), as opposed to debt offerings, and when their offering is public, as opposed to private (*Public Offering* $= 1$). If asymmetric information is a greater barrier to equity and public offerings then their issuers must place a higher value on credible signals of quality. These results are therefore consistent with the conjecture that issuers of equity and public offerings retain their relationship bank in order to send the most credible signal to investors. In contrast, there is a higher propensity for switching among IPO issuers (*IPO* $= 1$). This suggests that IPO issuers view their relationship bank as unequal to the associated informational problems and, hence, that they break the relationship in search of better certification. This could be because the IPO is a landmark that pressages higher fees and more frequent capital market business and, hence, can be used to attract a higher quality bank.

The greater propensity for switching in large transactions (*Proceeds*) is consistent with our conjecture that large issuers are of higher quality and so have more options among banks and also greater bargaining power. Finally, more active participants in the capital markets (*Client Deal Experience*) and those for whom there has been a longer period of time since their last transaction (*Last Deal*) are more likely to switch. The signs, magnitudes, and statistical significance of these control variables are generally insentive to model specification throughout Table V.

The OLS results in columns 1 and 2 provide a point of comparison for the 2SLS results. The coefficient for log(*Capital*) is negative in each OLS specification, but it is at most only marginally statistically different from zero. The negative sign on *RelationshipStrength* is consistent with the existing literature, which finds that issuers are less likely to switch away from, or more likely to select, a bank with which they have a strong relationship. The positive and statistically significant coefficient associated on the interaction between *RelationshipStrength* and log(*Capital*) suggests that bank complexity undermines the value of an existing relationship. The coefficient for *RelationshipStrength* is negative; at the 6.56 median level of log(*Capital*), the marginal effect of

*RelationshipStrength* is $-0.4560 + 0.451 \times 6.56 = 0.1601$, which is almost identical to the marginal effect reported in column 1.

Columns 3 and 4 report second-stage results for which *Technology Exposure* is the first-stage instrument for log(*Capital*). The first noteworthy result is that the estimated coefficient for log(*Capital*) in column 3 (0.4205) is large relative to the OLS coefficient (-0.0027) and is statistically signficant at the 1% level. This is consistent with the expected attenuation bias from measurement error in our proxy for the state of bank governance. The positive sign is consistent with the hypothesis that technological change undermines bank governance and therefore client relationships. A 1% increase in capital corresponds with an average increase in switching propensity of 0.42%. The coefficient for *Technology Exposure* from the reduced form switching regression is also positive and statistically significant at the 1% level.[38]

The coefficient estimate for *RelationshipStrength* is virtually identical to the OLS analog and it remains statistically significant at the 1% level. In column 4 we interact log(*Capital*) with *RelationshipStrength*. At the 0.43 median level of *RelationshipStrength*, the marginal effect of log(*Capital*) is $0.2870 + 0.0649 \times 0.43 = 0.3149$, which is somewhat smaller than the 0.4205 effect reported in column 3 in the absence of the interaction. At the median level of log(*Capital*), the marginal effect of *RelationshipStrength* is $-0.5874 + 0.0649 \times 6.56 = -0.1617$, which is nearly identical to the marginal effect in the absence of the interaction. The positive coefficient for the interaction term in column 4 indicates that greater organizational complexity diminishes the moderating effect of an existing relationship on client switching propensity. Moving to the 75th percentile level of log(*Capital*), the marginal effect of *RelationshipStrength* declines by roughly 60% in absolute value to -0.0632. At the 95th percentile level of the instrumented value of log(*Capital*), the marginal effect of *RelationshipStrength* on switching propensity is not statistically different from zero. In other words, at high levels of bank complexity, the strength of an existing relationship has little effect on the issuer's decision whether to break the relationship.

Columns 5 and 6 report second-stage results for which *Default Exposure* is the first-stage instru-

[38]The reduced form coefficient of 0.0238 is just the product of the coefficient for log(*Capital*) (0.4205) and the first stage coefficient for *Technology Exposure* (0.0567). See Angrist and Pischke (2009, p. 117). *Technology Exposure* is also statistically significant in the reduced form regressions in which it is interacted with *RelationshipStrength* and with *Mismatch*.

ment for log(*Capital*). The only significant difference from the results using *Technology Exposure* as the first-stage instrument is that the marginal effect of log(*Capital*) is now smaller and marginally statistically signficant.[39] Columns 7 and 8 report results for which both instruments are used in the first-stage regressions. The message remains same but the marginal effect of log(*Capital*) is again statistically different from zero at the 1% level.

Table A.II in the appendix provides analogous second-stage results using *Partners* as the complexity measure. The main results are qualitatively identical to those reported in Table V. For example, using *Technology Exposure* as the first-stage instrument for the model including the interaction between *Partners* and *RelationshipStrength* (column 4), the marginal effect of *Partners* at the median level of *RelationshipStrength* is 0.0025. In other words, an additional partner corresponds with an average increase in switching propensity of 0.25%. Once again, the effect of the complexity measure is smaller when either *Default Exposure* alone or both instruments are used in the first-stage regression and statistical significance is at the 5% level or greater. It is also worth noting that *RelationshipStrength* is more sensitive to an increase in complexity. As *Partners* increases from its median level of 127 partners to the 75th percentile level of 242 partners, the marginal effect of *RelationshipStrength* declines in absolute value by about 70%. In contrast to the results using log(*Capital*) as the complexity measure, at the 95th percentile level of *Partners* the marginal effect of *RelationshipStrength* remains statistically different from zero at the 1% level.[40]

In summary, the 2SLS results reported in Tables V and Table A.II are relatively insensitive to alternative model specifications and consistent with our theoretical framework and to prior research. Switching propensity is increasing in both measures of bank complexity regardless of the instrument(s) used in the first-stage regressions. Consistent with existing research on investment-banking relationships, issuers with relatively strong relationships are less likely to switch banks. However, increasing bank complexity undermines this effect. At high levels of bank complexity strong relationships have little moderating effect on the issuer's propensity to break its banking relationship.

[39]In column 6 the marginal effect of log(*Capital*) at the median level of *RelationshipStrength* is 0.2304.

[40]The main results are qualitatively the same if we lag either log(*Capital*) or *Partners* by one year.

### 3.3 *Bank Complexity and Positive Assortative Matching*

Our theoretical framework predicts that investment banking relationships are valuable because they underpin the formation of the trust that facilitates securities underwriting. But the need to establish trust is only one of the factors that influences the issuer's decision to maintain or to break a banking relationship. As we emphasize in Section 1, issuers trade off the value of the existing relationship against any benefits that could be realized by breaking it. For example, ceteris paribus, the demands of an issuer's transaction might better fit the capabilities of a different bank. In that case, the issuer would rationally choose to break its existing relationship if the cost of destroying the trust inherent in that relationship was outweighed by the benefit from switching to a bank whose capabilities better complemented the characteristics of its transaction. Similarly, a bank that is capacity-constrained or prefers not to turn away business that would present a threat to the client might wish to "fire" the client. Either effect would appear in our dataset as a broken relationship, caused by poor matching rather than by internal bank governance effects. In this Section, we control for this matching problem and examine how it interacts with bank complexity.

Using data from 1970–2000, Fernando, Gatchev, and Spindt (2005) ask whether an issuer's propensity to switch underwriters in its first seasoned equity offering (SEO) is related to a measure of the "quality" mismatch at the time of the SEO between the issuer and the underwriter of its IPO; Fernando *et al.* do not consider the tradeoff between trust and fit that we consider in the previous paragraph. In each year $t$, Fernando *et al.* rank underwriters by the total proceeds of deals for which they acted as lead underwriter in years $t-2$, $t-1$, and $t$, and they rank issuers by the total amount their issues raised in year $t$. The absolute difference in issuer and underwriter percentile ranks is a measure of quality mismatch. Fernando *et al.* show that switching propensity is increasing in this measure of quality mismatch and they interpret their results as evidence of positive assortative matching.

Our theoretical framework states that relationships are less valuable when it is harder for the bank to manage internal agency problems; that internal agency problems are harder to manage when banks are more complex; and, hence, that the cost to an issuer of switching banks is lower when its relationship bank is more complex. This reasoning suggests that an issuer that is poorly matched with its relationship bank is more likely to switch when the relationship bank is complex. To test this hypothesis, we exactly follow Fernando *et al.*'s methodology to calculate a mismatch measure *Mismatch* from our estimation sample. Table VI shows results from 2SLS estimation of linear probability models of switching propensity that include *Mismatch* and its interaction with either log(*Capital*) or *Partners*. For the sake of brevity, we report results only for the case in which both *Technology Exposure* and *Default Exposure* are included in the first-stage regression.

Note first that introducing *Mismatch* into the model has relatively little impact on the coefficient for log(*Capital*) reported in column 8 of Table V. In contrast, the coefficient for *Partners* declines by more than 50% from 0.0007 (see table A.II) to 0.0003. After accounting for the interactions, the marginal effect of log(*Capital*) is statistically significant at the 1% level. The marginal effect of *Partners* is statistically signficant only at relatively high levels of *Mismatch* and *RelationshipStrength*.

The marginal effect of *Mismatch* at the 6.56 median level of log(*Capital*) is 0.1738 (-0.1666 + [-0.0519 * 6.56]). The 0.1563 marginal effect of *Mismatch* at the median level of *Partners* (127) is similar in magnitude. Thus, like Fernando *et al.*, we find evidence of positive assortative matching in that switching propensity is increasing in the degree of mismatch between the issuer and its relationship bank. In each case, the marginal effect is statistically significant at the 1% level. Moving to the 95th percentile level of the complexity measure roughly doubles the marginal effect of *Mismatch*. In other words, as bank complexity increases, clients are more inclined to switch to a bank with capabilities that better complement the characteristics of their transactions. Moreover, the results are consistent with the broader hypothesis that there is a tradeoff between the trust inherent in an investment banking relationship and the benefits from pursuing a better match.

## 4. Robustness to Alternative Model Specifications

### 4.1 *Switching Conditional on Discrete Change in Organizational Structure*

As we note in Section 2.2, the NYSE first allowed its member firms to be publicly listed in 1970. Over the remainder of the sample period, most of our sample banks went public, were acquired by (or merged with) publicly-listed firms, or experienced an infusion of private equity funds. As discussed in Section 2.2, we code a binary variable *Public* $= 1$ in the year that a bank experiences one of these capital structure changes, and in every subsequent year.

When a bank sets *Public* $= 1$, it embraces a discrete organizational change that expands its scale and complexity of operations. For convenience, we therefore refer to the change of *Public* from 0 to 1 as an "organizational shift." By our earlier argument, an organizational shift undermines a bank's ability to control internal governance problems and so to maintain its long-term client relationships. In line with Morrison and Wilhelm (2008), we hypothesize that a bank nevertheless opts for an organizational shift when the efficiency gains that it can thereby realize outweigh the costs of weaker governance.

We test this by performing an exercise in "IPO time." Let the year in which a bank performs an organizational shift be $t$. For each bank, we construct a four-year event-time sample of transactions from year $t-2$ through year $t+1$.[41] This sampling procedure yields 2,078 observations, comprising roughly 13% of the estimation sample used in the preceding section.[42]

It is tempting to view an organizational shift as an exogenous shock, but it is not. Like our continuous measures of bank complexity, the decision to perform an organizational shift reflects the state of bank governance. Moreover, we cannot rule out the possibility that clients anticipate organizational shifts and select in or out of a "quasi-experiment" comparing switching decisions before and after the shift. Once again, we address the endogeneity of *Public* using *Technology Exposure* and/or *Default Exposure* as instruments in first-stage regressions.

Because *Public* is a binary variable, the conditional expectation function for the first-stage regression is likely to be nonlinear. We therefore estimate a probit model in which *Public* is regressed on the instrument(s) and the other covariates in the structural model. The vector of fitted

[41]The results described below are not materially different if we shift the event window to years $t-3$ through $t$. Narrowing the event window to three years increases the statistical significance of the interaction between *Public* and *RelationshipStrength*.

[42]The sampling procedure for Blyth and Eastman Dillon is complicated by the fact that Blyth was acquired by I.N.A Corporation in January 1970. I.N.A. then acquired Eastman Dillon in 1972 and merged its operations with Blyth's to form Blyth, Eastman Dillon. For Blyth, we define 1970 as year $t$ and sample transactions from 1968-1971 for which it was the relationship bank. For Eastman Dillon, year $t$ is 1972 and we include transactions from 1970-1973 for which it was the relationship bank.

values, $\hat{P}$, is included as a second (or third) instrument in the first-stage regression.[43] Finally, we control for sample-selection bias by estimating a MLE probit selection equation using transactions from time $t-10$ through $t+1$. The inverse Mills ratio obtained from the selection model is then included as an additional instrument in the first-stage regression and in the second-stage LPM regressions.[44]

Second-stage results are reported in Table VII. Comparing the results to those from Table V, where log(*Capital*) served as the proxy for bank complexity, we see among the control variables lower precision and some changes in the signs of the estimated coefficient. The former effect is not surprising given the much smaller sample size. Nevertheless, the coefficients for *Public* and *RelationshipStrength* retain their predicted signs and remain statistically significant. When both *Technology Exposure* and *Default Exposure* are included as instruments in the first-stage regression (column 6), we again see evidence from the interaction between *Public* and *RelationshipStrength* that issuers are more likely to break an existing banking relationship when bank governance is likely to be weaker.

### 4.2 *Bank Choice Specifications*

The switching models estimated in Section 3 are attractive for their simplicity but they assume that issuers do not condition the assignment of their underwriting mandate on characteristics of banks other than those we define as their relationship bank(s). We have addressed the sensitivity of our results to this potential concern by estimating LPMs in which the issuer selects one or more banks from the full set of banks in our sample at the time of their transaction. This approach brings more information to bear on the issuer's decision, including any history (embodied in *RelationshipStrength*) that the issuer had with banks other than the underwriter(s) of its preceding transaction, as well as concurrent information related to each bank's complexity, market share, and industry expertise (*SIC Share*). It also increases the transaction sample size because it does

[43]See Angrist and Pischke (2009, p. 190) for discussion of the use of nonlinearity as a source of identifying information in this situation.

[44]See Wooldridge (2010, p. 809, 939) for details. The second-stage coefficient for the inverse Mills ratio is not statistically different from zero, which suggests that selection bias is not a serious problem. There is evidence of selection bias when the event window is shifted to years $t-3$ through $t$.

not exclude transactions for which the issuer had no previous history with a sample bank. On the other hand, some banks in the choice set may not be plausible candidates for any given issuer or transaction while others may be relatively close substitutes for one another.

We do not report these results because they are qualitatively similar to those obtained from the switching models. Using either log(*Capital*) or *Partners* as the measure of bank complexity, issuers are less likely to select organizationally complex banks to underwrite their securities offerings. Similarly, issuers are more likely to select banks with which they have a stronger existing relationship (as measured by *RelationshipStrength*) but this effect is smaller among banks with greater organizational complexity.

### 4.3 *Sensitivity to Violations of the Exclusion Restriction*

We noted earlier that the strength of our instruments suggests that the precision of our results is relatively insensitive to violations of the exclusion restriction. In this section we use a Bayesian method suggested by Conley, Hansen, and Rossi (2012) to shed light on the sensitivity of inference at increasingly severe violations of the exclusion restriction. To set the stage for this analysis, it is useful to write our empirical model (with exogenous covariates suppressed) as follows:

$$Y = \beta \mathit{Complexity} + \mathbf{Z}\gamma + \varepsilon; \tag{2}$$

$$\mathit{Complexity} = \mathbf{Z}\Pi + \nu, \tag{3}$$

where $Y$ is a binary variable that is 1 when the client breaks its relationship, and the matrix of instruments $\mathbf{Z}$ is assumed to be uncorrelated with $\varepsilon$. Conley, Hansen, and Rossi (2012) note that the exclusion restriction is equivalent to a prior belief that $\gamma$ is identically zero; when there is prior information that $\gamma$ is *near* zero but perhaps not exactly zero they say that *plausible exogeneity* obtains. In the simple case of one instrument, the precision with which $\hat{\beta}$ is estimated is decreasing in $\gamma/\Pi$. The exercise that we carry out examines the sensitivity and precision of $\hat{\beta}$ to alternative prior beliefs about the magnitude of $\gamma$.

Given the relative insensitivity of $\hat{\beta}$ to the alternative model specifications we have considered, we simplify the analysis by estimating linear probability models that correspond with the columns 3 and 5 in Table V where we report results using a single instrument with no interactions in the second-stage regression. We also exclude 2-digit SIC fixed effects from these models to reduce computational demands of the estimation procedure. In each case, we assume that the distribution of $\varepsilon$ and $\nu$ is bivariate normal. We begin with *Technology Exposure* as the instrument for $\log(\textit{Capital})$ and we estimate the Bayesian benchmark model with a zero prior for $\gamma$ and set the prior for $\beta$ at 0.4 to correspond closely with the coefficient estimate for $\log(\textit{Capital})$ in column 3. Estimation of the model yields a 0.29 posterior median value for $\beta$ which corresponds quite closely with the 0.3334 coefficient obtained for $\beta$ when we run the LPM in column 3 of Table V without SIC fixed effects. We then estimate models in which the prior for $\gamma$ increases in 5% increments of the 0.29 median value of $\beta$. We carry out the same exercise using *Default Exposure* as the instrument, in which case $\gamma$ is scaled against a 0.27 median value of $\beta$.

The first panel in Figure 5 reports median values for $\beta$ and Bayesian 95% credibility intervals at increasing levels of $\gamma$ where *Technology Exposure* is the instrument. Note first that the median posterior for $\beta$ is decreasing in $\gamma$. With the prior for $\gamma$ set at 0.015 (or 5% of the 0.29 posterior median value of $\beta$) the median posterior for $\beta$ is 0.25. Increasing the prior for $\gamma$ to 10% of the 0.29 baseline median for $\beta$ yields a posterior median for $\beta$ of 0.24. At the 0.075 (or 25% of 0.29) maximum level of $\gamma$ reported in the figure, the posterior median for $\beta$ is 0.22. Over this entire range, the lower bound of the 95% credibility interval is positive. This remains true even at a prior for $\gamma$ equal to 40% of the median level of $\beta$, where the (unreported) lower bound is 0.17.

The second panel in Figure 5 reports similar results using *Default Exposure* as the instrument. Note, however, that in this case Bayesian estimates of $\beta$ are actually slightly larger than the LPM estimate in column 5 of Table V. Moreover, median estimates are less sensitive to assumed violations of the exclusion restriction than was the case for *Technology Exposure*. This is consistent with *Default Exposure* being a stronger instrument as evidenced by the larger Cragg-Donald $F$-statistics reported in column 4 of Table IV. Once again, the lower bound of the 95% credibility interval remains positive and changes little even at significantly higher levels of $\gamma$. In summary, the Bayesian method suggested by Conley, Hansen, and Rossi (2012) suggests that our instruments are *plausibly* *exogenous* over a significant range of priors regarding the degree to which the exclusion restriction is violated.

### 4.4 *Commercial Bank Entry to Securities Underwriting*

The years in which the Glass-Steagall restrictions on securities underwriting by commercial banks were incrementally relaxed constitute a small part of our sample period. It is nevertheless worth considering whether our results or their interpretation are affected by the incremental entry of commercial banks into securities underwriting. As noted above, there are no commercial banks in our sample. However, the sample includes 931 cases in which an issued switched from a sample bank to a commercial bank. Of these, 382 cases were before 1989, of which 188 occurred before 1987. Virtually all of those transactions were private placements of senior or secured notes or similar private debt instruments.[45] In 1997, only 5 of the top 25 debt underwriters were domestic commercial banks; those five banks accounted for about 16% of the dollar value of public debt underwritings reported by SDC. In the same year, only two domestic commercial banks were among the top 25 equity underwriters, and those two had a market share of about 3.5%.

One way to examine the sensitivity of our results to commercial bank entry is to ask whether they persist when we exclude the early stages of commercial bank entry from the estimation sample. To that end, we have experimented by truncating the estimation sample at 1986, 1989, and 1994. The results from these specifications are not meaningfully different from the full sample results. Of course, this does not imply that commercial bank entry had no impact on investment-banking relationships. For example, Chen, Morrison, and Wilhelm (2015, pp. 1181-4) argue that competitive pressure from commercial banks on investment banks' risk-taking functions may have amplified internal conflicts of interest that, in turn, *indirectly* undermined trust among their investment-banking clients. But these risk-taking functions expanded rapidly beginning in the 1980s, in no small part as a consequence of the same technological changes that we identify at the root of agency

[45]These transactions were motivated by the Federal Reserve Board's *Private Placement Study* in 1977 that concluded, among other things, that banks were not engaged in underwriting in private placements and thus a case could be made for such activities not being prohibited by Sections 16 or 21 of the Glass Steagall Act. See Pitt and Williams (1983, pp. 154-156) for details.

problems within investment banks. Similarly, Drucker and Puri (2005) provide evidence of benefits associated with concurrent lending and underwriting capacity for seasoned equity offerings during the 1996-2001 period.[46]

## 5. Discussion

We have presented a theoretical framework that emphasizes the importance of tacit assets, such as client relationships and reputation concerns, in enabling banks to make complex non-contractual promises to their clients. Those assets are most effectively fostered in close client relationships, and they rely upon the bank's ability to resolve difficult internal governance problems. Governance is harder in large and complex banks and, hence, governance is compromised by technological advances that favor greater operational scale and scope. We cannot observe the state of a bank's governance, but we hypothesize that governance failures that pose a threat to client relationships are more likely to occur at greater levels of bank complexity. We examine the effect of three measures of complexity on a client's decision to break or to preserve an existing relationship. Our identification strategy rests on two instruments for complexity that are designed to reflect the bank's senior leadership's receptivity to technology adoption. The evidence that we present is consistent with the theory and its predictions.

The most obvious alternative explanation for a connection between bank complexity and relationship strength is outlined in Section 1: one might expect a complex bank's ability to offer a wider range of services to render it better able to maintain its relationships. Our results are not consistent with this explanation. Nor is our theory; we argue that trust, not the replicable capabilities that scale enables, is the basis of a banking relationship.

We also considered the alternative possibility that client switching is driven by assortative matching of the type identified by Fernando, Gatchev, and Spindt (2005). Using Fernando *et al.'s* methodology, we control for the possibility that assortative matching drives switching. Our main results survive this change. Our analysis confirms that assortative matching can drive bank

[46]Among the 107 cases in our sample in which an issuer switched to a commercial bank between 1996 and 1998, only 20 were equity issues.

selection, but it also indicates that this type of matching is tempered by the need to maintain the close relationships within which trust is fostered. We find that issuers are more likely to break with their relationship bank in favor of a better-matched bank when their relationship bank is more complex and, hence, is less able to make the tacit promises that justify close client relationships.

Finally, we provide evidence that favors a causal interpretation of the relation between bank complexity and client switching behavior. The instruments for complexity are quite strong from a statistical perspective and the connection between complexity and client behavior is insensitive to the measure of complexity and a number of alternative specifications of the empirical model. Any remaining doubts must relate to our ability to satisfy the exclusion restriction for identification. The Bayesian analysis presented in Section 4.3 indicates that our conclusions withstand violations of the exclusion restriction over a significant range of priors on the degree of the violation.

## 6. Conclusion

We examine the effect that an investment bank's internal governance has upon the strength of its client relationships. Our analysis rests upon theories that identify a strong bank-client relationship as an important foundation for mutual trust. Trust is important in investment banking, where information asymmetries are rife and there are few formal devices for addressing them. But an investment bank's ability to sustain trust, and so to earn the resultant relationship rents, is only as good as the governance systems it uses to control opportunistic behavior by its investment bankers. We therefore hypothesize that, if an investment bank's corporate governance systems weaken, then the clients for whom it underwrites securities offerings are more likely to break their relationship with the bank.

We test this hypothesis using three alternative measures of bank complexity and a variety of alternative specifications of the empirical model. In every instance, we find that relationships involving more complex banks are more likely to be broken. Even highly exclusive relationships are unlikely to be preserved at high levels of complexity. We also provide evidence that parties to a relationship trade off the benefits of the relationship against its opportunity costs. Specifically, we show that issuers are more likely to break a relationship in search of a better (positive assortative) match when the relationship bank is more complex.

Investment bankers appear to have experienced a crisis of trust in the last decade: their clients seem no longer to believe that banks can be relied upon to look out for the clients' best interests and, in line with this observation and our theoretical framework, investment banking relationships are weaker and less exclusive than at any time in the past (Morrison, Thegeya, Schenone, and Wilhelm, 2018). Our results suggest that regulatory concern that bank complexity contributes to poor governance and loss of trust is well-placed.

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**Figure 1:** Average Technology Exposure ± one standard deviation.

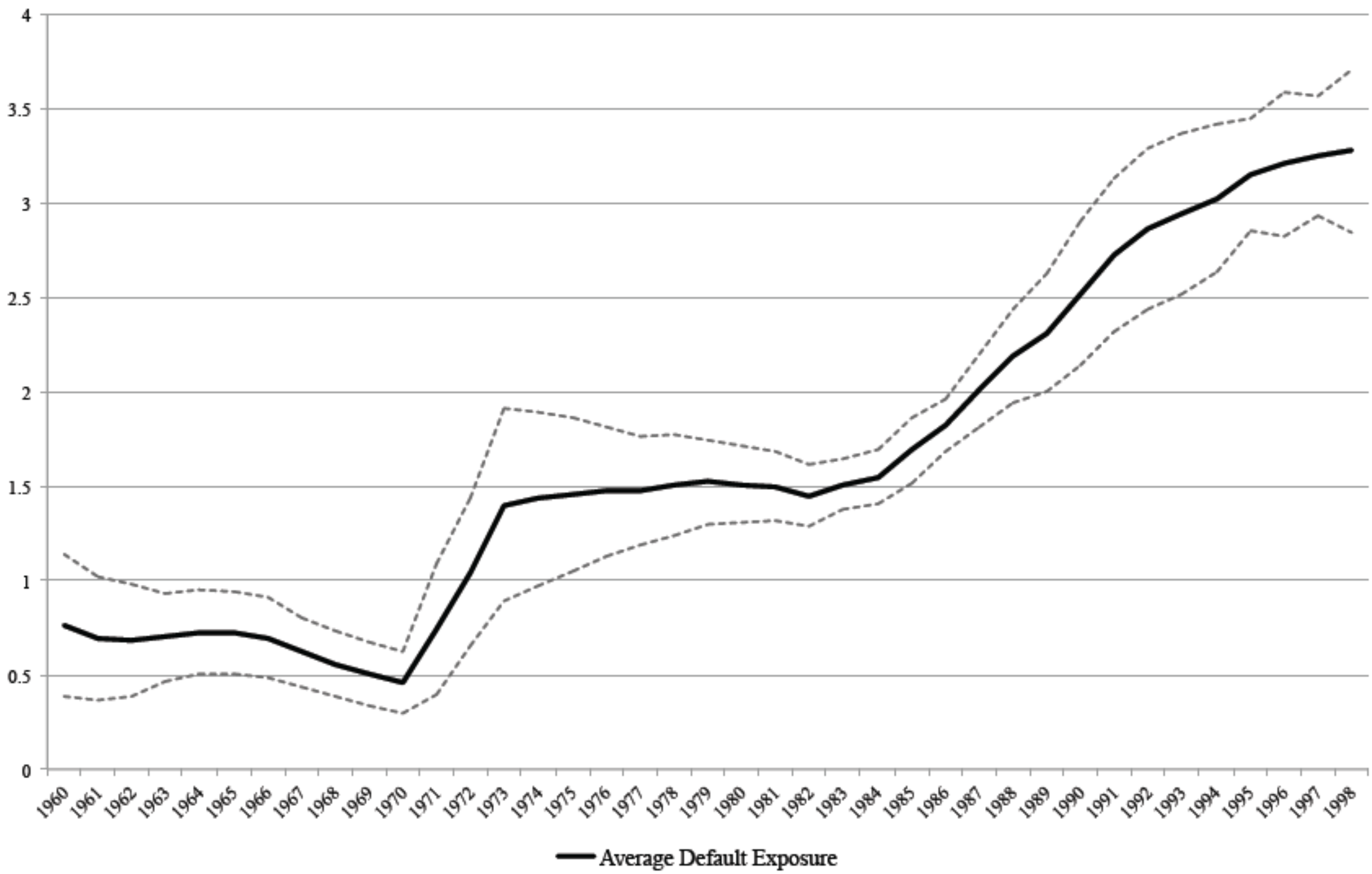



**Figure 2:** Average Default Exposure ± one standard deviation.

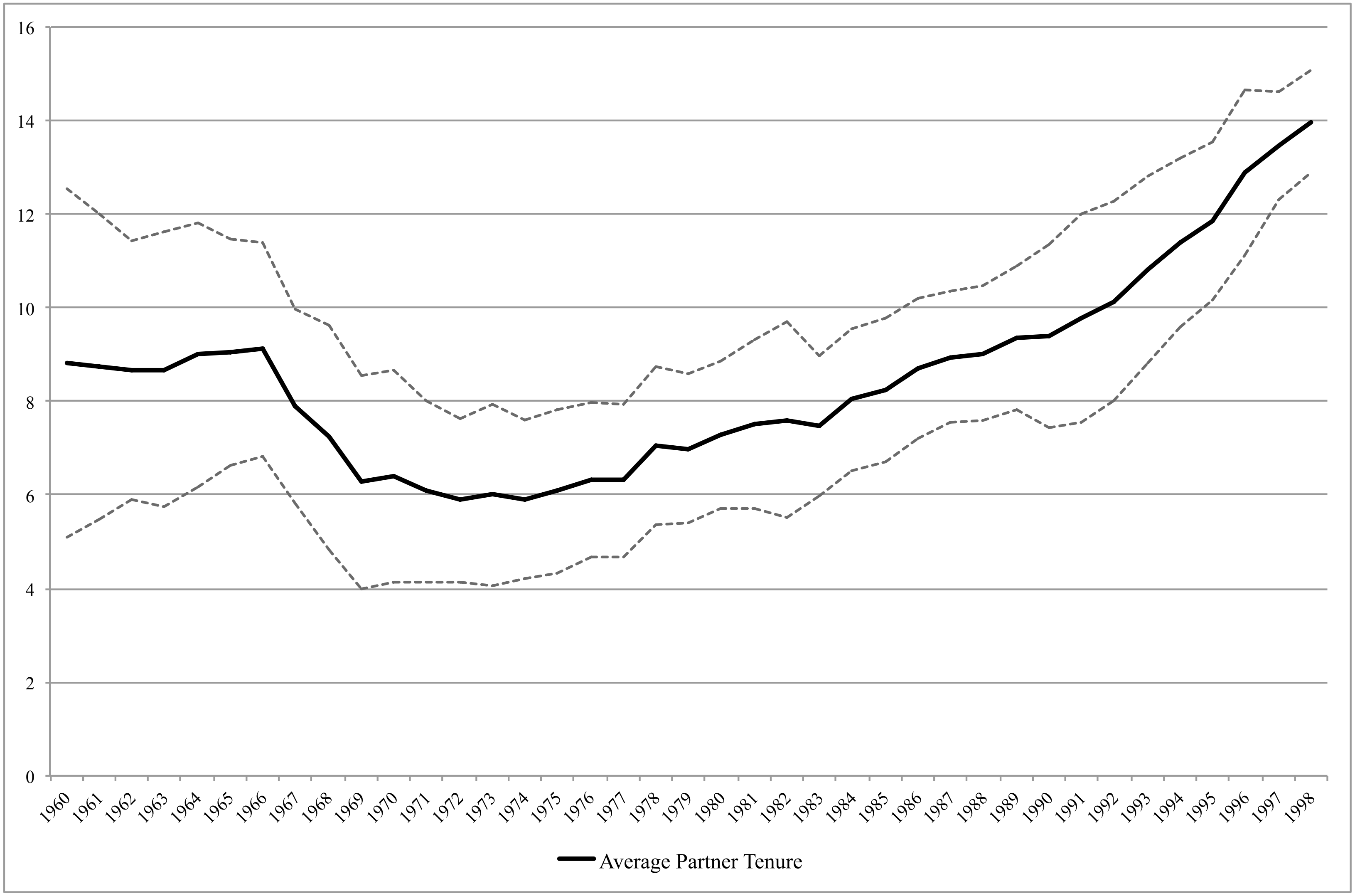



**Figure 3:** Average Partner Tenure ± one standard deviation.

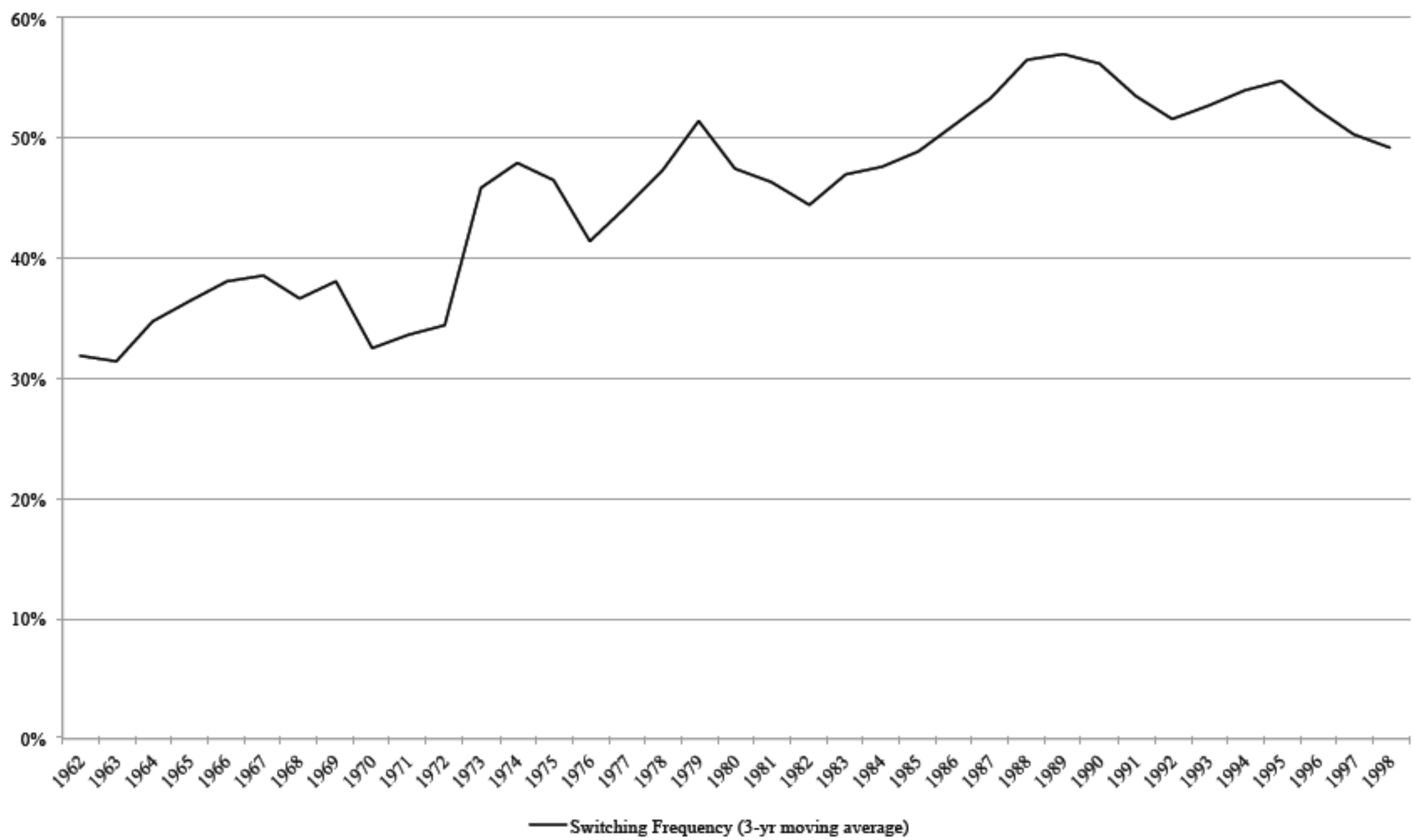
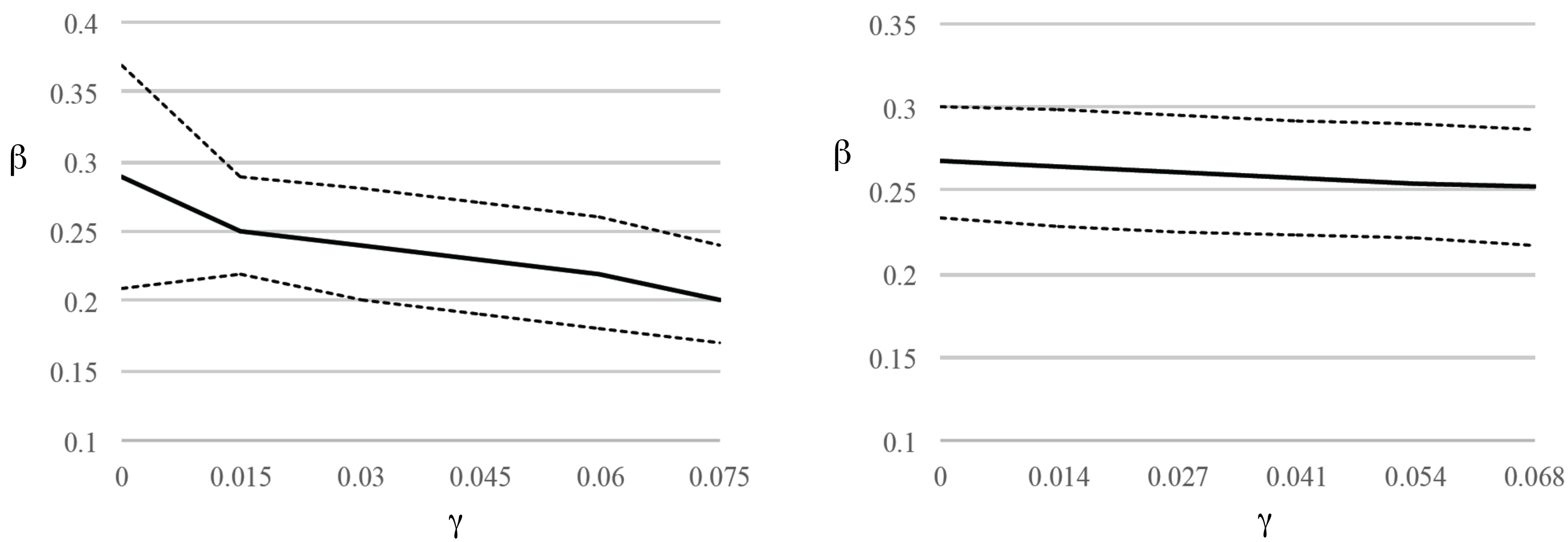



**Figure 4:** Switching Frequency (3-year moving average).




**Instrument:** *Technology Exposure*

**Instrument:** *Default Exposure*

**Figure 5:** The figure reports median posterior values and 95% Bayesian credibility intervals for the coefficient estimate, β, for *log(Capital)* as the prior on γ increases. The exclusion restriction corresponds with a prior belief of γ = 0. Increasing γ corresponds with relaxing the exclusion restriction. In each case, the level of γ increases in 5% increments to a maximum of 25% of the prior on β.

**Table I**

**Transaction Sample Summary Statistics**

The table reports summary statistics for underwritten capital-raising transactions by nonfinancial and nongovernmental U.S. issuers between January 1960 and December 1998. Pre-1970 data are collected from *Investment Dealers' Digest, Corporate Financing*. Data from 1970 forward are collected from the *Thomson Reuters SDC* database. The estimation sample includes nonfinancial and nongovernmental issues underwritten by at least one of 30 banks for which we have identified the first year of partnership for each of the bank's partners in 1960. Proceeds are converted to constant 1996 dollars using the annual GDP Deflator.

| | Number of Deals | % of Total Deals | Proceeds Raised ($m) | % of Total Proceeds |
|---|---|---|---|---|
| *Panel 1: Full Sample* | | | | |
| Equity Offerings | 23,490 | 44 | 1,152,730 | 23 |
| Debt Offerings | 29,393 | 56 | 3,960,963 | 77 |
| Total | 52,883 | 100 | 5,113,693 | 100 |
| *Panel 2: Switching Model Estimation Sample for Transactions led by at least one of 30 Sample Banks* | | | | |
| Equity Offerings | 4,604 | 28% | 414,978 | 19% |
| Public | 4,383 | 27% | 390,497 | 18% |
| IPO | 206 | 1% | 16,788 | 1% |
| Private | 221 | 1% | 24,481 | 1% |
| Debt Offerings | 11,676 | 72% | 1,804,291 | 81% |
| Public | 6,748 | 41% | 1,364,580 | 61% |
| Private | 3,495 | 21% | 280,620 | 13% |
| Public Preferred | 1,151 | 7% | 145,043 | 7% |
| Private Preferred | 282 | 2% | 14,048 | 1% |
| Total | 16,280 | | 2,219,269 | |
| | Mean | Median | Minimum | Maximum |
| Transactions per Year | 426 | 371 | 155 | 948 |
| % Issuer Switched Banks | 45% | 48% | 21% | 60% |

## Table II
## Sample Banks and Summary Statistics

The table reports summary statistics for 30 banks between January 1960 and December 1998. The total number of *transactions* (16,280) corresponds with panel 2 of Table I. The total number of *observations* (16,630) reflects the presence of 347 transactions with multiple bookrunners (344 with 2 bookrunners, and 3 with 3 bookrunners) from among the 30 sample banks, each of which is given full credit for the transaction. Proceeds are converted to constant 1996 dollars using the annual GDP Deflator.

| Banks | Number of Observations | % of Total Observations | Proceeds Raised ($m) | % of Total Proceeds | Switching Frequency | First year in Sample | Last Year in Sample | Years in Sample | First year *Public* = 1 |
|---|---|---|---|---|---|---|---|---|---|
| Goldman Sachs | 2,143 | 13 | 381,682 | 17 | 48.3% | 1960 | 1998 | 39 | 1986 |
| Salomon Brothers | 2,017 | 12 | 324,551 | 14 | 59.3% | 1960 | 1997 | 38 | 1981 |
| First Boston/CSFB | 2,006 | 12 | 323,993 | 14 | 49.5% | 1960 | 1995 | 36 | -- |
| Kidder Peabody | 1,381 | 8 | 117,650 | 5 | 41.6% | 1960 | 1994 | 35 | 1986 |
| Merrill Lynch | 1,362 | 8 | 168,862 | 7 | 50.0% | 1960 | 1988 | 29 | 1971 |
| Lehman Brothers | 1,086 | 7 | 141,594 | 6 | 43.1% | 1960 | 1991 | 32 | 1984 |
| Morgan Stanley | 1,045 | 6 | 227,232 | 10 | 40.6% | 1960 | 1986 | 27 | 1986 |
| Paine Webber | 953 | 6 | 92,265 | 4 | 50.7% | 1960 | 1997 | 38 | 1972 |
| Smith Barney | 549 | 3 | 59,896 | 3 | 43.4% | 1960 | 1993 | 34 | 1987 |
| Dillon Read | 498 | 3 | 75,342 | 3 | 31.7% | 1960 | 1997 | 38 | 1986 |
| Dean Witter (Reynolds) | 404 | 2 | 32,773 | 1 | 40.3% | 1960 | 1989 | 30 | 1972 |
| Donaldson Lufkin & Jenrette | 384 | 2 | 65,851 | 3 | 44.8% | 1969 | 1998 | 30 | 1970 |
| White Weld | 366 | 2 | 36,419 | 2 | 41.0% | 1960 | 1978 | 19 | 1978 |
| Alex. Brown | 326 | 2 | 21,117 | 1 | 34.0% | 1961 | 1997 | 37 | 1997 |
| Bear Stearns | 284 | 2 | 27,675 | 1 | 52.8% | 1960 | 1997 | 38 | 1985 |
| EF Hutton | 273 | 2 | 21,014 | 1 | 49.8% | 1960 | 1987 | 28 | 1972 |
| Blyth | 269 | 2 | 34,585 | 2 | 44.2% | 1960 | 1971 | 12 | 1970 |
| Blyth, Eastman Dillon | 259 | 2 | 37,268 | 2 | 57.5% | 1972 | 1978 | 7 | 1972 |
| Eastman Dillon | 203 | 1 | 13,269 | 1 | 33.5% | 1960 | 1971 | 12 | 1972 |
| Lazard | 147 | 1 | 29,995 | 1 | 49.7% | 1960 | 1997 | 38 | -- |
| Kuhn, Loeb | 146 | 1 | 24,238 | 1 | 32.9% | 1960 | 1977 | 18 | 1978 |
| Shearson Hammill | 135 | 1 | 7,021 | <1 | 46.7% | 1960 | 1984 | 25 | 1979 |
| William Blair | 104 | 1 | 4,221 | <1 | 30.8% | 1961 | 1997 | 37 | -- |
| Dupont | 80 | <1 | 3,342 | <1 | 65.0% | 1960 | 1972 | 13 | 1971 |
| Hornblower | 55 | <1 | 2,537 | <1 | 29.1% | 1964 | 1977 | 14 | 1977 |
| Loeb Rhoades | 52 | <1 | 4,070 | <1 | 26.9% | 1960 | 1979 | 20 | 1979 |
| Hayden Stone | 46 | <1 | 1,968 | <1 | 26.1% | 1960 | 1972 | 13 | -- |
| Reynolds Securities | 34 | <1 | 1,589 | <1 | 29.4% | 1960 | 1977 | 18 | 1971 |
| Cowen | 13 | <1 | 729 | <1 | 46.2% | 1987 | 1996 | 10 | -- |
| Goodbody | 10 | <1 | 290 | <1 | 50.0% | 1961 | 1970 | 10 | -- |
| Mean | 554 | | 76,101 | | 43% | | | 26 | |
| Median | 279 | | 31,384 | | 44% | | | 29 | |
| Total Number of Observations | 16,630 | | 2,283,038 | | | | | | |
| Total Number of Transactions | 16,280 | | 2,219,269 | | | | | | |

## Table III
## Explanatory Variable Summary Statistics

*Capital* equity plus long-term debt in 1996 dollars reported by the relationship bank in the year (*t*) of the client's transaction. *Partners* is the number of partners or senior officers reported by the relationship bank in year *t*. *Market Share* is a bank's share of the total dollar value of equity or debt in year *t-1*. *Relationship Strength* is a bank's share of the dollar value of a client's securities issued during the seven years preceding year (*t*). *SIC Share* is the client's share of total proceeds (inclusive of the client's proceeds) raised by the bank for firms in the client's 2-digit SIC code industry during the seven years preceding year *t*. *Mismatch* is the absolute difference between the issuer's proceeds percentile ranking and the bank's market share percentile ranking. *Proceeds* is the dollar value of securities issued in 1996 dollars. *Last Deal* is the number of years since the client's last transaction. Client Deal Experience is the number of deals by the client from 1930 to year *t*. *Equity* = 1 for equity issues. *Public Offering* = 1 for public debt and equity issues. *IPO* = 1 for initial public offerings of equity. *Technology Exposure* is a bank's annual partner-cohort-weighted measure of exposure to an annual index of -log(cost per million computations per second). Default *Exposure* is a bank's annual partner-cohort-weighted measure of exposure to Moody's annual default rate for speculative grade borrowers.

| | Obs. | Mean | Median | SD | Min. | Max. |
|---|---|---|---|---|---|---|
| Bank Characteristics | | | | | | |
| *Capital ($m)* | 16,630 | 3063.10 | 702.88 | 5287.96 | 4.67 | 27162.58 |
| *Partners* | 16,630 | 161.52 | 127.00 | 116.68 | 4.00 | 494.00 |
| *Market Share Debt(t-1)* | 16,630 | 0.07 | 0.07 | 0.06 | 0.00 | 0.27 |
| *Market Share Equity(t-1)* | 16,630 | 0.07 | 0.05 | 0.06 | 0.00 | 0.32 |
| Bank-Client Characteristics | | | | | | |
| *Relationship Strength* | 16,630 | 0.48 | 0.43 | 0.41 | 0.00 | 1.00 |
| *SIC Share* | 16,630 | 0.23 | 0.08 | 0.30 | 0.00 | 1.00 |
| *Mismatch* | 16,630 | 0.23 | 0.19 | 0.19 | 0.00 | 1.00 |
| Transaction and Client Characteristics | | | | | | |
| *Proceeds ($m)* | 16,630 | 137.29 | 75.17 | 232.39 | 0.10 | 5951.00 |
| *Last Deal* | 16,630 | 1.53 | 1.00 | 2.17 | 0.00 | 40.00 |
| *Client Deal Experience* | 16,630 | 17.07 | 9.00 | 20.85 | 1.00 | 157.00 |
| *Equity* | 16,630 | 0.28 | 0.00 | 0.45 | 0.00 | 1.00 |
| *Public Offering* | 16,630 | 0.69 | 1.00 | 0.46 | 0.00 | 1.00 |
| *IPO* | 16,630 | 0.01 | 0.00 | 0.12 | 0.00 | 1.00 |
| Instruments | | | | | | |
| *Technology Exposure* | 16,630 | 8.56 | 9.51 | 3.38 | -0.65 | 12.90 |
| *Default Exposure* | 16,630 | 1.75 | 1.71 | 0.87 | 0.16 | 3.72 |

## Table IV

### First-Stage Regressions: log(Capital)

The table reports first-stage regressions for the client switching model in which *log*(*Capital*) is the (endogenous) dependent variable. There are three sets of regressions using either *Technology Exposure, Default Exposure,* or both as instruments. In each set of regressions, the first corresponds with a second-stage regression in which *log*(*Capital*) is *not* interacted with *Relationship Strength*. The next two columns report the set of first-stage regressions that correspond with the second-stage model in which *log*(*Capital*) is interacted with *Relationship Strength*. Each regression includes year, bank, and (client) 2-digit SIC fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Instruments | | | | | | | | | |
| *Technology Exposure* | 0.0567*** | 0.0645*** | -0.1203*** | | | | 0.0429*** | 0.0628*** | -0.0008 |
| | (0.0092) | (0.0094) | (0.0099) | | | | (0.0071) | (0.0078) | (0.0096) |
| *Default Exposure* | | | | 0.1338*** | 0.1433*** | -0.6232*** | 0.1044*** | 0.0583*** | -0.3331*** |
| | | | | (0.0155) | (0.0161) | (0.0208) | (0.0163) | (0.0188) | (0.0233) |
| Bank-Client Characteristics | | | | | | | | | |
| *Relationship Strength* | 0.0073 | 0.1157*** | 3.2773*** | 0.0048 | 0.0399** | 3.9619*** | 0.0062 | 0.1195*** | 3.3993*** |
| | (0.0077) | (0.0229) | (0.0273) | (0.0076) | (0.0169) | (0.0219) | (0.0076) | (0.0209) | (0.0258) |
| *Relationship Strength x Technology Exposure* | | -0.0127*** | 0.3843*** | | | | | -0.0280*** | 0.1965*** |
| | | (0.0024) | (0.0034) | | | | | (0.0043) | (0.0053) |
| *Relationship Strength x Default Exposure* | | | | | -0.0204** | 1.5079*** | | 0.0733*** | 0.8611*** |
| | | | | | (0.0088) | (0.0113) | | (0.0167) | (0.0207) |
| *SIC Share* | 0.0483*** | 0.0499*** | 0.0034 | 0.0494*** | 0.0499*** | 0.015 | 0.0489*** | 0.0505*** | 0.0057 |
| | (0.0156) | (0.0156) | (0.0199) | (0.0141) | (0.0141) | (0.0183) | (0.0141) | (0.0141) | (0.0174) |
| Bank Characteristics | | | | | | | | | |
| *Market Share Equity(t-1)* | 1.3598*** | 1.3582*** | 0.3298*** | 1.3652*** | 1.3630*** | 0.5355*** | 1.3329*** | 1.3394*** | 0.3706*** |
| | -0.0659 | -0.0658 | -0.0913 | -0.0758 | -0.0758 | -0.098 | -0.0759 | -0.0758 | -0.0938 |
| *Market Share Debt(t-1)* | 4.3629*** | 4.3422*** | 2.1601*** | 4.2314*** | 4.2317*** | 1.3626*** | 4.2867*** | 4.2496*** | 1.8033*** |
| | (0.1143) | (0.1142) | (0.1330) | (0.1083) | (0.1083) | (0.1401) | (0.1085) | (0.1085) | (0.1343) |
| Client and Transaction Characteristics | | | | | | | | | |
| *log(Proceeds)* | -0.0143*** | -0.0135*** | -0.0110*** | -0.0139*** | -0.0136*** | -0.0086** | -0.0139*** | -0.0133*** | -0.0112*** |
| | (0.0030) | (0.0031) | (0.0039) | (0.0030) | (0.0030) | (0.0039) | (0.0030) | (0.0030) | (0.0037) |
| *Last Deal* | -0.0026* | -0.0019 | 0.0042** | -0.0025* | -0.0021 | 0.0038** | -0.0025* | -0.002 | 0.002 |
| | (0.0015) | (0.0015) | (0.0021) | (0.0014) | (0.0015) | (0.0019) | (0.0014) | (0.0014) | (0.0018) |
| *Client Deal Experience* | 0.0008*** | 0.0008*** | -0.0007*** | 0.0008*** | 0.0008*** | -0.0008*** | 0.0008*** | 0.0008*** | -0.0007*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| *Equity* | -0.0059 | -0.0048 | -0.0034 | -0.0041 | -0.0039 | 0.0141 | -0.0047 | -0.0033 | 0.0036 |
| | (0.0075) | (0.0075) | (0.0099) | (0.0075) | (0.0075) | (0.0098) | (0.0075) | (0.0075) | (0.0093) |
| *Public Offering* | 0.0518*** | 0.0504*** | 0.0225** | 0.0490*** | 0.0488*** | -0.004 | 0.0494*** | 0.0474*** | 0.0098 |
| | (0.0085) | (0.0085) | (0.0107) | (0.0083) | (0.0083) | (0.0108) | (0.0083) | (0.0083) | (0.0103) |
| *IPO* | 0.0127 | 0.0133 | 0.0194 | 0.0101 | 0.0108 | -0.017 | 0.011 | 0.01 | -0.0024 |
| | (0.0278) | (0.0278) | (0.0428) | (0.0256) | (0.0256) | (0.0332) | (0.0256) | (0.0256) | (0.0317) |
| Observations | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 |
| $R^2$ | 0.96 | 0.96 | 0.97 | 0.96 | 0.96 | 0.97 | 0.96 | 0.96 | 0.97 |
| Cragg-Donald F-statistic | 37.84 | 21.02 | | 59.58 | 29.98 | | 35.54 | 25.42 | |

**Table V**

**Second-Stage Regressions with Bank Capital as the Endogenous Explanatory Variable**

The table reports second-stage regressions for the linear probability model of client switching behavior in which the instrumented value of *log*(*Capital*) from the first-stage regression is the explanatory variable of interest. Results are provided for four sets of models. Each set includes two independent regressions where the second is distinguished by the interaction between *Relationship Strength* and *log*(*Capital*). OLS results are provided as a benchmark. *Log*(*Capital*) is instrumented with either *Technology Exposure* or *Default Exposure* in the next two sets of regressions. In the final set of regressions, both instruments were used in the first-stage regressions. Each regression includes year, bank, and (client) 2-digit SIC fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | OLS | | First-Stage IV: *Technology Exposure* | | First-Stage IV: *Default Exposure* | | First-Stage IV: Both | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *log(Capital)* | -0.0027 | -0.0180* | 0.4205*** | 0.2870** | 0.2405* | 0.2025 | 0.3260*** | 0.2711*** |
| | (0.0097) | (0.0098) | (0.1586) | (0.1421) | (0.1441) | (0.1419) | (0.1235) | (0.1034) |
| Bank-Client Characteristics | | | | | | | | |
| *Relationship Strength* | -0.1600*** | -0.4560*** | -0.1625*** | -0.5874*** | -0.1615*** | -0.5871*** | -0.1620*** | -0.5890*** |
| | (0.0096) | (0.0351) | (0.0101) | (0.0556) | (0.0097) | (0.0499) | (0.0099) | (0.0488) |
| *Relationship Strength x log(Capital)* | | 0.0451*** | | 0.0649*** | | 0.0649*** | | 0.0652*** |
| | | (0.0053) | | (0.0084) | | (0.0075) | | (0.0073) |
| *SIC Share* | -0.2185*** | -0.2201*** | -0.2391*** | -0.2360*** | -0.2303*** | -0.2319*** | -0.2345*** | -0.2352*** |
| | (0.0178) | (0.0179) | (0.0201) | (0.0196) | (0.0193) | (0.0193) | (0.0192) | (0.0189) |
| Bank Characteristics | | | | | | | | |
| *Market Share Equity(t-1)* | -0.4063*** | -0.4028*** | -1.0063*** | -0.8430*** | -0.7511*** | -0.7232*** | -0.8724*** | -0.8206*** |
| | (0.0945) | (0.0946) | (0.2462) | (0.2252) | (0.2255) | (0.2231) | (0.2005) | (0.1754) |
| *Market Share Debt(t-1)* | 0.0441 | 0.0454 | -1.7815** | -1.2985** | -1.0051 | -0.9339 | -1.3739** | -1.2302*** |
| | (0.1395) | (0.1391) | (0.6973) | (0.6325) | (0.6385) | (0.6313) | (0.5510) | (0.4712) |
| Client and Transaction Characteristics | | | | | | | | |
| *log(Proceeds)* | 0.0197*** | 0.0190*** | 0.0258*** | 0.0232*** | 0.0232*** | 0.0220*** | 0.0244*** | 0.0230*** |
| | (0.0039) | (0.0038) | (0.0047) | (0.0044) | (0.0044) | (0.0044) | (0.0044) | (0.0042) |
| *Last Deal* | -0.001 | -0.0023 | 0.0001 | -0.002 | -0.0003 | -0.0022 | -0.0001 | -0.0021 |
| | (0.0018) | (0.0018) | (0.0020) | (0.0019) | (0.0019) | (0.0019) | (0.0019) | (0.0019) |
| *Client Deal Experience* | 0.0027*** | 0.0028*** | 0.0024*** | 0.0026*** | 0.0025*** | 0.0027*** | 0.0025*** | 0.0026*** |
| | (0.0002) | (0.0002) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0002) |
| *Equity* | -0.0672*** | -0.0687*** | -0.0649*** | -0.0676*** | -0.0659*** | -0.0681*** | -0.0654*** | -0.0677*** |
| | (0.0094) | (0.0094) | (0.0099) | (0.0096) | (0.0095) | (0.0095) | (0.0097) | (0.0096) |
| *Public Offering* | -0.1024*** | -0.1008*** | -0.1245*** | -0.1163*** | -0.1151*** | -0.1119*** | -0.1196*** | -0.1155*** |
| | (0.0105) | (0.0105) | (0.0137) | (0.0130) | (0.0130) | (0.0129) | (0.0125) | (0.0120) |
| *IPO* | 0.1002*** | 0.0989*** | 0.0951** | 0.0945*** | 0.0973*** | 0.0955*** | 0.0962*** | 0.0947*** |
| | (0.0338) | (0.0334) | (0.0370) | (0.0353) | (0.0352) | (0.0345) | (0.0360) | (0.0351) |
| Observations | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 |
| $R^2$ | 0.129 | 0.132 | 0.001 | 0.051 | 0.070 | 0.077 | 0.041 | 0.056 |

## Table VI

### Bank Complexity and Positive Assortative Matching

The table reports second-stage linear probability models in which the endogenous explanatory variable of interest is either *log(Capital)* or *Partners* and first-stage regressions include both *Technology Exposure* and *Default Exposure* as instruments. *Mismatch* is an absolute measure of the "quality" difference between an issuer and its relationship bank. Each regression includes year, bank, and (client) 2-digit SIC fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | | |
|---|---|---|
| *log(Capital)* | 0.2310** | |
| | (0.1014) | |
| *Partners* | | 0.0003 |
| | | (0.0006) |
| Bank-Client Characteristics | | |
| *Mismatch* | -0.1666 | 0.0542 |
| | (0.1146) | (0.0566) |
| *Mismatch x log(Capital)* | 0.0519*** | |
| | (0.0167) | |
| *Mismatch x Partners* | | 0.0008** |
| | | (0.0003) |
| *Relationship Strength* | -0.5841*** | -0.3112*** |
| | (0.0481) | (0.0232) |
| *Relationship Strength x log(Capital)* | 0.0645*** | |
| | (0.0073) | |
| *Relationship Strength x Partners* | | 0.0009*** |
| | | (0.0001) |
| *SIC Share* | -0.2467*** | -0.2307*** |
| | (0.0188) | (0.0180) |
| Bank Characteristics | | |
| *Market Share Equity(t-1)* | -0.8253*** | -0.4736*** |
| | (0.1758) | (0.0944) |
| *Market Share Debt(t-1)* | -1.1863** | 0.0000 |
| | (0.4697) | (0.1345) |
| Client and Transaction Characteristics | | |
| *log(Proceeds)* | 0.0402*** | 0.0369*** |
| | (0.0047) | (0.0044) |
| *Last Deal* | -0.0023 | -0.0019 |
| | (0.0019) | (0.0019) |
| *Client Deal Experience* | 0.0026*** | 0.0028*** |
| | (0.0002) | (0.0002) |
| *Equity* | -0.0666*** | -0.0679*** |
| | (0.0095) | (0.0094) |
| *Public Offering* | -0.1070*** | -0.0959*** |
| | (0.0117) | (0.0106) |
| *IPO* | 0.0941*** | 0.1077*** |
| | (0.0346) | (0.0334) |
| Observations | 16630 | 16630 |
| $R^2$ | 0.069 | 0.098 |

## Table VII
## Second-Stage Regressions: Discrete Organizational Change

The table reports second-stage regressions for the linear probability model of client switching behavior in which the binary variable *Public* is the explanatory variable of interest. Results are provided for three sets of models. Each set includes two independent regressions where the second is distinguished by the interaction between *Relationship Strength* and *Public*. *Public* is instrumented with either *Technology Exposure* or *Default Exposure* in the first two sets of regressions. In the final set of regressions, both instruments were used in the first-stage regressions. Each regression includes decade, bank, and (client) 2-digit SIC fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | First-Stage IV: *Technology Exposure* | | First-Stage IV: *Default Exposure* | | First-Stage IV: Both | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Public* | 0.1212*** | 0.0792** | 0.1157*** | 0.0723* | 0.1309*** | 0.0795** |
| | (0.0244) | (0.0402) | (0.0256) | (0.0419) | (0.0247) | (0.0401) |
| Bank-Client Characteristics | | | | | | |
| *Relationship Strength* | -0.2208*** | -0.2755*** | -0.2262*** | -0.2681*** | -0.2267*** | -0.2772*** |
| | (0.0502) | (0.0566) | (0.0502) | (0.0570) | (0.0503) | (0.0566) |
| *Relationship Strength x Public* | | 0.0941* | | 0.0807 | | 0.0973* |
| | | (0.0555) | | (0.0576) | | (0.0555) |
| *SIC Share* | -0.1192 | -0.1176 | -0.1135 | -0.1173 | -0.1130 | -0.1177 |
| | (0.0968) | (0.0964) | (0.0967) | (0.0963) | (0.0969) | (0.0965) |
| Bank Characteristics | | | | | | |
| *Market Share Equity(t-1)* | 0.5685** | 0.5943** | 0.5684** | 0.5697** | 0.5950** | 0.5980** |
| | (0.2619) | (0.2620) | (0.2630) | (0.2626) | (0.2624) | (0.2620) |
| *Market Share Debt(t-1)* | 1.7986*** | 1.9819*** | 2.1448*** | 2.0205*** | 2.1253*** | 1.9743*** |
| | (0.6459) | (0.6744) | (0.6658) | (0.6749) | (0.6660) | (0.6744) |
| Client and Transaction Characteristics | | | | | | |
| *log(Proceeds)* | -0.0610*** | -0.0639*** | -0.0632*** | -0.0642*** | -0.0627*** | -0.0638*** |
| | (0.0195) | (0.0194) | (0.0194) | (0.0194) | (0.0194) | (0.0194) |
| *Last Deal* | -0.0107 | -0.0101 | -0.0102 | -0.0099 | -0.0104 | -0.0101 |
| | (0.0100) | (0.0100) | (0.0100) | (0.0100) | (0.0100) | (0.0100) |
| *Client Deal Experience* | 0.0019 | 0.0019 | 0.0023 | 0.0023 | 0.0018 | 0.0018 |
| | (0.0026) | (0.0026) | (0.0026) | (0.0026) | (0.0026) | (0.0026) |
| *Equity* | -0.0087 | -0.0085 | -0.0068 | -0.0081 | -0.007 | -0.0086 |
| | (0.0331) | (0.0330) | (0.0329) | (0.0329) | (0.0330) | (0.0330) |
| *Public Offering* | -0.2485*** | -0.2541*** | -0.2558*** | -0.2559*** | -0.2538*** | -0.2538*** |
| | (0.0384) | (0.0383) | (0.0383) | (0.0383) | (0.0383) | (0.0383) |
| *IPO* | -0.1717 | -0.1538 | -0.1621 | -0.1547 | -0.1625 | -0.1536 |
| | (0.1512) | (0.1484) | (0.1490) | (0.1482) | (0.1492) | (0.1484) |
| *Inverse Mills Ratio* | -0.3929 | -0.4146 | -0.4354 | -0.4392 | -0.408 | -0.411 |
| | (0.3266) | (0.3259) | (0.3271) | (0.3269) | (0.3260) | (0.3258) |
| Observations | 2078 | 2078 | 2078 | 2078 | 2078 | 2078 |
| $R^2$ | 0.141 | 0.145 | 0.144 | 0.145 | 0.144 | 0.145 |

**Table A.I**

**First-Stage Regressions: Partners**

The table reports first-stage regressions for the client switching model in which *Partners* is the (endogenous) dependent variable. There are three sets of regressions using either *Technology Exposure, Default Exposure*, or both as instruments. In each set of regressions, the first corresponds with a second-stage regression in which *Partners* is *not* interacted with *Relationship Strength* (*RelStr*). The next two columns report the set of first-stage regressions that correspond with the second-stage model in which *Partners* is interacted with *Relationship Strength*. Each regression includes year, bank, and (client) 2-digit SIC fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Instruments | | | | | | | | | |
| *Technology Exposure* | 7.2466*** | 7.6596*** | -3.9130*** | | | | 3.7863*** | 4.0081*** | -12.5957*** |
| | (0.8771) | (0.8926) | (0.6862) | | | | (0.8057) | (0.8790) | (0.8735) |
| *Default Exposure* | | | | 28.8642*** | 29.7033*** | -8.6133*** | 26.2721*** | 26.4056*** | 40.1887*** |
| | | | | (1.7533) | (1.8125) | (1.9688) | (1.8369) | (2.1257) | (2.1122) |
| Bank-Client Characteristics | | | | | | | | | |
| *Relationship Strength* | 1.3228 | 7.0498** | -0.8965 | 0.9096 | 4.0148** | 69.5270*** | 1.0279 | 4.9616** | -8.1475*** |
| | (0.8766) | (2.8293) | (1.9517) | (0.8633) | (1.9083) | (2.0728) | (0.8631) | (2.3590) | (2.3441) |
| *Relationship Strength x Technology Exposure* | | -0.6701** | 18.8556*** | | | | | -0.3452 | 27.1710*** |
| | | (0.2961) | (0.2469) | | | | | (0.4862) | (0.4831) |
| *Relationship Strength x Default Exposure* | | | | | -1.8036* | 52.5104*** | | -0.5704 | -37.2248*** |
| | | | | | (0.9885) | (1.0737) | | (1.8879) | (1.8760) |
| *SIC Share* | -3.6893** | -3.6055** | -1.526 | -3.4831** | -3.4380** | -0.3402 | -3.5242** | -3.4675** | -1.4878 |
| | (1.6677) | (1.6691) | (1.6226) | (1.5934) | (1.5935) | (1.7309) | (1.5924) | (1.5927) | (1.5826) |
| Bank Characteristics | | | | | | | | | |
| *Market Share Equity(t-1)* | -10.1906 | -10.2758 | 2.842 | -14.1132* | -14.3121* | 7.9029 | -16.9641** | -17.0284** | -5.5448 |
| | (7.8774) | (7.8735) | (8.8012) | (8.5572) | (8.5573) | (9.2952) | (8.5732) | (8.5746) | (8.5205) |
| *Market Share Debt(t-1)* | 22.6757** | 21.5772* | -13.5628 | -1.3819 | -1.3599 | -61.5340*** | 3.4924 | 3.0226 | -16.6465 |
| | (11.1898) | (11.1668) | (10.2892) | (12.2261) | (12.2252) | (13.2794) | (12.2622) | (12.2784) | (12.2008) |
| Client and Transaction Characteristics | | | | | | | | | |
| *log(Proceeds)* | 1.0548*** | 1.0922*** | -0.6500* | 1.1411*** | 1.1639*** | -0.2226 | 1.1399*** | 1.1660*** | -0.5702* |
| | (0.3458) | (0.3460) | (0.3359) | (0.3385) | (0.3387) | (0.3680) | (0.3383) | (0.3386) | (0.3364) |
| *Last Deal* | -0.2952* | -0.254 | -0.3555** | -0.2557 | -0.2268 | -0.0157 | -0.2597 | -0.2295 | -0.2395 |
| | (0.1678) | (0.1683) | (0.1681) | (0.1633) | (0.1640) | (0.1782) | (0.1632) | (0.1640) | (0.1629) |
| *Client Deal Experience* | 0.0393** | 0.0380* | -0.0320* | 0.0381* | 0.0372* | -0.0457** | 0.0378* | 0.0369* | -0.0338 |
| | (0.0198) | (0.0199) | (0.0178) | (0.0210) | (0.0210) | (0.0228) | (0.0210) | (0.0210) | (0.0208) |
| *Equity* | -0.5322 | -0.4744 | -0.6898 | -0.1881 | -0.1675 | 0.5496 | -0.2407 | -0.2058 | -0.7234 |
| | (0.8551) | (0.8548) | (0.8758) | (0.8520) | (0.8520) | (0.9255) | (0.8515) | (0.8518) | (0.8465) |
| *Public Offering* | 1.2632 | 1.19 | 0.6044 | 0.6358 | 0.616 | -1.196 | 0.6705 | 0.6296 | 0.5911 |
| | (0.9723) | (0.9728) | (0.9652) | (0.9384) | (0.9384) | (1.0194) | (0.9379) | (0.9384) | (0.9325) |
| *IPO* | -5.7141** | -5.6862** | -8.7532** | -6.2203** | -6.1604** | -10.0281*** | -6.1434** | -6.1080** | -8.2419*** |
| | (2.6017) | (2.5896) | (3.5469) | (2.8962) | (2.8962) | (3.1459) | (2.8944) | (2.8946) | (2.8763) |
| Observations | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 |
| $R^2$ | 0.87 | 0.87 | 0.80 | 0.87 | 0.87 | 0.77 | 0.87 | 0.87 | 0.80 |
| Cragg-Donald F-statistic | 68.25 | 35.56 | | 254.41 | 127.70 | | 147.20 | 73.97 | |

## Table A.II
## Second-Stage Regressions with Number of Partners as the Endogenous Explanatory Variable

The table reports second-stage regressions for the linear probability model of client switching behavior in which the instrumented value of *Partners* from the first-stage regression is the explanatory variable of interest. Results are provided for four sets of models. Each set includes two independent regressions where the second is distinguished by the interaction between *Relationship Strength* and *Partners*. OLS results are provided as a benchmark. *Partners* is instrumented with either *Technology Exposure* or *Default Exposure* in the next two sets of regressions. In the final set of regressions, both instruments were used in the first-stage regressions. Each regression includes year, bank, and (client) 2-digit SIC fixed effects. Robust standard errors (clustered at the deal level) are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

| | OLS | | First-Stage IV: *Technology Exposure* | | First-Stage IV: *Default Exposure* | | First-Stage IV: Both | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Partners* | -0.0001 | -0.0003*** | 0.0033*** | 0.0020* | 0.0011* | 0.0001 | 0.0015** | 0.0007 |
| | (0.0001) | (0.0001) | (0.0012) | (0.0011) | (0.0007) | (0.0007) | (0.0006) | (0.0006) |
| Bank-Client Characteristics | | | | | | | | |
| *Relationship Strength* | -0.1599*** | -0.2190*** | -0.1638*** | -0.3546*** | -0.1613*** | -0.4468*** | -0.1617*** | -0.3118*** |
| | (0.0096) | (0.0155) | (0.0101) | (0.0257) | (0.0096) | (0.0341) | (0.0097) | (0.0234) |
| *Relationship Strength x Partners* | | 0.0004*** | | 0.0012*** | | 0.0018*** | | 0.0009*** |
| | | (0.0001) | | (0.0002) | | (0.0002) | | (0.0001) |
| *SIC Share* | -0.2191*** | -0.2200*** | -0.2067*** | -0.2124*** | -0.2146*** | -0.2197*** | -0.2133*** | -0.2169*** |
| | (0.0178) | (0.0178) | (0.0192) | (0.0189) | (0.0180) | (0.0183) | (0.0181) | (0.0181) |
| Bank Characteristics | | | | | | | | |
| *Market Share Equity(t-1)* | -0.4105*** | -0.4141*** | -0.4010*** | -0.4146*** | -0.4071*** | -0.4247*** | -0.4061*** | -0.4161*** |
| | (0.0934) | (0.0935) | (0.0969) | (0.0964) | (0.0936) | (0.0953) | (0.0939) | (0.0942) |
| *Market Share Debt(t-1)* | 0.0343 | 0.0561 | (0.0216) | 0.0608 | 0.0141 | 0.1218 | 0.0085 | 0.0691 |
| | (0.1333) | (0.1334) | (0.1401) | (0.1383) | (0.1343) | (0.1355) | (0.1348) | (0.1347) |
| Client and Transaction Characteristics | | | | | | | | |
| *log(Proceeds)* | 0.0199*** | 0.0199*** | 0.0163*** | 0.0172*** | 0.0186*** | 0.0189*** | 0.0182*** | 0.0186*** |
| | (0.0039) | (0.0038) | (0.0042) | (0.0041) | (0.0039) | (0.0039) | (0.0039) | (0.0039) |
| *Last Deal* | -0.001 | -0.0013 | 0.0000 | -0.0013 | -0.0006 | -0.0024 | -0.0005 | -0.0015 |
| | (0.0018) | (0.0018) | (0.0020) | (0.0019) | (0.0019) | (0.0019) | (0.0019) | (0.0019) |
| *Client Deal Experience* | 0.0027*** | 0.0028*** | 0.0026*** | 0.0027*** | 0.0027*** | 0.0029*** | 0.0027*** | 0.0028*** |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| *Equity* | -0.0672*** | -0.0677*** | -0.0656*** | -0.0674*** | -0.0666*** | -0.0689*** | -0.0665*** | -0.0678*** |
| | (0.0094) | (0.0094) | (0.0098) | (0.0097) | (0.0094) | (0.0095) | (0.0094) | (0.0094) |
| *Public Offering* | -0.1024*** | -0.1017*** | -0.1069*** | -0.1035*** | -0.1040*** | -0.1002*** | -0.1045*** | -0.1022*** |
| | (0.0105) | (0.0105) | (0.0110) | (0.0109) | (0.0105) | (0.0106) | (0.0106) | (0.0105) |
| *IPO* | 0.0995*** | 0.1015*** | 0.1192*** | 0.1215*** | 0.1067*** | 0.1154*** | 0.1087*** | 0.1119*** |
| | (0.0339) | (0.0337) | (0.0354) | (0.0347) | (0.0340) | (0.0338) | (0.0341) | (0.0338) |
| Observations | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 | 16630 |
| $R^2$ | 0.129 | 0.130 | 0.017 | 0.045 | 0.093 | 0.080 | 0.086 | 0.091 |