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Can Relationship Banking Reduce Firms' IPO Underpricing

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Abstract

IPO underpricing harms pre-existing shareholders and reduces the capital firms can raise to fund their growth. This paper shows that relationship banking can reduce IPO underpricing by decreasing information uncertainty. I develop a theoretical model showing that good firms – those with a lower dispersion of market value – are harmed and bad firms benefit from IPO price uncertainty when there is no borrowing and, thus, no distinguishing information on firm quality. When investors receive signals about firm value only from publicly observable transaction lending, good firms benefit while bad firms suffer. However, when firms have access to loans through relationship banks and when such lending decisions are kept confidential, firms experience reduced IPO price uncertainty, which benefits both good and bad firms. I confirm this result empirically through difference-in-differences and reduced form instrumental variable regression designs. I use variation in the strength of the lending relationship between IPO firms and their underwriters generated by the repeal of the Glass-Steagall Act in 1999, which allowed commercial banks with close ties to their client firms to underwrite those firms' equity issuances.

Key words: Difference-in-differences, Instrumental variable, Glass-Steagall Act, IPO underpricing, Relationship banking, Information asymmetry, Underwriter, Investors

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1 Introduction

This paper investigates whether relationship banking can help reduce IPO underpricing. Previous literature relates IPO underpricing to information asymmetry (Allen and Faulhaber, 1989; Benveniste and Spindt, 1989; Benveniste and Wilhelm, 1990; Grinblatt and Hwang, 1989; Rock, 1986). If this is true, then relationship banking, which reduces both the information asymmetry between the firm and the underwriter and the information asymmetry between the firm and investors, should limit IPO underpricing.

The phenomenon of IPO underpricing has important consequences for financial markets. Underpricing harms pre-IPO shareholders because they receive lower proceeds from the IPO and reduces the capital raised in the IPO, which firms need to reinvest and grow. Over the last 50 years, IPOs in the United States have been underpriced by 16.8% on average. This translates to more than $125 billion left on the table in just the last 20 years. IPO underpricing plagues markets worldwide. In Britain, the average IPO was underpriced by 16.3% in the period ranging from 1959 to 2009. In most other countries, average IPO underpricing now exceeds 20%. In China, the phenomenon is particularly severe, averaging 137.4% from 1990 to 2010.[1] The prevalence of such astronomical IPO underpricing motivates this study. Previous research identifies information asymmetry as one of the key potential drivers of underpricing. I propose that there maybe a fixable-mechanism underlying this information asymmetry: the strength and nature of the relationship between the underwriter and the firm. In particular, I posit that relationship banking reduces the underwriter's and investors' uncertainty about the true value of the firm and, thus, generates more accurate IPO prices. I theoretically document, how this mechanism could affect firms of varying quality. Then, I empirically measure the portion of IPO underpricing that can be attributed to the absence of relationship banking.

There is some support in the literature for my theory that relationship banking offers a solution to IPO underpricing. Boot and Thakor (2000) illuminate the role of relationship banking from a theoretical standpoint. They argue that a relationship loan adds more value for the firm, but also imposes a greater cost, because a relationship bank must develop costly expertise (sector specialization) in order to add value. Thus, a relationship bank will generally understand the quality of the client firm better than a non-relationship bank. While these findings are related to my research, this paper is the first to study whether relationship banking can reduce the underpricing of IPOs.

First, I develop a theoretical model to address this question. This model distinguishes between two types of firms with the same expected value. Good firms, G, have a low dispersion of market value; their IPO offer proceeds is denoted by OP_G. Bad firms, B, have a high dispersion of market value; their offer

[1] "Strategic Financial Management Casebook" by Rajesh Kumar

proceeds is denoted by OP_B. Firm owners know their firm type, but don't know the firm's market value. The theoretical analysis predicts that, when there is no borrowing, uninformed investors cannot distinguish between the two types of firms. In this case, the offer proceeds (OP_P) are the same for both types of firms ($OP_B < OP_P < OP_G$). If their types were known, good firms would receive higher proceeds and bad firms would receive lower proceeds. Because uninformed investors face greater adverse selection risk in purchasing shares of bad firms and require greater underpricing to compensate for this risk (Beatty and Ritter, 1986). Thus, when firm types are unknown, good firms suffer and bad firms benefit. When we allow for publicly observable transaction lending (but not relationship lending), the outcomes may remain the same, as uninformed investors cannot reliably distinguish between good and bad firms by looking at whether the firm borrows. Even if they could identify the two types of firms, the bad firm would still be worse off, receiving lower offer proceeds than in the pooling case. In contrast, when relationship lending is available and lending decisions are confidential, IPO underpricing is reduced and the bad firm is better off, receiving higher offer proceeds than in the previous two cases.

The intuition behind these results follows from the existence of two levels of information asymmetry. First, there is information asymmetry between the firm and its investors. Second, there is information asymmetry between the firm and its underwriter. In my model, the first level of information asymmetry is reduced because the presence of relationship banking allows for a separating equilibrium in which bad firms borrow and good firms raise capital directly from equity markets. This leads to reduced underpricing for all IPO firms. The second level of information asymmetry is reduced because the underwriter is comparatively better informed through the process of relationship lending than other uninformed underwriters. This leads to more substantial reduction in IPO underpricing for firms that have a relationship bank as the underwriter than other firms.

Boot and Thakor (2000) show that the incremental benefit of a relationship loan is decreasing in firm quality. This result is driven by two facts: (i) banks can increase the project payoff more substantially for a bad firm than for a good firm; and (ii) it costs the bank more to provide a relationship loan than to provide a transaction loan, that is, a cost S is incurred for relationship loans. Because S is independent of firm quality but the benefit is decreasing in firm quality, at a sufficiently high quality, the cost of a relationship loan exceeds its marginal benefit. Boot and Thakor (2000) conceptualize a cutoff level such that the bank prefers to provide relationship loans to the firms below the cutoff and transaction loans to the firms above the cutoff. Following this idea, in my paper, the bank makes relationship loans to bad firms (high dispersion) and transaction loans to good firms (low dispersion). At the same time, the firm's expected cost of capital market funding is decreasing in firm quality; thus, the bank's rents on a transaction loan decline as firm quality improves, since the competition bank faces from the capital market is greater for higher-quality firms. Boot and Thakor (2000) propose another cutoff – the level of firm quality at which the bank's rent on transaction loans becomes zero (and above which the rent becomes negative). These highest-quality firms rely on the capital market for funding.

Thus, this paper assumes that good firms forgo bank loans and go directly to the capital market, while bad firms' higher expected cost of capital market funding prevents them from doing the same. This allows uninformed investors to distinguish between the two types of firms: good firms go directly to the capital market without borrowing while bad firms borrow.[2] Thus, the second level of information asymmetry is reduced. Consequently, IPOs are priced more accurately because uninformed investors do not require underpricing as compensation for risk[3] and investment banks do not need to compensate informed investors (institutional investors) for revealing information about the firm by offering a higher allocation of underpriced shares.[4]

Through this theoretical model, I form three testable predictions: (1) relationship banking can reduce IPO underpricing for all firms that go public, regardless of the strength of their relationships with their underwriters; (2) firms that have a relationship bank experience a larger reductions in IPO underpricing compared to other firms; (3) relationship banking reduces information asymmetry between the underwriter and the firm as well as between the firm and investors. Confirmation of these three predictions would imply that relationship banking reduces IPO underpricing by limiting information uncertainty.

My empirical strategy for testing these predictions relies on changes to the rules governing IPO underwriting. With the repeal of the Glass–Steagall Act on November 12, 1999, commercial banks with close ties to their client firms gained permission to underwrite those firms' equity issuances.[5] A close lending relationship almost necessarily entails a more detailed understanding on the part of the bank of the quality of the client firm. In contrast, underwriters that are comparatively uninformed about IPO client quality potentially send more noisy signals to investors about prices. When a relationship bank lends to a firm, it obtains proprietary, firm-specific information that cannot be easily and credibly conveyed to others (Schenone, 2004). The 1999 repeal of the Glass–Steagall Act allows me to compare IPO underpricing before and after commercial banks were allowed to underwrite their client firms' IPOs through a difference-in-differences design. Firms with an IPO underwriter that is not a relationship bank are designated as control firms. Treated firms have

[2] I assume that bad firms receive only relationship loans, which are not publicly observable like transaction loans; however, uninformed investors can still distinguish bad firms from good ones because only bad firms borrow.

[3] IPO underpricing can be thought of as compensation for the uninformed investors, as illustrated in previous studies such as Allen and Faulhaber, 1989; Benveniste and Spindt, 1989; Benveniste and Wilhelm, 1990; Grinblatt and Hwang, 1989; Rock, 1986.

[4] Cornelli and Goldreich, 2001; Cornelli and Goldreich, 2003 and Aggarwal et al., 2002 find evidence that investment banks compensate informed investors (institutional investors) for revealing information about the firm by offering a higher allocation of underpriced shares.

[5] Between 1998 and 1999, commercial banks could manage client firms' IPOs only indirectly through the bank's Section 20 subsidiary. Since 1999, commercial banks have been able to directly underwrite IPOs.

an IPO underwriter that is a relationship bank.

This empirical approach could produce biased estimates if firms self-select into treatment (i.e., choose to use relationship banks as underwriters) for unobserved reasons. For example, certain firms may have reason to believe that being underwritten by their relationship banks would benefit them. This selection issue may generate a significant difference in underpricing between treated and control firms even if, on average, there is no effect of underwriter's choice on underpricing.[6] To address possible selection bias, I employ a reduced form instrumental variable (IV) approach. Instead of defining treated firms as firms with IPO underwriters that are relationship banks, I use as an instrument for treatment IPO firms that had relationship banks before their IPO. Such firms should be more likely to choose a relationship bank as their IPO underwriter for convenience reasons rather than for reasons related to their beliefs about IPO pricing. To the extent that selection of a relationship bank at least three years before an IPO is likely exogenous to the IPO decision, selection into treatment should be exogenous to IPO prices. All other IPO firms are considered control firms.[7]

Since the theoretical model implies that only bad firms (treated firms) borrow, good firms (control firms) go directly to the capital market. Following this logic, all IPO firms are good firms. However, after bad firms receive relationship loans, their project payoffs (and consequently their quality) are improved through the relationship banks' sector specialization. Thus, these bad firms can later tap the capital market at a lower cost than would have been otherwise possible, since a firm's expected cost of capital market funding is decreasing in firm quality.

My results are as follows. First, I find that IPO underpricing is reduced for all firms after the repeal of the Glass–Steagall Act. This is indicative of a link between allowing relationship banks to underwrite client firms' IPOs and more accurate IPO pricing. As further evidence, between the two periods, underpricing for the treated group fell by 6.5 more percentage points relative to the change for the control group, after controlling for other determinants of IPO underpricing. Additional analyses on the changes in the outcome variable and control variables (including the levels of macroeconomic variables) over time reinforce my interpretation of the effect of relationship banking on IPO underpricing. While this evidence is indicative, it is not necessarily causal.

I employ the propensity score matching method to obtain control firms that are similar to the treated firms as a robustness check. I also include the dot-com bubble of 1998-2000 in the sample period as a second robustness check. In both cases, the results are consistent with my original findings.

[6]This scenario would likely bias my estimate of the effect of relationship banking on IPO prices upward, possibly generating a statistically positive coefficient when the true relationship is null or even negative.

[7]In the theoretical model, treated firms are bad firms and control firms are good firms.

If the degree of underpricing is related to the amount of uncertainty the underwriter and the investors have about the true value of the firm, then I should find that relationship banking reduces this uncertainty and, hence, reduces the underpricing. To demonstrate a causal relationship between information asymmetry and the reduction in IPO underpricing, I employ a triple difference-in-differences approach. I use the average standard deviation of daily returns over the sample period for all firms in the same industry as the firm pursuing an IPO as the proxy for information asymmetry. It is reasonable to assume that, during the sample period, firms in higher-volatility industries are in general more opaque than firms in lower-volatility industries. I find that, between the two periods, underpricing for treated firms with higher information uncertainty fell by 3.3 more percentage points relative to the change in underpricing for more transparent treated firms. This indicates that firms facing higher information asymmetry problems experience less underpricing because of relationship banking, supporting my argument that relationship banking reduces information asymmetry, which in turn affects the degree of underpricing.

My findings make two key contributions to the literature. First, my findings contribute to the strand of literature on IPO underpricing. Prior studies have largely focused on identifying the underlying causes of IPO underpricing, whereas I both confirm the causes and suggest a new possible solution that is superior to the few that have been written about in the past. There is an extensive literature claiming that asymmetric information causes IPO underpricing from a theoretical standpoint (see, for example Allen and Faulhaber, 1989; Benveniste and Spindt, 1989; Benveniste and Wilhelm, 1990; Grinblatt and Hwang, 1989 and Rock, 1986). These studies argue that, when a firm goes public, the investors and the firm are asymmetrically informed about that firm's true value. Thus, IPO underpricing can be thought of as compensation for the uninformed investors. From informed investors' perspective, Cornelli and Goldreich (2001), Cornelli and Goldreich (2003) and Aggarwal et al. (2002) find evidence that investment banks compensate informed investors (institutional investors) for revealing information about the firm by offering a higher allocation of underpriced shares. James and Wier (1990) is the first paper in the literature that offers a solution for reducing IPO underpricing. James and Wier (1990) point out that issuing private debt before an IPO is a signal to the market of high value, since only high-value firms will be approved for loans. The authors' hypothesis is that this signal reduces asymmetric information, thus lowering IPO underpricing for firms with private debt before an IPO. More recently, Schenone (2004) propose a solution that uses banking relationships[8] established before the firm's IPO to reduce the information asymmetry behind high IPO underpricing. The solutions proposed by James and Wier (1990) and Schenone (2004) only reduce IPO underpricing for certain

[8] This paper defines a banking relationship as any situation where an IPO underwriter has previously made a loan to the firm pursuing IPO. This definition is different from my definition of relationship banking.

treated firms while hurting firms with a higher dispersion of market value by exposing them as bad firms. In contrast, my solution to the information asymmetry problem reduces IPO underpricing for all firms and, at the same time, benefits firms with a higher dispersion of market value. Second, my findings contribute to the strand of literature on relationship banking (Boot and Thakor, 2000; Gopalan et al., 2011). A large literature in banking argues that banks help overcome information and agency problems. This literature has typically settled on identifying the benefits of lending relationships in loan terms. An innovation of my work is to test for the benefits of lending relationships in the IPO market.

My findings also have implications for financial policy going forward. In recent years, demands have persisted to bring back Glass-Steagall because some people believe that commercial banks' engagement in investment banking caused the financial crisis of 2007-2008. The Republican Party's official 2016 platform called for it. So did the 2016 Democratic Party platform. Whether a restoration of Glass-Steagall would prevent another collapse is up for debate. My findings suggest that bring back Glass-Steagall has very real costs of hurting IPO firms. By allowing relationship banks to underwrite their client firms' equity issuances, financial regulators can help IPO firms receive more proceeds to reinvest and grow and especially help firms with a high dispersion of market value, as relationship banks can offer these firms a lower cost of capital.

The rest of the paper is organized as follows: Section 2 is literature review, Section 3 presents a theoretical analysis of the effect of relationship banking on IPO underpricing, Section 4 presents the empirical analysis of the theoretical model in Section 3, and Section 5 concludes.

2 Literature Review

My paper is related to the literature that discusses relationship banking from both theoretical and empirical perspectives. In my theoretical model, I use the definition for relationship loans introduced in Boot and Thakor (2000): a loan that permits the bank to use its expertise to improve the firm's project payoff. The extent of the payoff improvement depends on the bank's sector-specific expertise. Through this sector specialization, a relationship bank almost certainly determines the true market value of the client firm. I also use Boot and Thakor (2000) payoff structure for firms with relationship banks. In the empirical analysis, I use Gopalan et al. (2011) definition for relationship bank as a lead bank of any prior syndicated loan to the client firm that had ever lent to this firm in the past. Gopalan et al. (2011) finds that firms form new banking relationships to expand their access to credit and capital market services. This corresponds to my argument that a bad firm benefits from improved project payoffs after receiving a relationship loan due to relationship bank's sector specialization, ultimately lowering its cost of capital in the capital market.

My theoretical model builds on the model in James and Wier (1990), with four key distinctions. First, since James and Wier (1990) assume an uninformed underwriter, the information asymmetry between the firm and the underwriter in their model is reduced to a lesser extent relative to my model, where the underwriter is informed. Second, the signal that investors observe in James and Wier (1990) model is noisier than the corresponding signal in my model.[9] Thus, the information asymmetry between the firm and investors is also reduced to a lesser extent in James and Wier (1990) model. Third, James and Wier (1990) model only reduces IPO underpricing for good firms. My model reduces both types of firms' IPO underpricing. Fourth, bad firms are better off in my model since they receive higher proceeds when they go to the capital market.

Schenone (2004) is the only paper of which I am aware that examines IPO underpricing through the pre-IPO banking relationship after the repeal of the Glass-Steagall Act. Her study compares the firm's pre-IPO banking relationships to the underwriters managing the firm's new equity issuance and tests whether relationships established before the firm's IPO ameliorate asymmetric information problems behind IPO underpricing. The results show that, on average, firms with a pre-IPO banking relationship with a prospective underwriter experience about 17% less underpricing than firms without such banking relationships. However, this paper has several limitations. First, the sample period is very short, from January 1, 1998 to December 31, 2000. Between 1998-1999, commercial banks could underwrite equity issuance only indirectly through the bank's section 20 subsidiary. Also, this sample period includes the dot-com bubble (1998-2000), during which IPO underpricing was unusually severe. The paper addresses this with a robustness test which removes the dot-com bubble and shows that the results still hold; however, this leaves only one year in the sample period. Second, the sample includes only 306 firms, raising concerns over the external validity of the regression model. Third, this paper defines any situation in which a firm's IPO underwriter has lent to the firm in the past as relationship banking. This definition is not as strong as those used in the prior literature. For example, Gopalan et al. (2011) limit relationship banking to cases in which the lead arranger has lent to the firm in the past. A fourth concern is the empirical setting and model specification of the paper. The simple OLS regression model is just a preliminary test. Treated firms are those for which a pre-IPO lender could have or managed the firm's IPO, while control firms have not received loans from their IPO underwriters. However, in this setting, different levels of underpricing between treated firms and control firms may be caused by unobserved differences between them, and not necessarily due to relationship banking. More importantly, results are affected by the selection issue here I discussed in the introduction. My empirical

[9] James and Wier (1990) signal is that good firms take out loans and bad firms do not. However, as I explain more in detail below, it is possible for a bad firm to apply for and receive a loan and thus inadvertently be pooled with the good firms. In this case, it would be difficult for investors to distinguish between the two types of firms. In contrast, in my model, the signal is that bad firms borrow while good firms go directly to the capital market.

design partially addresses these concerns by employing difference-in-differences regression design, using variation in the strength of the lending relationships between IPO firms and their underwriters generated by the random event of the repeal of the Glass-Steagall Act. I also employ reduced form instrumental variable regression. Instead of defining treated firms as firms with IPO underwriters that are also relationship banks, I use as an instrument for treatment IPO firms that had relationship banks at least three years before their IPO.

3 Theoretical Analysis

3.1 The Model

3.1.1 Assumptions

There are two types of firms with the same expected value in the model. The good firms, denoted by G, are characterized by low dispersion of market value, while bad firms, denoted by B, are characterized by high dispersion of market value. Each firm has a project that needs financing of D dollars such that $OP_B < D < OP_G$.[10] The project payoff represents the firm's true market value. Both types of firms can obtain financing from either the debt market or the capital market. In the capital market, some underpricing is necessary to compensate uninformed investors for their anticipated losses on overpriced issuances and to compensate informed investors (institutional investors) for revealing information about the firm. The underpricing is necessary to ensure these investors' continued participation in the capital market.[11]

3.1.2 Major Players

My model includes three types of players: relationship banks (they are also IPO underwriters), firms (borrowers), and investors.

Banks that choose lending relationships (the key focus of this paper) use relationship loans[12] or use transaction loans. Costly sector specialization is necessary for relationship loans. Banks that choose underwriting relationships (not the key focus in this paper) act as a broker to help the firm by underwriting its debt or equity issuance in the capital market. Their role differs from making transaction loans since the underwriter does not have federal deposit insurance and thus incurs search costs to find the highest valuations

[10] OP_J is the offer proceeds to firm type J.

[11] Please refer to the Appendix for more details on the model assumptions.

[12] Permitting the bank to use its expertise to improve the firm's project payoff, which ultimately improves the market value of the firm.

from investors, introducing randomness into the firm's cost of funding, which depends on realized demand for the firm's securities.

The distributions of possible market values ($\widetilde{V}$) for each type of firm are uniform: $\widetilde{V_G} \sim U[a_G, b_G]$, $\widetilde{V_B} \sim U[a_B, b_B]$, where $a_G > a_B$, $b_G < b_B$. Each firm has a project that needs financing of D dollars, which can be either raised from a bank through a lending or underwriting relationship or by the equity market through an IPO. Each firm has project payoff representing its realized market value.

Investors are risk-neutral agents who demand an expected return at least equal to the riskless rate. They purchase corporate debt, participate in IPOs, and invest in bank deposits for investment purposes. Investors know the probability distributions of $\widetilde{V_G}$ and $\widetilde{V_B}$ and the proportion of good and bad firms in the market but cannot classify ex ante individual firms by type.

3.1.3 Sequence of Events

At $T = 0$, each bank assesses a probability $G(\theta)$ over a firm quality θ. Banks decide whether they want to pursue a lending relationship or an underwriting relationship with the firms. If they choose a lending relationship, they need to choose whether they want to offer relationship lending or transaction lending. For relationship lending, they choose their degree of specialization γ.

At $T = 1$, firms can attempt to borrow D dollars repaid at $T = 3$. They pursue an IPO if the loan request is denied. Firms may also decide not to apply for a loan and instead go directly to the equity market. Each firm is stochastically matched with a bank. Each bank observes the quality (I will define this when I describe the firms) of the firms. The bank then makes a decision about whether to allocate service capacity to transaction lending or relationship lending. Firms now observe the sector specialization of the banks they were initially paired with. Banks choosing underwriting relationships search for investors to purchase underwritten debt issuances.

At $T = 2$, shares issued at $T = 1$ are traded in the secondary market. Loans are made by banks. Debt issuances are sold by underwriters in the capital market.

At $T = 3$, for firms that borrowed private debt, project payoffs are realized and banks are repaid if possible. For firms that borrowed public debt, debt issuances are repaid if possible.

3.1.4 More Model Details

The types of securities are: Unsecured loans (banks) or corporate debt (market), IPOs with primary and secondary shares.

A firm's payoff with transaction loans is Y with probability $\theta \in (0,1)$ and 0 with probability $1-\theta$.

Higher quality firm has higher θ. A borrow's payoff with relationship lending is Y with probability $\theta + \nu_i[1-\theta]$ and 0 with probability $[1-\theta][1-\nu_i]$, where $\nu_i \in (0,1)$is a variable that depends on the bank's type i, which represents the sector specialization of the bank. Firms can attempt to borrow D dollars repaid at $T=3$. If they are approved, they receive a loan; if they are denied, they pursue an IPO for funding. Firms may also decide not to apply for a loan, instead going directly to the equity market to raise D dollar via an IPO.

Under lending relationships, banks obtain completely insured deposits at an expected all-in cost $r_d > r_f$, from Boot and Thakor (2000) we know that banks make two decisions. The first decision is the sector-specialization (γ_j) decision for relationship lending at $cost = \bar{C}_i(\gamma) = \mu_b(\theta)C_i(\gamma)$, where $\gamma \in (0,1)$ is the degree of sector specialization and $\mu_b(\theta)$is a function that depends on the measure of the set of firm θ's served by banks with relationship loans. $C_i(\gamma) \geqslant 0$, with $C_i^{'} > 0$, and $C_i^{''} > x$ (for x sufficiently large). A bank choose $\gamma = \gamma_j$ enhances the firm's success probability by $\nu_i = \gamma_j \nu_H + (1-\gamma_j)\nu_L$, with $\nu_H > \nu_L$. Thus if a bank chooses not to specializing at all $(\gamma_j = 0)$, then $\nu_i = \nu_L$. The second decision is the allocation of bank's lending capacity between relationship lending and transaction lending at $T=2$. With relationship lending, in addition to $\bar{C}_i(\gamma)$, there is a variable cost S per loan, where $S < \nu_L[1-\underline{\theta}]Y$; this restriction ensures that relationship loans are feasible for all γ, even if $\gamma = 0$ the incremental value added by a relationship loan exceeds the cost for at least the lowest-quality firm. In the underwriting relationship, we know from Boot and Thakor (2000) that the banks must search for investors. $\widetilde{D}$ is the random demand for securities with a uniform density function. Banks' funding cost is $r_f\theta^{-1}$if $\widetilde{D} \geq \$D$; $r_f\theta^{-1} + \tau$ if $\widetilde{D} < \$D$, where τ is a penalty cost measuring underwriting efficiency.

I assume that interbank competition level is low throughout the paper.

3.2 Analysis of Offer Pricing

3.2.1 Model Case One (no borrowing exists)

First, I assume that no borrowing exists. In this case, firms are indistinguishable to uninformed investors; all firms are pooled. Thus, IPO proceeds are the same regardless of firm type. If firm types were known, Beatty and Ritter (1986) and Carter and Manaster (1990) show that equilibrium in the primary market would require:

$$NC = \lambda \left\{ \pi_B \int_{OP_B}^{b_B} \left[\widetilde{V_B} - OP_B\right] f\left(\widetilde{V_B}\right) d\widetilde{V_B} \right\} + (1-\lambda)\left\{ \pi_G \int_{OP_G}^{b_G} \left[\widetilde{V_G} - OP_G\right] f\left(\widetilde{V_G}\right) d\widetilde{V_G} \right\} \tag{1}$$

and

$$0=\lambda\left\{\int_{a_B}^{OP_B}\left[OP_B-\widetilde{V_B}\right]f\left(\widetilde{V_B}\right)d\widetilde{V_B}+(1-\pi_B)\int_{OP_B}^{b_B}\left[\widetilde{V_B}-OP_B\right]f(\widetilde{V_B})d\widetilde{V_B}\right\}$$
$$+(1-\lambda)\left\{\int_{a_G}^{OP_G}\left[OP_G-\widetilde{V_G}\right]f\left(\widetilde{V_G}\right)d\widetilde{V_G}+(1-\pi_G)\int_{OP_G}^{b_G}\left[\widetilde{V_G}-OP_G\right]f(\widetilde{V_G})d\widetilde{V_G}\right\} \qquad (2)$$

Where OP_J is the offer proceeds to firm J, N is the number of informed investors, C is the cost per investor of becoming informed, and π_J is the proportion of shares of firm J that are acquired by informed investors.

Equation (1) shows that in equilibrium, the profits from underpricing reaped by informed investors should be equal to the aggregate cost of becoming informed. Thus, informed investors earn zero expected profits. Meanwhile, equation (2) states that, in equilibrium, uninformed investors' expected losses from overpricing are equal to their underpricing gains.[13] OP_P denotes the offer proceeds when firm types are not observable ex ante to outsiders and firms are all pooled together. The expected market values of both types of firms are the same, but because offer proceeds are decreasing in ex ante uncertainty,

$$OP_B < OP_P < OP_G$$

Where OP_B = offer proceeds for bad firms, assuming firm types are known ex ante, and OP_G = offer proceeds for good firms, assuming firm types are known ex ante. That is, good firms would receive higher proceeds and bad firms would receive lower proceeds if their types were known, because uninformed investors face greater adverse selection risk in purchasing shares of bad firms and therefore require greater underpricing to participate in IPOs (Beatty and Ritter, 1986). Thus, in this case, the good firm suffers and the bad firm benefits, since the former would receive higher proceeds and the latter would receive lower proceeds if their types were known.

3.2.2 Model Case Two (borrowing exists & update on James and Wier (1990) model)

In this second case, both transaction lending and relationship lending are available. All transaction lending decisions are public. All relationship lending decisions are confidential. The underwriting bank can be informed about the firm's value.

[13] Uninformed investors' expected losses from overpricing $=\lambda\int_{a_B}^{OP_B}\left[OP_B-\widetilde{V_B}\right]f\left(\widetilde{V_B}\right)d\widetilde{V_B}+(1-\lambda)\int_{a_G}^{OP_G}\left[OP_G-\widetilde{V_G}\right]f\left(\widetilde{V_G}\right)d\widetilde{V_G}$; their underpricing gains $=\lambda(1-\pi_B)\int_{OP_B}^{b_B}\left[\widetilde{V_B}-OP_B\right]f(\widetilde{V_B})d\widetilde{V_B}+\lambda(1-\pi_G)\int_{OP_G}^{b_G}\left[\widetilde{V_G}-OP_G\right]f(\widetilde{V_G})d\widetilde{V_G}$.

Since we assume that $OP_B < D < OP_G$, the good firm will always borrow. Bad firms' loan applications may be denied, since the lending decision depends on the bank's estimate of the firm's market value. If the bank's estimate of the firm's value falls below D, then the application will be denied. Thus, bad firms will compare expected IPO proceeds if they do apply for a loan to the expected IPO proceeds if they do not. The expected offer proceeds (OP_{BP}) for a bad firm if it applies for a loan is:

$$F_B(D)\,OP_{BR} + [1 - F_B(D)]\,OP_{BG} = OP_{BP} \tag{3}$$

Where

$F_B(D)$ = probability that the true market value of a bad firm is less than D, which also represents the probability of denial when the bad firm applies to borrow D dollars,

OP_{BR} = offer proceeds for bad firms conditional on being rejected a loan of size D dollars,

OP_{BG} = offer proceeds for bad firms conditional on being granted a loan of size D dollars.

Since banks' lending decisions are public, any firm whose loan application is denied will be revealed as a bad firm. This is the downside risk for a bad firm applying for a loan of D dollars. On the other hand, if the bad firm receives the loan, then its expected market value will be higher than that of the good firm, since the bad firm's value is distributed over $U[D, b_B]$, while the good firm's market value is distributed over $U[a_G, b_G]$, and $D > a_G$, $b_B > b_G$. Thus OP_{BG} will be higher than OP_G. This is the upside for a bad firm applying for a loan. The reason that the bad firm can receive OP_{BG} when it receives the loan is because in my paper, the commercial bank acts as an underwriter knows the firm value when it grants a loan to a bad firm. Thus this bad firm will receive higher offer proceeds (compared to a good firm) due to the higher expected market value. In James and Wier (1990), the bad firm receives the same offer proceeds OP_G with the good firm since the underwriter is uninformed of the firm value. The underwriter in their model views all firms with loans as good firms and provides the same offer proceeds to all the good firms.

If OP_{BP} is lower than OP_B, then the bad firm bears the entire cost of applying for loans and doesn't reap the full benefits. In this case, the bad firm will have no incentive to borrow while the good firm will always borrow. As a result, the two kinds of firms can be distinguished, decreasing information asymmetry and IPO underpricing. The good firm is better off in this case because $OP_G > OP_P$. In contrast, the bad firm will be worse off than in the no-borrowing pooling case, because $OP_{BP} < OP_B < OP_P$, which means that no matter whether the bad firm borrows (getting OP_{BP}) or not (getting OP_B), its payoff will be lower than in the pooling case (getting OP_P).

However, if OP_{BP} is higher than OP_B, the bad firm will borrow. By borrowing, it collects an expected payoff of OP_{BP}, which is higher than the expected payoff from not borrowing (OP_B). In this case, the two kinds of firms cannot be distinguished by the borrowing behavior alone.

Thus, in this second model scenario, it's uncertain whether we can distinguish between the two kinds of firms just by observing whether a firm borrows. Even if we do manage to distinguish good from bad firms, the bad firm will be worse off, receiving lower proceeds than it would have in the pooling case.

In sum, both cases above result in one type of firm being worse off. Thus, we ask whether a case exists in which both types of firms can be better off. In the following case, I develop a new model in order to determine whether relationship lending can help reduce underpricing while improving outcomes for both types of firms.

3.2.3 Model Case Three (borrowing exists & new model)

In this case, both transaction lending and relationship lending are available. All transaction lending decisions are public. All relationship lending decisions are confidential. The underwriting bank can be informed about the firm's value.

There is very low competition among banks in my model. Then according to Boot and Thakor (2000) we can assume that banks can extract full rents. Good firms receive transaction loans, and bad firms receive relationship loans. The intuition behind this, according to Boot and Thakor (2000), is that, when competition is limited, banks can capture most of the incremental benefit of a relationship loan: by relying on their sector specialization, banks can improve the bad firm's project payoff much more than that of the good firm. Boot and Thakor (2000) show that the incremental benefit of a relationship loan is decreasing in firm quality, and it costs the bank more to provide a relationship loan than to provide a transaction loan; that is, a cost S is incurred for relationship loans.[14] Because this cost is independent of firm quality but the benefit is decreasing in firm quality, at a sufficiently high quality the cost of a relationship loan exceeds its marginal benefit. This leads to a cutoff level in Boot and Thakor (2000) such that the bank prefers to provide relationship loans to the firms below the cutoff and transaction loans to the firms above the cutoff. Thus, in this paper, we can assume that the bank makes relationship loans to bad firms (high dispersion) and transaction loans to good firms (low dispersion). If the investors can easily observe and identify which firms receive transaction loans and which firms receive relationship loans, then a separating equilibrium, which decreases information asymmetry, is possible.

It is sometimes difficult for investors to identify exactly which firms receive relationship loans and which receive transaction loans. Even if this occurs, relationship lending makes a separating equilibrium

[14] Transaction loans do not have this variable cost S.

possible.

Bad firms receive relationship loans, so the true market value of the bad firm can be calculated as follows:

$V_B = [\theta + \nu_i(1-\theta)]Y - \phi - RR - S$

Where $Y = (a_B + b_B)/2$, θ is the measure of the firm's quality (with higher θ representing higher-quality firms with lower dispersion of market value), ϕ is the bank's expected all-in funding cost (which is also the borrowing cost from the firm's perspective), RR is the relationship loan rent, and S is the bank's cost of servicing a relationship loan. Let $V_B > OP_B$, which implies that bad firms find it profitable to borrow since the bank, as the underwriter, knows the firm's true market value, and investors recognize this; thus, borrowing raises the offer proceeds.

In comparison, good firms, receive transaction loans, thus the true market value of the good firm can be calculated as follows:

$V = \theta Y - \phi - TR$

Where Y= $(a_G + b_G)/2$, and TR is the transaction loan rent. Let $V_G < OP_P$, which implies that good firms find it unprofitable to borrow, since their project payoff – with the transaction loan representing its true market value – is smaller than the pooling equilibrium offer proceeds.

Thus, the separating equilibrium in this case is that bad firms borrow, while good firms do not borrow, instead going directly to the equity market. Hence, information asymmetry is reduced and, consequently, IPO underpricing is also reduced.

The intuition behind this concept is similar to an idea proposed in Boot and Thakor (2000). Banks' expected funding cost for transaction loans is independent of firm quality, whereas the firm's expected cost of capital market funding is decreasing in firm quality. So, the bank's rents on a transaction loan decline as firm quality improves, because the competition that bank faces from the capital market is greater for higher-quality firms. Thus Boot and Thakor (2000) propose another cutoff, representing a firm quality so high that the bank's rent on transaction loans to that borrower is zero. For borrowers above this cutoff, the bank's rent becomes negative. Thus, the highest-quality firms reply on the capital market. For this reason, I can plausibly assume that good firms go directly to the capital market. Note that I assume very low interbank competition; if competition intensifies, these results may change.

Thus, the conditions for a separating equilibrium are:

$$[\theta + \nu_i(1-\theta)]Y - \phi - RR - S > OP_B \tag{4}$$

and

$$\theta Y - \phi - TR < OP_P \tag{5}$$

Taken together, expressions (4) and (5) imply that for a common cost of establishing credit ($\phi = \phi_G = \phi_B$), Separation requires:

$$\theta Y - TR - \lambda OP_B - (1-\lambda)\, OP_G < \phi < [\theta + \upsilon_i (1-\theta)]\, Y - RR - S - OP_B \tag{6}$$

Thus the cost of borrowing required to separate firms by type will depend on the degree of dispersion of the firm's market value (θ), the expected market value of the firm (Y), transaction lending rent (TR), offer proceeds for the bad firm (OP_B), offer proceeds forthe good firm (OP_G), the proportion of bad firms in the population (λ), bank's degree of sector specialization (ν_i), the relationship lending rent (RR), and the variable cost of relationship lending (S).

4 Empirical Analysis

4.1 Testable Hypotheses

The prior section suggests three testable predictions regarding the relation between relationship banking and IPO underpricing:

Prediction 1: Relationship banking can reduce IPO underpricing for all firms that go public, regardless of the strength of their relationships with their underwriters.

Prediction 2: Firms that have a relationship bank experience larger reduction in IPO underpricing compared to other firms.

Prediction 3: Relationship banking reduces information asymmetry between the underwriter and the firm as well as between the firm and investors.

To define relationship banking, I observe a firm's pre-IPO lenders. If, three years before an IPO, the firm at least has a lead bank of a syndicated loan that has also lent to the firm in the past (Gopalan et al., 2011), that bank is defined as the firm's relationship bank. This makes sense because banks learn about their client firms through continuous monitoring, which is not likely to continue once a loan is repaid. Also, given that an important aspect of bank-firm relationship is a bank's faith in the management of the firm, a termination of relationship is not a positive signal. Hence, I do not consider past lending that has long been terminated as relationship banking.

To identify the lead bank for the loan I follow standard practice in bank relationship literature.[15] The lead arranger for any facility of the deal is considered a lead arranger for the syndicated loan. For a sole lender facility, I consider the lender to be the lead bank. To identify the lead arranger for a multiple-lender facility, I follow Ivashina and Scharfstein (2010). In particular, the administrative agent of a syndicated loan is defined as the lead bank in cases where the database identifies an administrative agent. If the syndicate does not have an administrative agent, then any lenders that act as agent, arranger, bookrunner, lead arranger, lead bank, or lead manager are defined as lead banks.

To measure the degree of the firm's information uncertainty, I use the average standard deviation of daily returns over the sample period for all firms in the same industry as the firm pursuing an IPO as the proxy for information asymmetry. It is reasonable to assume that, during the sample period, firms in higher-volatility industries are in general more opaque than firms in lower-volatility industries.[16]

4.2 Data and Empirical Methodology

4.2.1 Data

Various data sources are used for this study. First, I construct the sample by identifying all IPOs in the US between January 1, 1990 and December 31, 2006 that appear in the Securities Data Corporation (SDC) database, list common stock on the NYSE, NASDAQ, or AMEX, file registration statements on form S-1 with the SEC, and make available the stock price and accounting information necessary for my tests.[17] Because the dot-com bubble (1998-2000) featured severe IPO underpricing and allegations of underwriter misconduct such as "spinning" and "laddering", I exclude this period in my analyses. Thus, the period prior to the repeal of the Glass-Steagall Act ("pre-repeal") is 1990-1997 and the period after the repeal ("post-repeal") is 2001-2006. From SDC I obtain the issuer, SIC, ticker, industry, IPO date, IPO offer price, the lead underwriter, the listed exchange, industry, proceeds, first day closing price, primary shares, total issued shares, whether the firm was venture-backed or not and net proceeds. I obtain the revenue, net income, total assets, total debt, long-term debt, cash and short-term investment, EBIT, EBITDA, gross profit, operating cash flow, working capital, and book value of equity of all IPO firms from Compustat and make sure each firm has at least 5 years of pre-IPO data. Then I exclude IPOs that are leveraged buyouts, closed-end funds, open-end funds, trusts, and special purpose vehicles (i.e., SIC codes 6091, 6371, 6722,6726,6732,6733, and 6799).

[15] Please see Hertzel and Officer (2012) for details and justification.

[16] The reason for using this measure as the proxy for information asymmetry is explained in detail in the empirical methodology section under *Prediction 3*.

[17] In which the contract between the underwriting bank and the issuing firm is a firm commitment contract.

To identify those firms that had relationship banks before their IPO,[18] I use the Dealscan database of bank loans. Finally, I link the data from Compustat and SDC with the data from Dealscan database.[19]

4.2.2 Empirical Methodology

4.2.2.1 Prediction 1

The regression model is as follows:

$$Y_i = \beta_0 + \beta_1 * Post + \tau X_i + \delta_k + \varepsilon_i \tag{7}$$

The subscript i refers to IPO firms in the sample. I employ a cross-sectional dataset of IPO firms with a reduced form instrumental variable regression design. Corresponding to the theoretical prediction that relationship banking can reduce IPO underpricing for all firms that go public, regardless of the strength of their relationship with their underwriter, I employ three sets of regressions in this step. All three regressions have the same regression model as (7) and consist of all firms, treated firms only, and control firms only, respectively. For the group difference, I observe each firm's pre-IPO lenders three years before the IPO. If the firm has a lead bank of a loan that has also lent to it in the past (Gopalan et al., 2011), that bank is defined as the firm's relationship bank. Thus, a firm with a relationship bank at least three years before an IPO is defined as a treated firm. The other firms are defined as control firms.

Considering all firms that use their relationship banks as underwriters to be treated firms could lead to selection bias if these firms are in some way different from firms that do not choose to be underwritten by a relationship bank. Firms that choose a relationship bank as their underwriter presumably do so because it is beneficial to them; similarly, firms that do not choose a relationship bank as their IPO underwriter likely do not find it beneficial for them to do so. If this is true, my estimate of the effect of relationship banking on IPO prices is likely too high. I might even observe a statistically positive relationship when a null or negative relationship exists. This is why I employ a reduced form instrumental variable approach.

If most of the treated firms' IPO underwriters are also their relationship banks, then the instrument I use is valid. Indeed, I find that, in the post-repeal period, 96 of the 144 treated firms (nearly 70%) have their relationship bank as their underwriter. The control firms in the empirical analysis correspond to the good firms (low dispersion of market value) in the theoretical model; similarly, the treated firms correspond to bad firms (high dispersion of market value). In the theoretical model, the good firms go directly to the

[18] These are treated firms.

[19] To link the data from Compustat and SDC with the data from Dealscan database, I use the Dealscan_link_Compustat dataset, which is available on Michael Roberts's website. This dataset connects the Dealscan database with Compustat.

capital market (and do not have relationship banks), while the bad firms receive relationship loans. Due to the relationship banks' sector specialization, the bad firms' projects payoffs improve, as does their quality; thus, they can later go to the capital market at a lower cost. Table 8 shows that treated firms' degree of information uncertainty is 5.88 higher than control firms' degree of information uncertainty, as measured by the average standard deviation of daily returns over the sample period for all firms in the same industry as the firm pursuing an IPO. This result confirms that the treated firms have a higher dispersion of market value than control firms.

Post is a dummy variable that equals to one if the IPO date is after the repeal of the Glass–Steagall Act on November 12, 1999 and zero otherwise.[20] X_i is a vector of control variables. I include industry fixed effects. Since the *Post* dummy is included in the regression, I exclude year fixed effects. I include three sets of control variables: firm characteristics, IPO characteristics and macroeconomic environment.

For firm characteristics, I use the following variables: *TobinQ* is the firm's Tobin's Q and accounts for the firm's intangible assets and growth prospects. Following Chung and Pruitt (1994), I approximate Tobin's Q as the ratio of the market value of the firm's common stock plus the book value of preferred stock and debt to the firm's total assets. The book value of debt and assets are collected from Compustat in the pre-IPO year. The market value of equity is the product of the IPO offer price and the number of shares offered in the IPO. *lnRealAge* is the natural logarithm of the number of years from the firm's founding date, or from incorporation if the founding date is unavailable, to the date of the IPO.[21] *PreIPOlnassets* variable is the natural logarithm of the firm's total assets in the pre-IPO year. The *PreIPOdebt_assets* variable is calculated as total debt divided by total assets in the pre-IPO year. This variable is used to control for the firm's financial leverage. The *PreIPOcash_assets* variable is calculated as total cash and short-term investments divided by total assets in the pre-IPO year. This variable is used to control for the firm's liquidity.

For IPO characteristics, I include the following variables: *lnIPO_sharesoffered* is the natural logarithm of the number of total shares offered in a firm's IPO. *VC* is a dummy variable that equals one if the firm is venture-backed pre-IPO, and zero otherwise. I also control for the stock exchange hosting the IPO, using *IPO_major_exchange*, a dummy variable equal to one if the firm is listed either on NYSE or Nasdaq (Ragozzino and Reuer, 2006). Listing on the major exchanges can enhance the firm's visibility; exchanges also differ markedly in the listing requirements imposed on firms (Draho, 2004). For example, the NYSE requires that all its listed companies' trade at no less than $1 per share, and that their market capitalizations be no less than $50 million. NASDAQ poses identical requirements for the stock price, but it only demands

[20]The time period between January 1, 1990 and December 31, 1997 is the pre-repeal period and the time period between January 1, 2001 and December 31, 2006 is the post-repeal period.

[21]The firms' founding dates are collected from Jay Ritter's web-page.

a minimum capitalization of \$1.1 million. Major stock exchanges such as the NYSE or NASDAQ also impose administrative fees and regulatory restrictions on their companies, such as heightened expectations regarding corporate responsibility, conflicts of interest, auditing, etc.; in contrast over-the-counter markets (OTC) often have no requirements at all. *IPOproceeds_assets* is the total proceeds from the IPO divided by firm assets in the pre-IPO year.

To control for the macroeconomic environment as well as industry differences, I include two variables: *Internet_IPO* and *lnnumber_of_IPOs*. *Internet_IPO* is a dummy variable assuming a value of one if the firm is an internet related firm, and zero otherwise.[22] Finally, the variable *lnnumber_of_IPOs* is included in the specification to account for broader, macroeconomic factors over time that might influence the features of IPOs. This variable is computed as the total number of initial public offerings in the firm's IPO year, using data obtained from Ibbotson et al. (1994).

To test *Prediction 1*, I employ *IPO_underpricing* as the outcome variable to analyze the effect of relationship banking on firms' IPO underpricing.

4.2.2.2 Prediction 2

The regression model is as follows:

$$Y_i = \beta_0 + \beta_1 * Treated * Post + \beta_2 * Treated + \tau X_i + \delta_k + \delta_t + \varepsilon_i \tag{8}$$

In this regression model, the subscript i refers to IPO firms in the sample. I employ a cross-sectional dataset of IPO firms to test my second prediction, which anticipates that firms that have a relationship bank experience larger reductions in IPO underpricing than other firms. Ideally, I want to compare IPO underpricing for a firm with relationship banking to the same firm's hypothetical IPO underpricing had they not chosen the relationship bank as the IPO underwriter. Since the latter is not observable, I employ difference-in-differences regression design. The identifying event is the repeal of the Glass–Steagall Act on November 12, 1999, and the sample period is from 1990 to 2006. The IPO firms in the pre-repeal and post-repeal periods are different firms. *Post* is defined in the same way as before. I also employ reduced form instrumental variable regression as in *Prediction 1* with the same instrument and the same definition for treated and control firm. X_i represents the same vector of control variables as in *Prediction 1, and IPO_underpricing* remains the outcome variable.

4.2.2.3 Prediction 3

[22] I use the list of internet IPO firms provided on Jay Ritter's web-page.

The regression model in this step is as follows:

$$Y_i = \beta_0 + \beta_1 * InformationAsymmetry * Treated * Post + \beta_2 * InformationAsymmetry * Treated$$
$$+\beta_3 * InformationAsymmetry * Post + \beta_4 * InformationAsymmetry$$
$$+\beta_5 * Treated * Post + \beta_6 * Treated + \tau X_i + \delta_k + \delta_t + \varepsilon_i \quad (9)$$

The subscript i refers to IPO firms in the sample. All other specifications are the same as in regression model (8).

I argue that the degree of IPO underpricing is related to the amount of uncertainty the underwriter and investors have about the true value of the firm. Relationship banking reduces this uncertainty and, consequently, minimizes IPO underpricing. I employ a triple difference-in-differences approach. As the proxy for information asymmetry, I use the average standard deviation of daily returns over the sample period for all firms in the same industry as the firm pursuing an IPO. This proxy for information asymmetry is calculated once and is not allowed to vary over time. This variable allows me to make sure that it is the cross-sectional variation in information asymmetry that influences the interaction term, rather than any industrywide changes in information asymmetry over time. Hence this measure is better than the time-varying measure, which calculates the average standard deviation of daily returns on an industry level for each year in the sample. This measure is also better than most firm-specific measures since it does not involve any post-IPO data.

For *Prediction 3*, I also employ *IPO_underpricing* as the outcome variable.

4.3 Summary Statistics

This section presents summary statistics for independent and dependent variables employed in the regression model. Summary statistics are reported in Tables 1-2. The total number of firms is 2,376. In the pre-repeal period, there are 1,787 firms, including 235 treated firms and 1,552 control firms. In the post-repeal period, there are 589 firms in total, including 144 treated firms and 445 control firms. Panel A of Table 1 shows the summary statistics for the independent variables. Panel B of Table 1 reports the results of univariate tests for the null hypothesis that differences in independent variables between treated and control firms are equal to zero. The biggest differences between treated firms and control firms are in the ratio of IPO proceeds to assets, Tobin's Q, and total assets. Control firms have higher IPO proceeds relative to their assets and higher Tobin's Q measures than treated firms. The treated firms are larger than the control firms. It is interesting to note that these differences all decrease in the post-repeal period. I control for these differences by (i) including these characteristics as additional independent variables, and (ii) using a propensity-score matched sample.

Panel A of Table 2 shows summary statistics for the outcome variable. Panel B of Table 2 reports the results of univariate tests for the null hypothesis that the difference in the of outcome variable between treated and control firms is equal to zero. As we can see from Panel B of Table 2, treated firms' IPO underpricing is lower on average than the control firms' IPO underpricing. Specifically, treated firms' IPO underpricing in the pre-repeal period is 5.7% lower than that of control firms; this difference nearly doubles to 11.28% in the post-repeal period.

4.4 Empirical Results

In this section, I discuss the empirical results of this study related to my three central predictions.

4.4.1 Prediction 1

Table 3 reports the results of the regression model shown in Equation (7). The coefficients for *Post* are negative and statistically significant for all three columns. After the repeal of the Glass–Steagall Act, which allowed firms' relationship banks to underwrite their IPOs, IPO underpricing decreases for all firms by about 5.3 percentage points on average. This decrease is larger for treated firms than control firms (10.2 percentage points vs. 2.6 percentage points, respectively). These results confirm *Prediction 1*: relationship banking reduces all firms' IPO underpricing. The results suggest that the decrease in IPO underpricing is larger for treated firms than control firms; I further examine this phenomenon in the next subsection.

4.4.2 Prediction 2

Table 4 column (1) reports the results of the regression model shown in Equation (8). The coefficient for *Treated* is negative and statistically significant. The coefficient for *Treated*Post* is also negative and significant. These results confirm that (i) average IPO underpricing is lower for treated firms, and (ii) that IPO underpricing for the treated firms fell by 6.5 percentage points more relative to the change in the control firms between the two periods (after controlling for other determinants of underpricing). These results confirm *Prediction 2*: relationship banking reduces IPO underpricing more substantially for firms that have a relationship bank before their IPO than other firms.

4.4.3 Prediction 3

Table 5 column (1) reports the results of the regression model shown in Equation (9). The coefficients for *Average_SD_sic* and *Average_SD_sic_Post* are both positive and statistically significant[23] confirming that firms facing higher information asymmetry have higher IPO underpricing. The coefficient for *Average_SD_sic_Treated* is negative, which means that among firms with relationship banks pre-IPO, relationship banking reduces IPO underpricing more for those with higher information asymmetry. The coefficient for *Average_SD_sic_Treated_Post* is negative and statistically significant, showing that, between the two periods, underpricing for treated firms with higher information uncertainty fell by 3.3 more percentage points relative to the change in more transparent treated firms. This supports *Prediction 3*: relationship banking reduces IPO underpricing by decreasing the firm's information asymmetry.

4.5 Robustness

4.5.1 Parallel Trend Assumption

The difference-in-differences approach relies on the parallel trend assumption. From Figure 1, we can see that before the repeal of the Glass–Steagall Act, both treated firms and control firms have similar patterns in underpricing though control firms have higher underpricing on average. For both sets of firms, IPO underpricing spiked sharply during the dot-com bubble (1998-2000).[24] Thus, including 1998-2000 in the sample period could potentially bias the results.[25] By focusing on the period 2001-2006, we can see difference between treated firms' and control firms' underpricing becomes larger on average after Glass–Steagall is repealed. Most importantly, Figure 1 also confirms that the decrease in control firms' underpricing in the post-repeal period is not simply a continuation of pre-repeal period trend: treated firms' underpricing is not decreasing in the pre-repeal period.

4.5.2 Unobservable IPO Characteristics

As we can see from Panel B of Table 1, all of the control variables are significantly different between the treated firms and control firms in the pre-repeal period. These differences lead to the concern that unobservable variables may be driving the changes in treated firms' IPO underpricing after the repeal of the Glass–Steagall Act. In order to address this concern, I analyze the trends in all control variables that

[23] *Average_SD_sic* is the proxy for information asymmetry, I use the average standard deviation of daily returns over the sample period for all firms in the same industry as the firm pursuing an IPO.

[24] For reasons why IPO underpricing rose during the dot-com bubble, please refer to Loughran and Ritter (2002).

[25] While the fact that the increase is larger for the control group actually supports Prediction 2, but for wrong reasons, so it might artificially inflate the significance of relationship banking.

differ significantly between treated and control firms in the pre-repeal period. These control variables are: *IPO proceeds/asset*s, *IPO shares offered*, *Tobin's Q* and *pre-IPO asset*s. If these trends change from the pre-repeal period to the post-repeal period, it is possible that unobservable factors are causing the change.

Figure 2 and 3 plot the evolution of the two control variables representing IPO characteristics: *IPO proceeds/asset*s and *IPO shares offered*. Figure 2 shows that *IPO proceeds/assets* follows a similar pattern for both treated and control firms over the pre-repeal and post-repeal periods. This control variable spikes during the dot-com bubble of 1998-2000. Since IPO underpricing during this period is severe while *IPO shares offered* don't change substantially from other periods, total IPO proceeds are much lower during 1998-2000. This means that the increase in *IPO proceeds/assets* is caused by a decrease in firms' total assets.[26] The trends in *IPO shares offered* are also similar across both treated and control firms over the pre-repeal and post-repeal periods.

4.5.3 Unobservable Firm Characteristics

Figure 4 and 5 plot the evolution of the two control variables representing firm characteristics: *Tobin's Q* and *preIPOlnassets.* Figure 4 shows that *Tobin's Q* follows a similar pattern for both treated and control firms over the pre-repeal and post-repeal periods. This control variable spikes during the dot-com bubble of 1998-2000. *Tobin's Q* is calculated as the ratio of the firm's market value of common stock plus the book value of preferred stock and debt, divided by its total assets. The market value of common stock is calculated by multiplying the firm's IPO offer price by the number of shares issued. Since IPO underpricing is severe during 1998-2000, average IPO offer prices are very low. Hence, we can interpret this spike in the same way as the spike in *IPO proceeds/assets* during 1998-2000 is caused by the increasing number of internet and high-tech firms pursuing IPOs, which translates to lower total firm assets on average. Figure 5 shows that treated firms are on average larger than control firms in terms of pre-IPO assets. There is a potential concern that larger firms may be more likely to have a relationship bank and consequently, lower IPO underpricing; this concern is mitigated by the fact that, in the post-repeal period, control firms' size increases on average, moving closer to treated firms' average size.

4.5.4 Unobservable Underwriter Characteristics

Panel B of Tables 3, 4 and 5 includes control variables for underwriter characteristics. If there are some underwriters more likely to underprice more on average, or underwriters more likely to fall prey to a corrup-

[26] In 1999, 57.4% of IPOs involved internet firms, compared to 2.9%-14.8% in prior years and 36.9% in 2000. High-tech companies accounted for around one third of the sample in 1998 and nearly half the sample in 1999-2000 (Ljungqvist and Wilhelm, 2003).

tion hypothesis, then including underwriter fixed effects should control for this effect. However, underwriter fixed effects are not feasible in this setting due to the lack of variation among the underwriters. In other words, underwriter fixed effects in this setting would capture the average difference in the underpricing between treated and control firms. Alternatively, I include a measure of the underwriter's reputation to control for potential unobservable underwriter characteristics.[27] I also control for IPO underwriter's pre-IPO loan amount in the IPO firm. Banks face a potential conflict of interest that arises from the possibility that a bank's existing claims might be retired from the firm's security proceeds. The results of this paper are robust to these controls.

4.5.5 Propensity Score Matching

In order to mitigate the concern that control firms are significantly different from treated firms in the pre-repeal period, I employ the propensity score matching method to obtain control firms that are more similar to the treated firms. To estimate the propensity scores, I select three control variables exhibit the greatest differences in means between treated and control firms in the pre-repeal period before matching and match firms on the basis of these variables. Table 6 presents the univariate analysis for the control variables in the propensity score matched sample. The matched sample consists of 761 firms in total. The average differences in all three control variables between treated and control firms are lower compared to the initial sample, and are no longer significant. These findings suggest that the propensity score matching approach achieve covariate balance and hence a successful match.

Column (3) of Tables 4 and 5 shows that my results hold for the propensity score matched sample, as the key coefficient is still significantly negative.

4.5.6 Economic Factors

Finally, I examine the levels of economic conditions during the sample period in Figures 6-7. Although I use time fixed effects in my analysis, it is necessary to examine the two periods on a macro level, since time fixed effects control only for the average effects of macro-economic factors on all firms. Suppose, for instance, that the GDP growth rate affects IPO underpricing more strongly for treated firms than control firms; in this case, GDP growth rate might be the driving force behind differences in IPO underpricing between these firms. Only examining GDP growth in the two periods can address its differential effects on the two types of firms.

[27]The measure of the underwriter's reputation is a discrete ranking taking values between 0 and 9 as described in Carter and Manaster (1990).

As we can see from Figures 6, the levels of both unemployment rate and annual returns on an investment in S&P 500 are similar over the pre-repeal and post-repeal periods. However, the levels of the annual GDP growth rate and the annual inflation rate in Figure 7 look quite different in the pre-repeal and post-repeal periods, raising concern that these differences may affect IPO underpricing. To rule out this concern, I run simple OLS regressions of average annual underpricing each year on annual GDP growth rate each year and annual inflation each year respectively to see whether underpricing is affected by these two factors. The results are shown in Table 7 and suggest that IPO underpricing is not related to GDP growth rate but is correlated with the inflation rate. Thus, I add an interaction term of annual inflation and *Treated* as a control variable in my regression. This does not change the results.

To further ensure that the pre-repeal and post-repeal periods in my sample are similar in terms of economic conditions, I explore the economic background of the two periods. Both periods started in a mild recession during the first two years, followed by a recovery period in the remaining years. During the pre-repeal period of 1990-1997, the US economy entered into recession in July 1990; this recession lasted 8 months, through March 1991. The recession, which was mild relative to other post-war recessions, was characterized by a sluggish employment recovery, most commonly referred to as jobless recovery. During the post-repeal period of 2001-2006, many developed countries experienced recession of the early 2000s, which was characterized by a decline in economic activity. This recession affected the US in 2002 and 2003; similar to the previous recession in 1990-1991, it was relatively mild.[28] Based on these similar economic trajectories, I conclude that the pre-repeal and post-repeal periods are largely comparable.

4.5.7 Controlling for the Dot-Com Bubble

Although I have demonstrated the reasons for excluding the dot-com bubble from in my sample, concerns may exist about this decision because, typically difference-in-differences regression designs do not include gaps in their sample periods. To address this potential concern, I add 1998-2000 to the sample period as a robustness check. There are a total of 2,966 firms in the sample including the dot-com bubble of 1998-2000.

Column (2) in Tables 4 and 5 shows that including the dot-com bubble period does not substantially change the results. The key coefficient is still significantly negative, though its absolute value and significance level are both lower.

[28]Some economists object to characterizing it as a recession since no two consecutive quarters experienced negative growth.

5 Conclusion

Prior studies relating IPO underpricing to information asymmetry focus on a single level of asymmetry. To the best of my knowledge, this is the first paper propose a fixable-mechanism underlying two levels of information asymmetry.[29]

My theoretical model suggests that, given publicly observable transaction lending and no relationship lending, investors may not be able to distinguish good firms from bad firms just by observing whether a firm borrows. Even if the two types of firms can be separated, the bad firm suffers, receiving lower IPO proceeds than it would in the pooling case. In contrast, when relationship lending is available and lending decisions are confidential, IPO underpricing decreases and both types of firms benefit.

Empirical results confirm that relationship banking reduces the amount of uncertainty that the underwriter and investors have about the true value of the firm and, thus, generates more accurate IPO prices. I apply difference-in-differences and reduced form instrumental variable regression designs to a sample of 2,376 IPO firms, using variation in the strength of the lending relationship between IPO firms and their underwriters generated by the repeal of the Glass-Steagall Act in 1999, which allowed commercial banks with close ties to their client firms to underwrite those firms' equity issuances. I show that, after the repeal of the Glass–Steagall Act on November 12, 1999: (i) IPO underpricing drops by an average of 5.3% for all firms; (ii) underpricing for the treated group falls by 6.5 more percentage points relative to the change in the control group; and underpricing for treated firms with higher information uncertainty falls by 3.3 more percentage points relative to the change in more transparent treated firms.

Under plausible assumptions, these estimates translate into substantial economic effects. For example, if we assume that average IPO underpricing is 16.8%, then calculations suggest that firms can receive an additional $2 billion per year on average to reinvest and grow.

[29]The information asymmetry between the firm and underwriter and the information asymmetry between the firm and investors.

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Figure 1: Average IPO Underpricing (units in %)

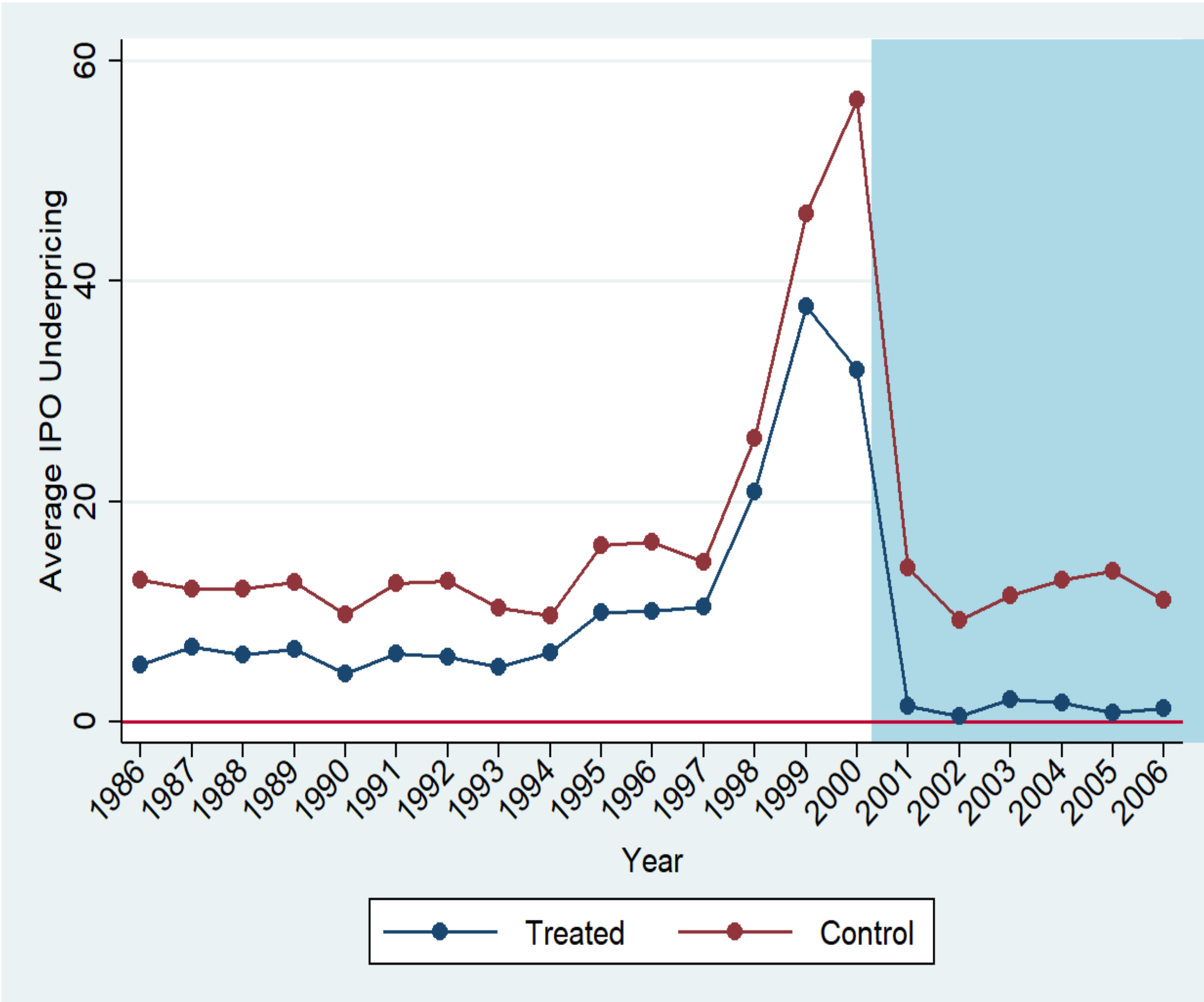


Figure 2: IPO proceeds/assets (units in millions)

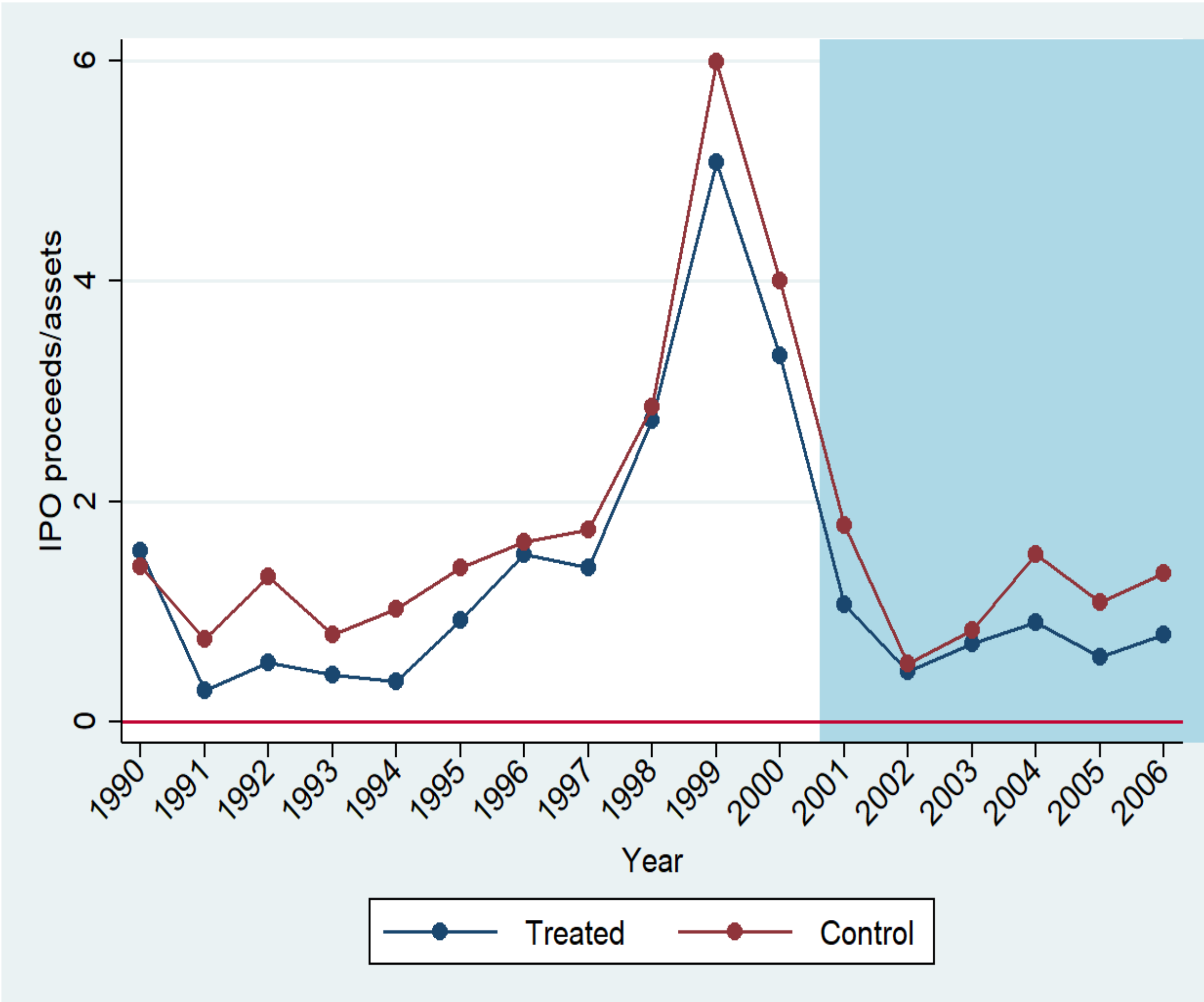


Figure 3: IPO Shares Offered (units in millions)

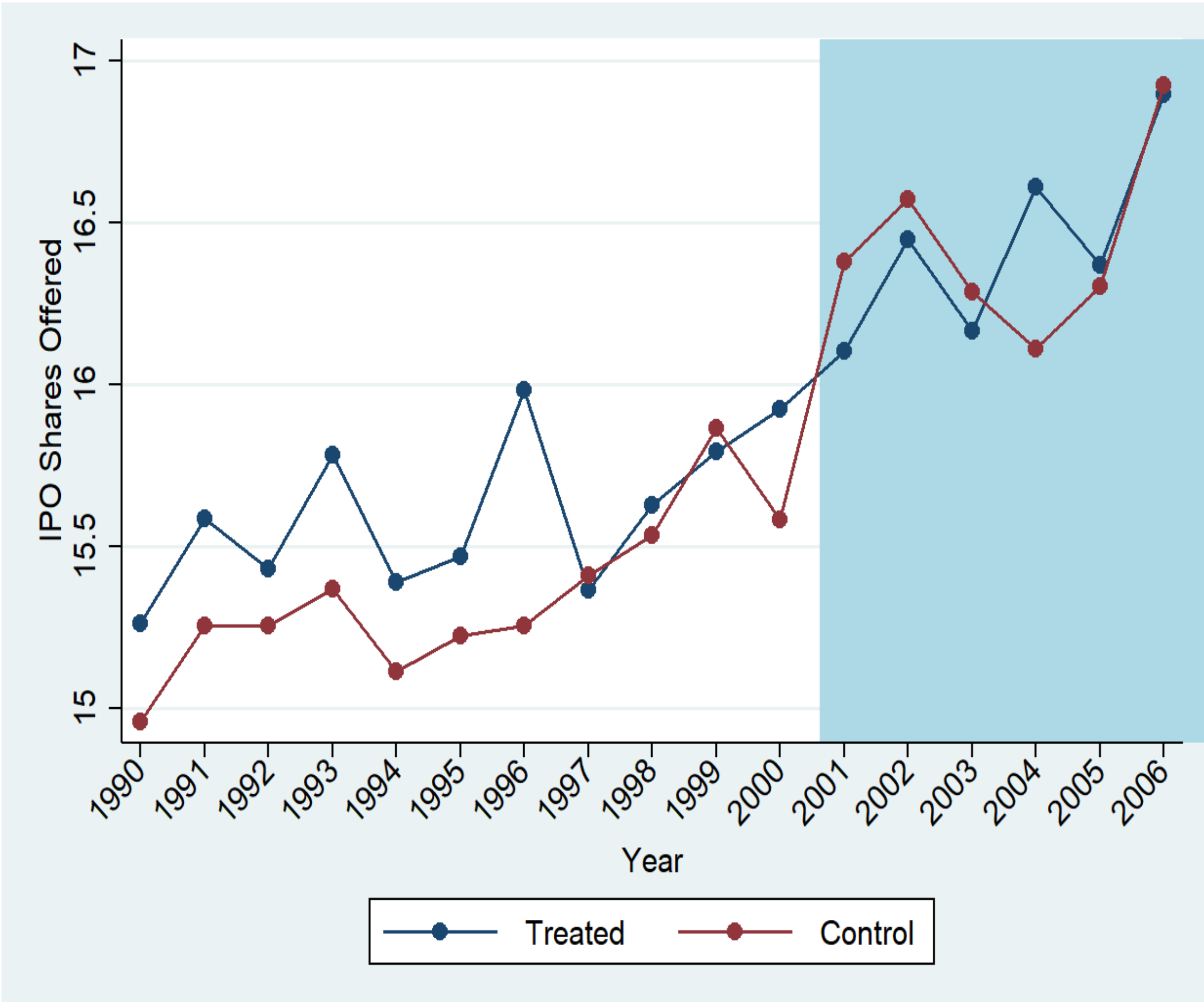


Figure 4: Tobin's Q

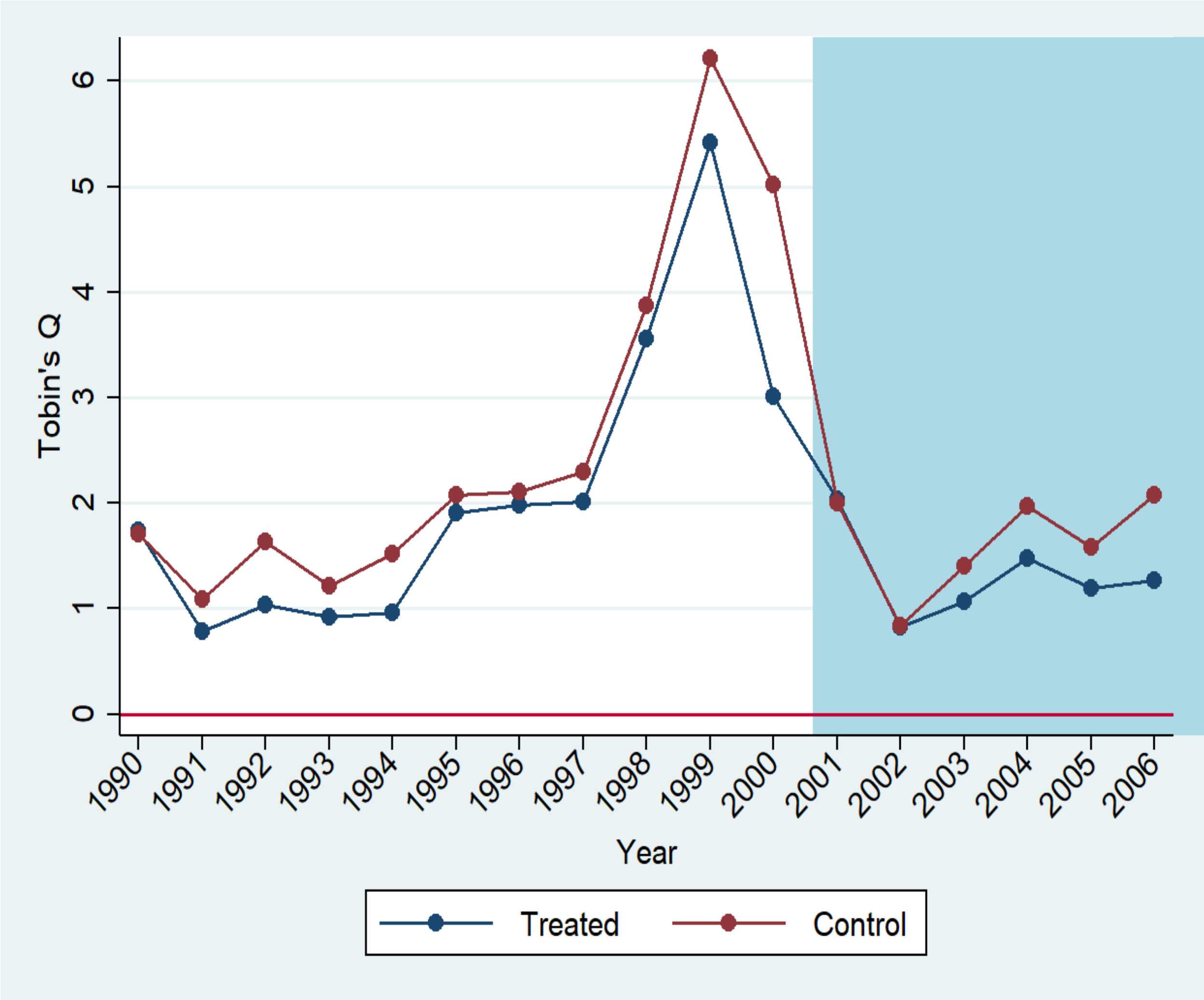


Figure 5: LnAssets (units in ln millions)

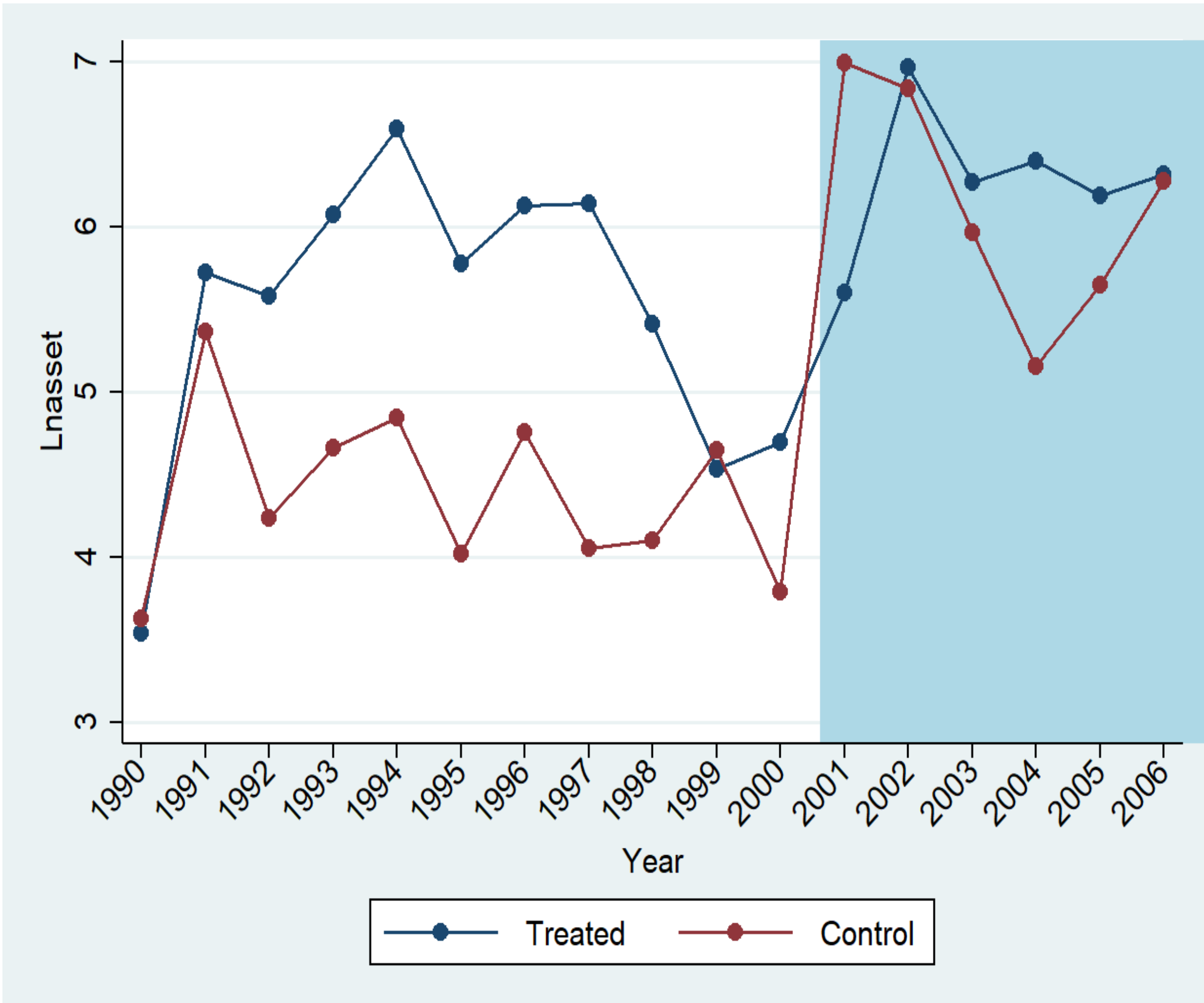
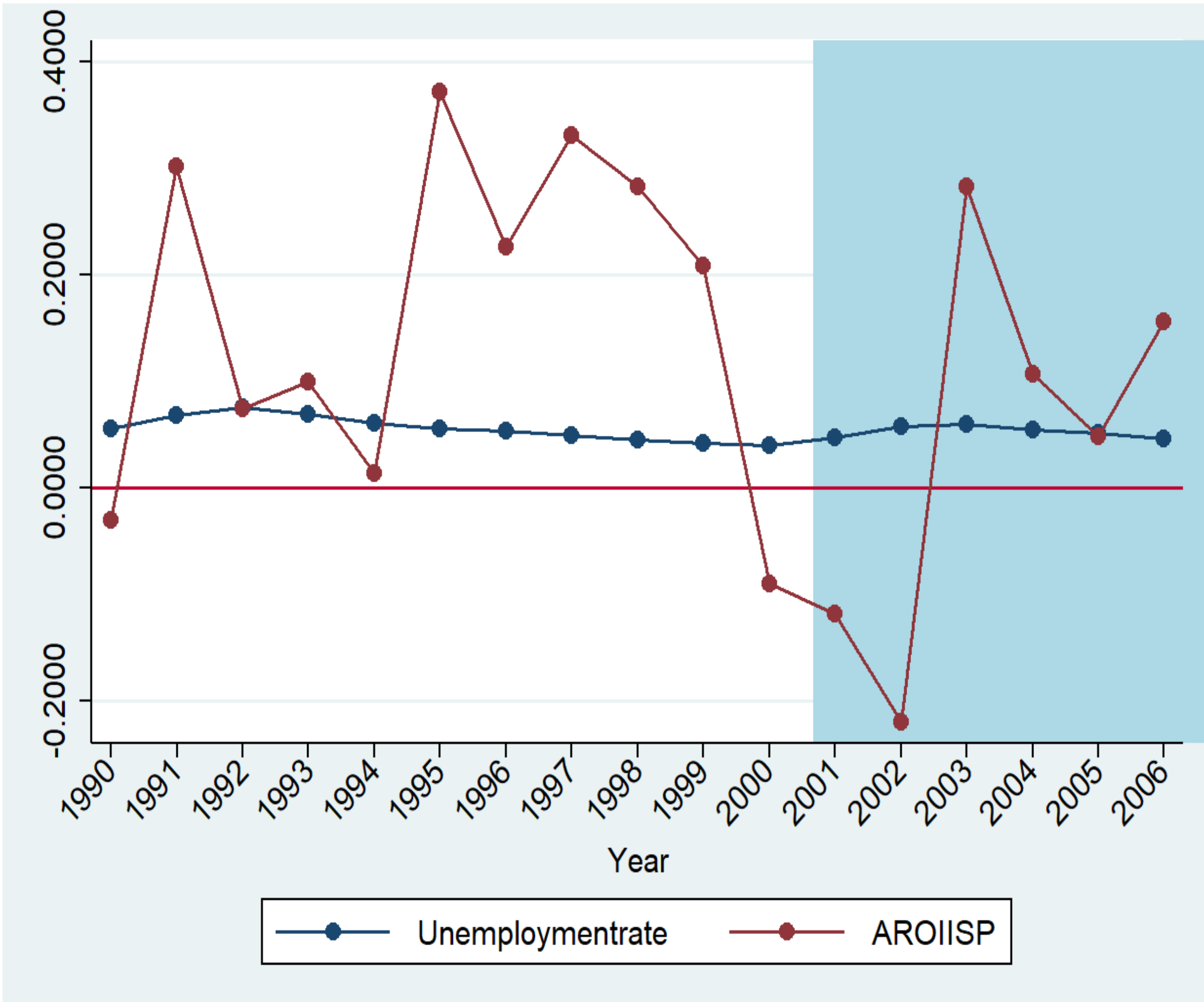
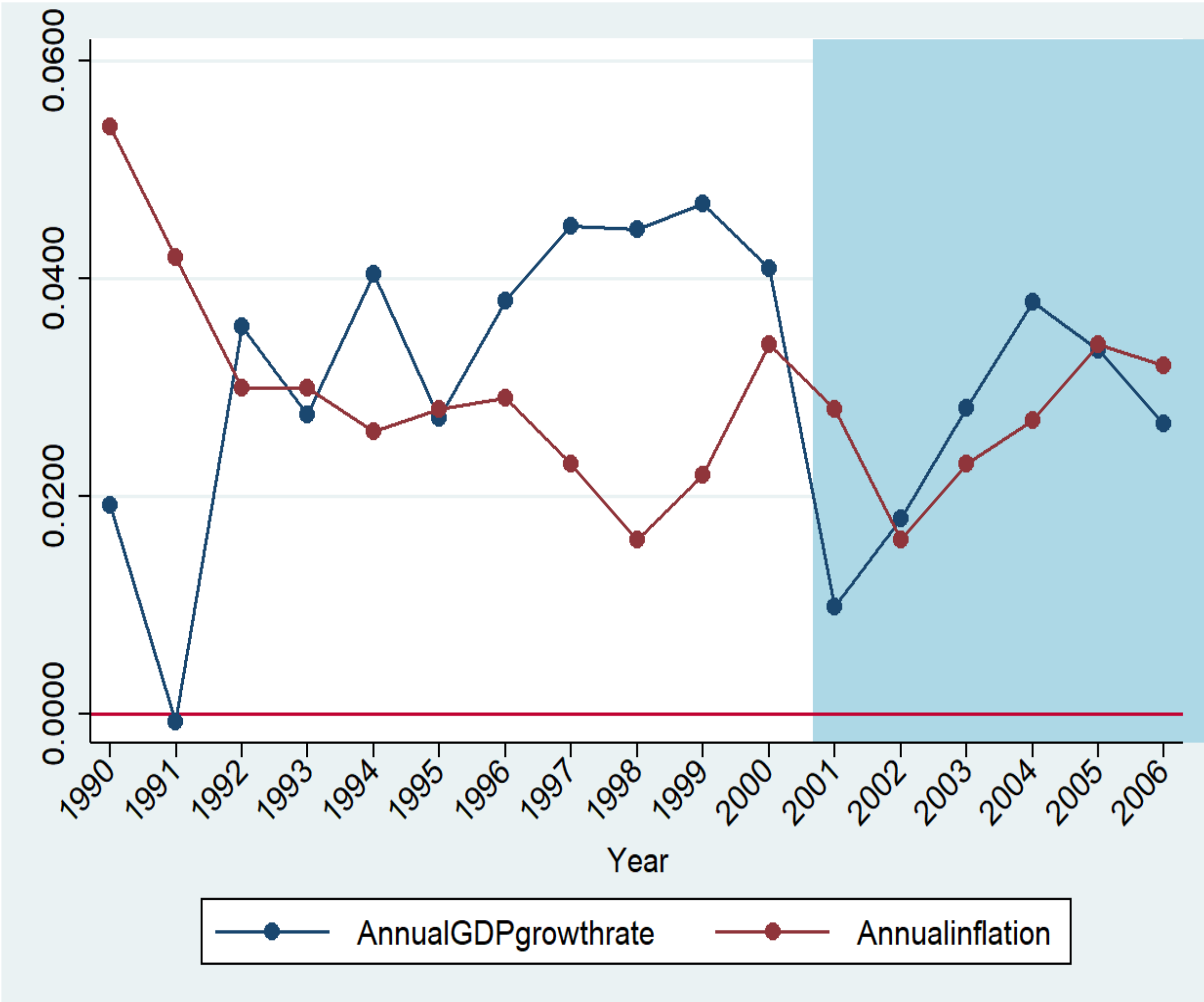


Figure 6: Unemployment Rate in US and Annual Returns on Investment in S&P 500



Source: United States Department of Labor, Bureau of Labor Statistics & Federal Reserve Database in St. Louis

Figure 7: Annual GDP Growth Rate and Annual Inflation in US



Source: World Bank & Federal Reserve Bank of Minneapolis

Figure 8: Channel of Relationship Banking's Effect on IPO Underpricing

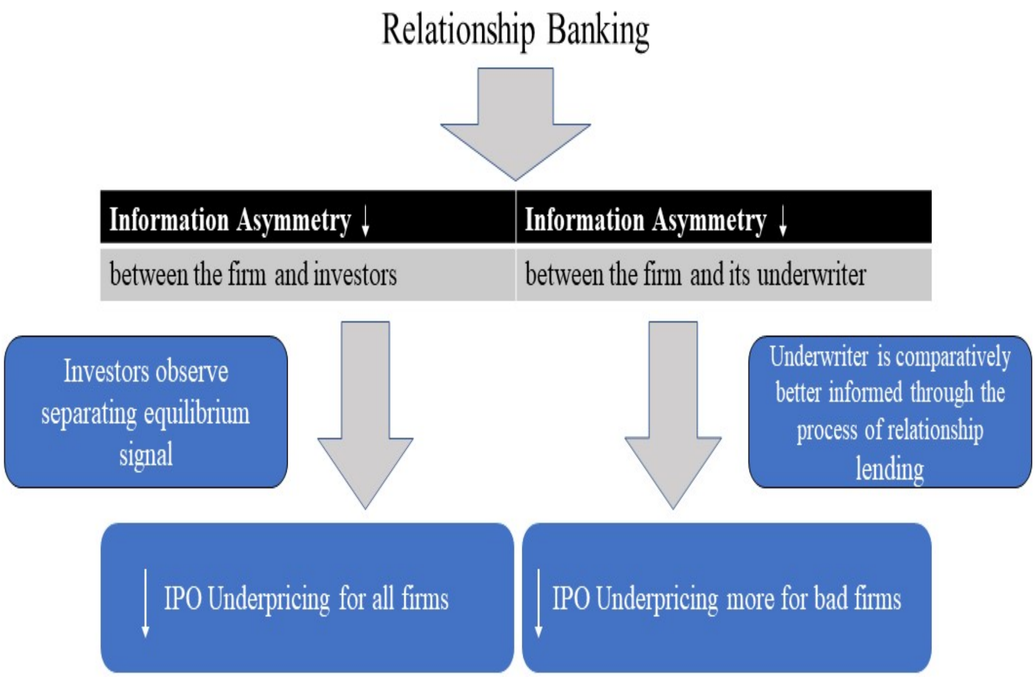


Table 1: Summary statistics for the control variables

Panel A reports summary statistics for independent variables in the regression. Panel B reports the results of univariate tests. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. The t-statistics are in parentheses.

Panel A: Summary statistics

				Percentile Distribution		
	N	Mean	S.D.	25th	Median	75th
IPOproceeds_assets	56,322	1.575	5.774	0.184	0.514	1.042
TobinQ	55,834	2.031	5.875	0.522	0.987	1.634
lnRealAge	63,035	3.505	0.565	3.135	3.401	3.784
lnIPO_sharesoffered	63,035	15.639	0.996	14.878	15.499	16.278
preIPOlnassets	56,322	5.292	2.224	3.820	5.479	6.666
preIPOcash_assets	56,194	0.098	0.147	0.015	0.040	0.111
secondaryshares_percent	55,179	0.073	0.160	0.000	0.000	0.097

Panel B: Univariate analysis

	Post = 0			*Post* = 1		
	Treated = 1	*Treated* = 0	(1)	*Treated* = 1	*Treated* = 0	(2)
	Mean	Mean	Diff	Mean	Mean	Diff
TobinQ	1.0698	2.7509	-1.681***	1.3879	1.602	-0.214***
			(-23.30)			(-4.37)
lnRealAge	3.6193	3.5148	0.104***	3.2796	3.4418	-0.162***
			(21.65)			(-13.41)
InternetIPO	0.0017	0.0121	-0.0104***	0.0059	0.1583	-0.152***
			(-5.14)			(-7.49)
lnIPO_sharesoffered	15.5265	15.2569	0.270***	16.4945	16.4826	0.0118
			(31.97)			(0.81)
VC	0.1004	0.2347	-0.134***	0.0917	0.149	-0.0573***
			(-34.31)			(-10.39)
IPO_major_exchange	0.8992	0.9326	-0.0333***	0.9838	0.9706	0.0132***
			(-12.42)			(5.16)
preIPOlnassets	6.1488	4.3882	1.761***	6.4093	6.0357	0.374***
			(75.32)			(13.73)
preIPOcash_assets	0.0554	0.1071	-0.0517***	0.0969	0.1273	-0.0304***
			(-34.57)			(-11.48)
secondaryshares_percent	0.0328	0.0531	-0.0203***	0.2015	0.1207	0.0808***
			(-17.04)			(19.99)
N of observations	14,341	32,265	46,606	5,572	10,857	16,429
N of firms	235	1,552	1,787	144	445	589

Table 2: : Summary statistics for the outcome variable

Panel A reports summary statistics for *IPO_underpricing*, the dependent variable in the regression. Panel B reports the results of the univariate test. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. The t-statistics are in parentheses.

Panel A: Summary statistics

				Percentile Distribution		
	N	Mean	S.D.	25th	Median	75th
IPO_underpricing	62,473	9.886	15.113	0.000	5.000	14.875

Panel B: Univariate analysis

	Post = 0			*Post* = 1		
	Treated = 1	*Treated* = 0	(1)	*Treated* = 1	*Treated* = 0	(2)
	Mean	Mean	Diff	Mean	Mean	Diff
IPO_underpricing	6.6686	12.403	-5.735***	0.275	11.559	-11.280***
			(-35.95)			(-64.16)
N of observations	14,341	32,265	46,606	5,572	10,857	16,429
N of firms	235	1,552	1,787	144	445	589

Table 3: Empirical results for Prediction 1

This table reports results from the regressions relating firms' IPO underpricing to relationship banking (Prediction 1). The regression model is as follows:

$$Y_i = \beta_0 + \beta_1 * Post + \tau X_i + \delta_k + \varepsilon_i$$

X_t is a vector of control variables. δ_k imply industry fixed effects. Standard errors are clustered at the firm level. The appendix provides definitions for each variable. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. The t-statistics are in parentheses.

Panel A

Dependent variable:	*IPO_underpricing*		
	(treated and control firms)	(treated firms only)	(control firms only)
	(1)	(2)	(3)
Post	-5.316***	-10.215***	-2.553*
	(-4.46)	(-3.59)	(-1.75)
Control variables	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	No	No	No
Underwriter Characteristics	No	No	No
N of firms	2,376	379	1,997
Adj R^2	0.670	0.511	0.675

Panel B

Dependent variable:	*IPO_underpricing*		
	(treated and control firms)	(treated firms only)	(control firms only)
	(1)	(2)	(3)
Post	-4.332**	-8.587**	-2.393*
	(-2.22)	(-2.31)	(-1.72)
Control variables	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	No	No	No
Underwriter Characteristics	Yes	Yes	Yes
N of firms	2,376	379	1,997
Adj R^2	0.771	0.580	0.750

Table 4: Empirical results for Prediction 2

This table reports results from the regressions that relate to Prediction 2. The regression model is as follows:

$$Y_i = \beta_0 + \beta_1 * Treated * Post + \beta_2 * Treated + \tau X_i + \delta_k + \delta_t + \varepsilon_i$$

X_t is a vector of control variables. δ_k and δ_t represent industry fixed effects and year fixed effects respectively. Standard errors are clustered at the firm level. The appendix provides definitions for each variable. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. The t-statistics are in parentheses.

Panel A

Dependent variable:	*IPO_underpricing*		
	(Excluding 1998-2000)	(Including 1998-2000)	(Matched sample)
	(1)	(2)	(3)
*Treated * Post*	-6.479***	-4.999**	-6.252**
	(-3.43)	(-2.14)	(-2.10)
Treated	-4.128***	-4.517***	-5.273***
	(-3.05)	(-3.02)	(-2.84)
Control variables	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Underwriter Characteristics	No	No	No
N of firms	2,376	2,966	1,087
Adj R^2	0.679	0.679	0.548

Panel B

Dependent variable:	*IPO_underpricing*		
	(Excluding 1998-2000)	(Including 1998-2000)	(Matched sample)
	(1)	(2)	(3)
*Treated * Post*	-6.278***	-4.867**	-6.033**
	(-3.67)	(-2.25)	(-2.20)
Treated	-4.133***	-4.727***	-5.575***
	(-3.25)	(-3.22)	(-2.97)
Control variables	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Underwriter Characteristics	Yes	Yes	Yes
N of firms	2,376	2,966	1,087
Adj R^2	0.703	0.711	0.596

Table 5: Empirical results for Prediction 3

This table reports results from the regressions that relate to Prediction 3. The regression model is as follows:

$$Y_i = \beta_0 + \beta_1 * InformationAsymmetry * Treated * Post + \beta_2 * InformationAsymmetry * Treated$$
$$+ \beta_3 * InformationAsymmetry * Post + \beta_4 * InformationAsymmetry + \beta_5 * Treated * Post$$
$$+ \beta_6 * Treated + \tau X_i + \delta_k + \delta_t + \varepsilon_i$$

InformationAsymmetry is proxied by *Average_SD_sic*. X_t is a vector of control variables. δ_k and δ_t represent industry fixed effects and year fixed effects respectively. Standard errors are clustered at the firm level. The appendix provides definitions for each variable. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. The t-statistics are in parentheses.

Panel A

Dependent variable:	*IPO_underpricing*		
	(Excluding 1998-2000)	(Including 1998-2000)	(Matched sample)
	(1)	(2)	(3)
*Average_SD_sic * Treated * Post*	-3.335**	-2.035**	-1.591**
	(-2.41)	(-2.40)	(-2.02)
*Average_SD_sic * Treated*	-1.776	-4.156**	-4.835***
	(-1.19)	(-1.98)	(-12.50)
*average_SD_sic * Post*	3.779***	4.441***	4.207***
	(2.90)	(3.66)	(22.92)
Average_SD_sic	15.231***	13.569***	12.289**
	(34.65)	(24.80)	(2.00)
*Treated * Post*	-23.652***	-20.752***	-15.681***
	(-5.91)	(-4.93)	(-9.22)
Treated	-5.889	-4.936	-11.223***
	(-0.69)	(-0.39)	(-8.30)
Control variables	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Underwriter Characteristics	No	No	No
N of firms	2,376	2,966	1,087
Adj R^2	0.695	0.695	0.843

Panel B

Dependent variable:	*IPO_underpricing*		
	(Excluding 1998-2000)	(Including 1998-2000)	(Matched sample)
	(1)	(2)	(3)
*Average_SD_sic * Treated * Post*	-3.867**	-2.445**	-1.735**
	(-2.31)	(-2.24)	(-2.32)
*Average_SD_sic * Treated*	-1.972	-4.675**	-4.998***
	(-1.44)	(-1.99)	(-14.55)
*average_SD_sic * Post*	4.832***	4.879***	4.659***
	(3.22)	(3.78)	(25.33)
Average_SD_sic	15.877***	14.355***	13.332**
	(35.67)	(25.88)	(2.24)
*Treated * Post*	-23.677***	-20.689***	-15.981***
	(-6.96)	(-4.98)	(-9.56)
Treated	-6.348	-5.665	-11.567***
	(-0.78)	(-0.45)	(-8.96)
Control variables	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Underwriter Characteristics	Yes	Yes	Yes
N of firms	2,376	2,966	1,087
Adj R^2	0.702	0.705	0.864

Table 6: Univariate analysis for the control variables of matched sample

This table reports the results of univariate tests for the key control variables in the propensity score matched sample. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. The t-statistics are in parentheses.

	Post = 0			*Post* = 1		
	Treated = 1	*Treated* = 0	(1)	*Treated* = 1	*Treated* = 0	(2)
	Mean	Mean	Diff	Mean	Mean	Diff
TobinQ	1.0797	1.4837	-0.404	1.3879	1.6036	-0.216
			(-0.66)			(-0.87)
lnIPO_sharesoffered	15.5086	15.3183	0.19	16.4941	16.2197	0.274
			(1.13)			(1.12)
preIPOlnassets	6.1369	5.2721	0.865	6.4093	5.8014	0.608
			(0.96)			(1.10)
N of firms	208	264	472	139	150	289

Table 7: OLS regressions for Figure 7

This table reports results from the regressions relating firms' IPO underpricing to macro-economic conditions. The regression model is as follows:

$$Y_i = \beta_0 + \beta_1 * X_t + \varepsilon_i$$

X_t is a vector of two variables: *Annual GDP growth rate* and *Annual inflation*. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. The t-statistics are in parentheses.

Dependent variable:	*IPO_underpricing*	
	(1)	(2)
AnnualGDPGrowthRate	-0.410	
	(-0.79)	
AnnualInflation		1.083**
		(2.17)
Control variables	No	No
Industry fixed effects	No	No
Year fixed effects	No	No
N	14	14
Adj R^2	-0.039	0.270

Table 8: Confirmation of the connection between the theoretical model and the empirical test

This table reports results from the regressions confirming the connection between the good and bad firms as defined in the theoretical model and the treated and control firms as defined in the empirical part. The regression model is as follows:

$$Y_i = \beta_0 + \beta_1 * Treated + \tau X_i + \delta_k + \delta_t + \varepsilon_i$$

X_t is a vector of control variables. δ_k and δ_t represent industry fixed effects and year fixed effects respectively. Standard errors are clustered at the firm level. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. The t-statistics are in parentheses.

Dependent variable:	*Average_SD_sic*
Treated	5.88**
	(1.99)
Control variables	Yes
Industry fixed effects	Yes
Year fixed effects	Yes
N	2,367
Adj R^2	0.660

A Assumptions of the Model

1. Some underpricing is necessary to compensate uninformed investors for their anticipated losses on overpriced issuances and to ensure their continued participation in the IPO market;

2. The degree of underpricing is directly related to the ex-ante uncertainty about the market value of the firm;

3. There are two types of firms with the same expected value. The good firms, denoted by G, have a low dispersion of market value; their offer proceeds, denoted by OP_G, is high. The bad firms, denoted by B, have a high dispersion of market value; their offer proceeds, denoted by OP_B, is low. Firm owners know their firm's type, but not its market value;

4. Each firm has a project requring financing of D dollars ($OP_B < D < OP_G$). The project payoff represents the firm's true market value;

5. Investors can't discover a firm's type without any cost. They only invest if the value of the firm $V_j \geq OP_j$;

6. Underwriters are informed;

7. The distributions of possible market values for each type of firm are uniform: $\widetilde{V_G} \sim U[a_G, b_G]$, $\widetilde{V_B} \sim U[a_B, b_B]$, where $a_G > a_B$, $b_G < b_B$. With relationship lending, $\widetilde{V_B}$ could reach close to b_B after banks' sector specialization improves project payoff;

8. Relationship lenders can participate in IPO as underwriters;

9. There are two types of banking relationships: (i) an underwriting relationship, where the relationship bank underwrites the firm's prior debt issuance (public debt placement); (ii) a lending relationship, where the bank lends its own funds to the firm (term loans or revolver loans). Since the bank has a financial stake in the lending relationship but not in the underwriting relationship, a relationship bank has more incentives to monitor or screen firms, thus generating more information than is available in an underwriting relationship.

B Variable Definition

Variable	Definition	Source
Treated	A dummy variable equal to one if the IPO firm has a relationship bank at least three years before IPO and zero otherwise.	N/A
Post	A dummy variable equal to one if the IPO date is after the repeal of the Glass–Steagall Act on November 12, 1999 and zero otherwise.	N/A
TobinQ	The ratio of the firm's market value of common stock plus the book value of preferred stock and debt, divided by its total assets. This variable is winsorized at 1 and 99 percent level each year.	Compustat&Securities Data Corporation (SDC) database
lnRealAge	The natural logarithm of the number of years since the firm was founded (or since incorporation if founding date is unavailable) to the date of the IPO.	www.site.warrington.ufl.edu
preIPOlnassets	The natural logarithm of the total assets of the firm in the pre-IPO year.	Compustat
PreIPOdebt_assets	Calculated as total debt divided by total assets in the firms' pre-IPO year.	Compustat
preIPOcash_assets	Calculated as total cash and short-term investments divided by total assets in the firms' pre-IPO year.	Compustat
lnIPO_sharesoffered	The natural logarithm of the number of total shares offered in a firm's IPO.	Securities Data Corporation (SDC) database

VC	A dummy variable equal to one if the firm is venture-backed pre-IPO, and zero otherwise.	Securities Data Corporation (SDC) database
IPOproceeds_assets	The total proceeds from a firm's IPO divided by its assets in the pre-IPO year.	Compustat&Securities Data Corporation (SDC) database
secondaryshares_percent	Calculated as secondary shares divided by total shares offered in a firm's IPO	Securities Data Corporation (SDC) database
IPO_major_exchange	A dummy variable equal to one if the firm is listed either on NYSE or Nasdaq, and zero otherwise.	Securities Data Corporation (SDC) database
Internet_IPO	A dummy variable equal to one if the firm is an internet-related firm, and zero otherwise.	www.site.warrington.ufl.edu
lnnumber_of_IPOs	The total number of initial public offerings in the firm's IPO year.	www.quandl.com
Annual_inflation	Calculated based on CPI from the Federal Reserve Bank of Minneapolis.	www.minneapolisfed.org
Average_SD_sic	The average standard deviation of daily returns over the sample period for all firms in the same industry as the firm pursuing an IPO.	CRSP
IPO_underpricing	Calculated as (Price at closing of 1st trading day–Offer price)/Offer price*100	Securities Data Corporation (SDC) database