ESSAYS ON VENTURE CAPITAL SYNDICATION AND THE INFORMATIONAL EFFICIENCY OF THE CORPORATE BOND MARKET

BY

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Abstract

The first two essays in this dissertation examine the phenomenon of venture capital syndication, or co-investment. In the first essay, I construct measures of syndicate heterogeneity and find that when venture capital firms from different geographic regions syndicate their investments, this has a strong positive impact on the company receiving the financing. However, I find no equivalent positive impact from heterogeneity in terms of organizational structure of the venture capital firms. My results are robust to selection effects and are consistent with the notion that syndicate partners add value through their access to different business networks. In the second essay, I find that syndication is positively associated with both the investment amount and the information asymmetries between the entrepreneur and the venture capitalist(s). I also find that syndication is more prevalent in Boston, California, and the Pacific Northwest. After controlling for these factors, I still find that syndication rates cycle and argue that current elevated syndication rates are a symptom of overinvestment by the venture capital community. In the third essay, I find that a firm's traded corporate bonds partially anticipate its stock price movements by one to three months. A decline of 10% over three months of a firm's bonds is associated with an ensuing cumulative stock-price decline of 3% to 6%. The effect is non-linear, with bond price declines signaling lower future stock prices, but bond price increases having no effect. Possible explanations include the focus of bond analysts on negative results, the use of credit-default swaps as venues for informed trading (including insider trading), and the influence of noise traders on equity prices.

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For little Caroline (but don’t feel obligated to read)

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CHAPTER 2

Chapter 1

The Impact of Investor Heterogeneity: Evidence from Venture Capital Syndication

Abstract

The number of syndicate partners in the first round of venture capital financing is strongly positively related to the success of the entrepreneurial company. I examine whether heterogeneity within the syndicate drives this positive relationship. I find that syndicates composed of venture capital firms from different geographic regions perform better than syndicates composed of venture capital firms from the same region. Additionally, I find evidence that syndicates that are more diverse in terms of age are more successful. Lastly, syndicates that are diverse in terms of organizational structure (traditional, corporate, bank, angel) perform no better than those that are not. My results are robust to selection effects and are consistent with the notion that syndicate partners add value through their access to different business networks.

1. Introduction

Entrepreneurial companies that receive funding from a syndicate of venture capital (VC) firms are more likely to go public or become acquired than companies financed by a single venture capitalist (Brander, Amit, and Antweiler (2002), and Tian (2008)). I confirm this finding and also find that the relation is roughly monotonic, i.e., the larger the syndicate in the first round of VC financing the higher the probability of a successful outcome (IPO or acquisition) for the entrepreneurial company (see Figure 1). Given this, a natural question is: What is the source of this improved performance among larger syndicates? This study examines the role that investor heterogeneity plays. Members of VC syndicates vary in terms of size, age, experience, organizational structure, geography, prior success, and expertise, but existing research does not address the effects of these potential complementarities between partnering VC firms. My study fills this gap by illuminating the value-added role that a partnership of VC firms plays above and beyond the provision of capital.

There is a potential value-added role for heterogeneity across investors because venture capitalists (VCs) provide not only equity financing but also monitoring and advice for risky new ventures (Lerner (1995)). In many cases, this non-financial support comes from more than one VC. For example, Tian (2008) reports that 70% of entrepreneurial companies that received VC funding between 1980 and 2005 did so from a syndicate of VC firms in at least one of the rounds. Academic studies focus on the possibility that VC syndication reduces the information asymmetries inherent in financing their portfolio companies. Lerner

(1994) posits that a VC firm seeks out a syndicate partner to obtain an independent evaluation of a portfolio company's prospects, while Brander, Amit, and Antweiler (2002) suggest that VC firms value a syndicate partner's complementary skills or information set. Casamatta and Haritchabalet (2007) build a model in which experienced VCs are more desired as syndicate partners, while Cestone, Lerner, and White (2006) theorize that there are instances where a lead VC may instead prefer a syndicate partner with less experience. Other rationales for VC syndication cited in the academic literature concern the management of a VC firm's portfolio or maintenance of deal flow. Thus, syndication may be the only way for a VC firm to acquire small stakes in a large number of firms to enhance portfolio diversification and manage liquidity risks (Sahlman (1990), Lockett and Wright (1999)). Inviting other experienced VCs to join a syndicate may also result in reciprocal invitations, ensuring future deal flow (Lerner (1994)).

Some of these explanations for syndication, such as Brander, Amit, and Antweiler (2002), Cestone, Lerner, and White (2006), and Casamatta and Haritchabalet (2007), have a role for syndicate heterogeneity and complementary skills. Others, such as Sahlman (1990) and Lockett and Wright (1999), emphasize portfolio diversification, deal flow, liquidity, and other benefits that should accrue even in the absence of complementary skill sets.

Syndication might not always be beneficial. Constraints or costs to syndication include diffusion of incentives and potential opportunism among syndicate members, such as expropriation of information, talent, or investment opportunities (Guler and McGahan (2007)). Additionally, disagreements and coordination problems with items such as contract writing may arise as the portfolio company grows and becomes more complex. However, I find that on average, syndication is correlated with better outcomes. In the univariate, each additional syndicate partner in the first round of VC financing is associated with a 3.2 percentage-point increase in the probability of a successful outcome (IPO or acquisition) for the portfolio company that receives the VC funding. I also find that certain types of heterogeneity play a role in this increased performance.

One such possibility is geographic heterogeneity. In 1986 Office Depot opened its first store in Fort Lauderdale, Florida. The next year, it raised $11 million in first-round financing from VC firms located in Texas, California, New York, New Jersey, Connecticut, and London. In 1988 Office Depot went public, and by 1990, it had opened 173 stores in 27 states. Different syndicate partners have different access to business networks outside the portfolio company's geographic region. Venture capitalists are often former entrepreneurs themselves and are very familiar with their local business networks, which include customers, suppliers, and investment bankers. Additionally, Hellmann and Puri (2002) find that VCs are instrumental in bringing in executives such as CEOs when new management is needed and VPs of Sales and Marketing when the portfolio company needs to expand. VCs from different geographic regions can provide access to these value-added customers, suppliers, investment bankers, and managers that are unfamiliar to the portfolio company. Consistent with this notion, I find evidence that syndicates composed of VCs from different geographic regions outperform syndicates composed of VCs that are all from the same region. Specifically, I find that after controlling for multiple factors, a syndicate that has two or more VC firms from different geographic regions (there are 18 total) is associated with a 3.4 percentage-point increase in the probability of a successful outcome (IPO or acquisition) relative to a syndicate composed of two VC firms both from the same geographic region. Hochberg, Ljungqvist, and Lu (2008) find that more densely networked markets experience less entry from VC firms from outside geographic regions. My finding suggests that when this barrier to entry is overcome, improved performance from the VC-backed portfolio company is realized.

Age, or experience, is another dimension along which syndicates can exhibit heterogeneity. Cestone, Lerner, and White (2006) build a theoretical model in which a lead VC may prefer a syndicate partner with less investing experience. In their model, when the lead VC holds a manipulable signal, the incentive costs of syndication are increasing with the experience of the syndicate partner. Walske and Zacharakis (2008) find via interviews with VC firms that experienced VC firms may prefer working with younger VC firms as the younger firms are more likely to “stay out of the way”. Bottazzi, da Rin, and Hellmann (2008) find that older VCs excel at future fund raising for the portfolio company. Younger VCs are more likely to be familiar with the products and technology of the portfolio company. Thus, age-diverse syndicates may offer firms with different skills, knowledge, and business networks. I find evidence to support this notion: as the standard deviation of VC firm ages within a syndicate increases, so does the probability of a successful outcome (IPO or acquisition) for the portfolio company.

Finally, syndicates can differ in terms of organizational structure. Consider the case of corporate VCs, which differ markedly from traditional VCs in terms of organizational and incentive structures (Gompers and Lerner (1999)). Corporate VCs are often more interested in fulfilling strategic objectives such as learning about and/or capturing new technologies. Additionally, their incentives differ in that they are not faced with the same pressure to realize financial returns before a fund expires. However, they often have firsthand knowledge of the industry and technology of the portfolio company they invest in. Traditional VC firms tend to focus on management performance and financial benchmarks. As such, it is possible that corporate VCs add a different type of value than the traditional VC firm does. In the mid-1990s, VeriSign Inc. received VC funding not only from traditional VC stalwarts Bessemer Venture Partners and Kleiner Perkins Caufield & Byers, but also from Visa, Microsoft, and Cisco. This investment worked well, but overall, I do not find that corporate VC firms add value to a syndicate above and beyond a typical VC partner, despite their different skills and knowledge bases. This is somewhat surprising given the strong value-added effects found in the extant literature (Gompers and Lerner (1999)).

I find a similar lack of an incremental effect for bank VCs. Bank VCs have structures and compensation plans similar to those at traditional VC firms, but are likely to be even more in tune with profitable exit channels, i.e. IPOs and acquisitions. However, I find that adding a bank VC to a syndicate does not improve the probability of the portfolio company going public or being acquired above and beyond what a typical VC partner would add.

An angel investor is an individual who provides capital from his or her own funds to a private business, owned by neither a friend nor a family member (Shane – 2008). Angels may have different incentives than traditional VC firms. So at first blush, they may be expected to provide complementarities. However, angels are typically passive investors. They are often previous or current entrepreneurs that are interested in cultivating local entrepreneurs. In some sense, they may have a more philanthropic motive rather than an interest in pure financial returns. I find that adding an angel to a syndicate decreases the probability of success, albeit at a statistically insignificant level. Thus, I conclude that angels don't provide value-added complementarities to a typical syndicate.

Overall, I find that VC heterogeneity in terms of geography plays the biggest role in adding value to portfolio companies. My findings are most consistent with the notion that syndicate partners' business networks are more important than syndicate partners' complementary skills and knowledge. Of course, selection could be driving this result, i.e., geographically heterogeneous syndicates may be more likely to select stronger ventures in which to invest. To account for this, I utilize both a treatment-effects model and a Heckman selection model (Heckman (1979)) and find that my results are even stronger after controlling for selection.

My work is most similar to Du (2008). However, she focuses on heterogeneity in terms of prior performance and industry experience and arrives at a different conclusion: that syndicate heterogeneity is associated with lower performance.

My finding on geographic heterogeneity relates to Chen, Gompers, Kovner, and Lerner (2009). They find that VC firms located in the three most active cities (San Francisco, Boston, and New York) perform better on their investments outside of their home city. Although they do not examine syndicate characteristics, their results are consistent with mine in that VC firms investing in faraway companies are likely to be co-investing with VC firms from different geographic regions than their own.

2. Sources of data

I construct the sample spanning the 1975-1997 time period using Securities Data Corporation's VentureXpert (formerly Venture Economics). Kaplan, Sensoy, and Stromberg (2002) investigate the completeness of the database and find that it contains most VC investments. However, some of the older data are not considered as reliable (e.g., there are a disproportionate number of investment dates of January 1, 1960). Gompers and Lerner (2004) find data quality concerns for investments prior to 1975, so I exclude them. VC investment picked up considerably after ERISA changed its 'prudent man' rule in 1979 to explicitly allow pension funds to invest in venture capital. As such, excluding investments prior to 1975 is unlikely to make my data set unrepresentative. Finally, I exclude investments in international portfolio companies, also due to data quality concerns. I find that exits of international companies via acquisition are on the order of 5%, suggesting that not all exits are being captured.

Because VCs are almost always contractually required to return their investments to their limited partners (pensions, endowments, insurance companies, etc.) within ten years, I exclude all investments made after 1997. This ensures that all investments in my data set have had at least ten years to potentially go public or be acquired so that I capture the vast majority of the possible successful exits that a VC fund may realize.

I also restrict my analysis to the first round of funding. One reason for this is that VC investors in later rounds have more information to assess the strength of the venture. Also, VC firms often offer late-round investment opportunities to other VC firms hoping that those other VC firms will reciprocate for future ventures (Lerner (1994)). For both of these reasons, later investors are more likely to be passive investors that provide just financing and little advice or monitoring. Thus, their investment is more endogenous to the success of the venture. Including later rounds would impose an upward bias on the syndicate size coefficient.

Finally, I take great care to ensure that my data set does not contain leveraged buyouts. This is necessary because the VentureXpert database contains both VC financings and leveraged buyouts. It is not uncommon for VC firms to participate in these buyouts, so I can not just include all activity by VC firms. As such, I only include portfolio companies that are classified as seed/startup stage, early stage, expansion stage, or later stage.

In total, the data set contains 10,191 portfolio companies that received VC financing. More than half (53.9%) of these companies received first-round VC financing from a syndicate of VC firms. 24.1% received first-round VC financing from a syndicate of two firms, 12.4% from a syndicate of three, and 17.4% from a syndicate of four or more. The mean first-round syndicate size in my data set (including singletons) is 2.3.

3. Data variables

3.1. Motivating the dependent variable

There is no publicly available, comprehensive database of specific VC fund performance due to the fact that VC firms are hesitant to disclose their funds' return data. Thus, the VC literature is forced to rely on noisy proxies of fund performance, i.e., exits. Following Gompers and Lerner (1999), I denote success as the occurrence of one of the two most profitable exits, IPOs and acquisitions. Of course, these proxies don't incorporate investment costs or ownership stakes, but Cochrane (2005) and Kaplan and Schoar (2005) examine proprietary return data and conclude that most of the returns are comprised of the returns from these two exits. For most of the analyses, the dependent variable is *Portfolio Company Success*, which takes the value 1 for an IPO or acquisition and 0 otherwise. Table 1 contains descriptive statistics for the dependent variable and all of the independent variables. 52.1% of the portfolio companies in my data set either had been acquired or had gone public at the time I collected my data (August 2008).

3.2. Motivating the independent variables

Tian (2008) finds that syndicated deals perform better, in terms of exits of the portfolio companies, and uses instrumental variables to demonstrate that the relationship is causal. He also finds that each additional syndicate partner being added to a syndicate causes better performance. I confirm the association between syndicate size and success in Figure 1, which shows the success rates for each category of syndicate sizes, along with their frequencies. A company that receives initial funding from a syndicate of two VC firms has a 9.4% higher likelihood of being acquired or going public relative to a company that receives initial funding from just one VC. Additionally, success rates continue to increase roughly monotonically with syndicate size, so I include the variable *First-Round Syndicate Size* in all of my regressions. It should be noted that there is a curious dip at five first-round syndicate members, suggesting that may be a point where coordination costs or misaligned incentives are associated with poorer performance. This dip holds up across the three major industry groups detailed in Figure 1 (information technology, medical, and non-high-technology).

Figure 2 shows that syndication was more prevalent in the 1980s than in the 1990s. Despite the fact that I find syndication is associated with stronger performance, the conclusion is not evident from this graphic as success rates are similar in both the 1980s and 1990s. This could be due to the fact that the supply of VC money increased in the 1990s (Gompers and Lerner (2000)), lessening the marginal VC firm's need to syndicate (share) its investment. In unreported regressions, I find that the effect of syndication on success is actually stronger in the 1990s, suggesting that there were many investments in the 1990s that perhaps could have benefitted from additional investment partners. To control for any cohort effects and the impact of capital flowing into the VC industry, I include *Total VC Industry Annual Investment* (2007 dollars) in the regressions that follow. Because the variable is right-skewed, I use the natural logarithm. For robustness, I replace this variable with year dummies.

Because different geographic regions have different supplies of venture capitalists and thus different syndication and success rates, I include an indicator variable for all but one (region = South) of the 18 portfolio company geographic regions in the regressions that follow.

Different industries have different levels of information asymmetry, uncertainty, and risk. Tian (2008) finds that syndication and success rates are higher in the five high-technology industries (biotechnology, communications, computer, medical, and semiconductor) than in the non-high-technology industries. Thus, I include an indicator variable for all but one portfolio company industry (biotechnology) in the regressions that follow.

The main goal of this paper is to explore whether syndicate heterogeneity is driving the relationship between syndicate size and success of the portfolio company. VC firms can vary in terms of what geographic region they reside in. As one measure of geographic heterogeneity, I use an indicator variable that takes the value 1 if the first-round syndicate contains two or more VC firms from different geographic regions, and 0 otherwise. The average value for this measure is 0.277 which indicates that 27.7% of the syndicates include at least one pair of VC firms from different geographic regions. A list of the 18 different geographic regions can be found at the bottom of Table 1.

For robustness, I use an entropy measure ($-\Sigma\ p_i * \ln p_i$), a commonly used proxy for diversity when variables are categorical (Jacquemin and Berry (1979)), where i indexes the 18 geographic regions and p_i is the proportion of VCs in the syndicate from region_i. To illustrate, a syndicate of VC firms all from the same region would have an entropy measure of 0. A two-firm syndicate with VC firms from different regions would have an entropy measure of 0.69 [-(0.5*ln(0.5)+0.5*ln(0.5))]. A three-firm syndicate with VC firms from three different regions would have an entropy measure of 1.1. As shown in Table 1, the average geographic entropy measure in my data set is 0.228.

VC firms can also vary in terms of age or experience. As a measure of this type of variability, I calculate a standard deviation of syndicate members' ages for each portfolio company. So as to not lose any observations, I impute zero for all undefined standard deviations, i.e. singletons. As shown in Table 1, the mean standard deviation of ages in my data set is 3.14, suggesting that VCs tend to co-invest with VCs of similar tenure, consistent with Lerner (1994).

VC firms can also vary in terms of organizational structure. The first of four organizational structure heterogeneity measures I include is an indicator variable that takes the value 1 if the first-round syndicate contains at least one traditional (independent) VC firm and at least one that is not, and 0 otherwise. The average value of this measure in my data set is 0.170, as shown in Table 1. This means that 17.0% of the first-round syndicates contain at least one traditional VC and at least one of the three non-traditional VCs (corporate, bank, angel). I construct similar measures for these three non-traditional VCs and find that 5.1% of the first-round syndicates contain at least one corporate VC and one non-corporate VC, 9.8% contain at least one bank VC and one non-bank VC, and 5.9% contain at least one angel and one non-angel.

Sorensen (2007) finds that more experienced VC firms have higher levels of success with their investments. Given this, one of my control variables is average age of the syndicate members at the time of the investment. The average value of this variable is 9.25 years, as shown in Table 1.

It is intuitive that the amount of the first-round VC investment should impact the success of the venture. As such, I include this amount in 2007 dollars as a control variable. Due to the right-skewness of the absolute amount, I use the natural logarithm.

I also control for the stage that the portfolio company is at when it receives its first round of funding. Companies in the seed/startup phase have a product that is under development but not operational. As shown in Table 1, 38.4% of the companies in my data set fall into this category. Early-stage ventures are younger portfolio companies that have a product in testing or pilot production. They make up 29.3% of my data set's companies. 27.0% of the companies are in the expansion stage. This means that their product is in production and commercially available. Lastly, just 5.2% of the companies are later-stage. This means that their products are widely available. In general, those four phases are listed in declining order of information asymmetry. Broadly speaking, seed/startup investments would require the highest risk tolerance whereas later-stage investments would be relatively more certain.

Table 1 also displays the industry distribution and the geographic distribution of the portfolio companies. The two most common industries are computers (hardware and software) and non-high-technology. The three most common regions are Northern California (includes Silicon Valley), New England (includes Boston/Cambridge), and New York Tri-State. Together, these three regions make up nearly half of the locations for portfolio companies.

4. Econometric Specification

4.1. Baseline Models

Table 2 displays the baseline specification of a Probit regression. The dependent variable is success of the venture (portfolio company), where success is defined as going public or being acquired. The coefficients displayed are marginal effects on the probability of success of the venture. Column 1 confirms the relationship detailed in Figure 1 – that syndicate size is positively associated with level of success. Each additional syndicate partner in the first round of VC financing is associated with a 3.2 percentage-point increase in the probability of a successful outcome for the portfolio company. Column 2 adds all control variables other than the variables of interest that measure syndicate heterogeneity. The first thing to notice is that the *First-Round Syndicate Size* variable is subsumed significantly by the other controls as its value is roughly one-third its size in the univariate.

I confirm Sorensen (2007), who finds that more experienced VC firms are more successful, by finding a positive coefficient on average age of the syndicate members. Additionally, I find that the total amount of the first-round investment is associated with higher success, even after controlling for the size of the syndicate. I also find that the stage of the venture is strongly associated with success. Not surprisingly, seed/startup ventures are 5.1 percentage points less likely (controlling for other factors) to go public or be acquired than companies in the expansion stage. Later-stage companies are much more likely to go public or be acquired (a 7.8 percentage-point increase).

Column 3 adds the measure for geographic heterogeneity: *2+ VCs from different geographic regions*. Its coefficient of .034 is statistically significant at the 5% level. This means that a syndicate with at least two VCs from different geographic regions is associated with a 3.4 percentage-point increase in the probability of going public or being acquired, controlling for other factors. VC firms are known to provide portfolio companies with contacts in terms of customers, suppliers, management, or investment banks. It is intuitive that VC firms from different geographic regions would provide a broader network of entities that could add value for an portfolio company, and this specification provides strong empirical support for this notion.

Column 4 looks at age heterogeneity by including the standard deviation of the age of the syndicate members. Walske and Zacharakis (2008) find via interviews with VC firms that experienced VC firms may prefer working with younger VC firms as the younger firms are more likely to “stay out of the way”. Additionally, Bottazzi, Da Rin, and Hellmann (2008) find that older VC firms are more likely to excel at raising future funds. Since younger VCs are likely more current on technologies of their portfolio companies’ industries, it is possible that efficiencies can be reached through the complementary skills of older and younger syndicate partners. The coefficient on this measure (0.002) is close to statistically significant at the 10% level and does not carry the economic significance of the geographic heterogeneity measure. Moving from the 25^{th} to the 75^{th} percentile of age heterogeneity yields a 1.1 percentage-point increase in the probability of portfolio company success (IPO or acquisition).

Column 5 examines organizational structure heterogeneity by including the measure *1+ Independent VC and 1+ Non-Independent VC*. Its coefficient is positive, but essentially zero. Table 4 will take a deeper dive into looking at specific types of organizational structure.

Column 6 includes all three syndicate heterogeneity measures. The geographic heterogeneity measure is still statistically significant at the 10% level despite multicollinearity inflating the standard errors; all three heterogeneity measures are highly positively correlated. Column 7 is a robustness check using year dummies rather than *Ln(Total VC Industry Annual Investment)*. Results are quite similar.

4.2. Are the heterogeneity results driven by syndication?

Table 2 includes all VC investments, including singletons. A natural question is whether the results are being driven by the fact that only syndicates can have nonzero heterogeneity measures. Since all singletons have zero heterogeneity measures, I exclude them in Table 3. The results are strikingly similar. The most important result (geographic heterogeneity) drops by roughly one-tenth of a percentage point. I conclude that my results are not being driven by the way I have constructed my heterogeneity measures.

4.3 Alternate Measures of Heterogeneity

Table 4 includes an alternate measure of geographic heterogeneity: the previously mentioned entropy measure. Its coefficient of .033 is statistically significant at the 10% level, indicating that my finding on geographic heterogeneity is robust to alternate measures. This is not the case with age heterogeneity: the measure *Average Age Difference from the Youngest Syndicate Member* is not statistically significant at the 10% level.

For organization structure, I look at three non-traditional types of organizational structures: corporate VCs, bank VCs, and angel investors. Corporate VC firms have different skills and knowledge bases and may provide a complementarity to traditional VC firms. However, column 3 indicates that having at least one corporate VC and at least one non-corporate VC in a syndicate is not associated with an increase in the probability of success. This is rather surprising given the strong value-added effects Gompers and Lerner (1999) find for corporate VCs. This may be driven by the fact that they examine all rounds of financing whereas I examine only the first round.

Bank VCs have similar organizational structures and incentives relative to traditional VCs, but may be particularly useful in finding exit channels given their expertise in taking companies public or finding a buyer. However, I find no such evidence, as shown in Column 4.

Angel investors are usually more passive which may explain why the coefficient for them in column 5 is an economically significant -0.025. This suggests that having an angel in a syndicate decreases performance of the venture, although the coefficient is not statistically significant.

5. Selection

Because my data set is observational, it could be exposed to selection biases. If this were the case, the heterogeneity variables would be correlated with the regression error terms, and OLS results are biased. In this data set, the main concern is reverse causality. In other words, it may not be the case that heterogeneous syndicates cause ventures to perform better, but rather that strong ventures attract heterogeneous syndicates in the first place. Li and Prabhala (2007) review the most common fixes for selection biases used in the corporate finance literature. I use two methods to attempt to control for firm-specific differences that may increase the probability of syndication: the treatment effects model and the Heckman model.

Table 5 examines the first-stage regression, or the selection equation. This illuminates which types of firms are more likely to be syndicated in the first round. Seed investments are the most likely to be syndicated. This is intuitive given that one of the main reasons for syndication is to reduce information asymmetries. Along these same lines, the only consistently statistically significant portfolio company industry is non-high-technology, and its coefficient is negative. Since these companies' businesses are less complex, it is not surprising that they are syndicated less frequently; VC firms are less likely to seek a confirmatory opinion if the business is easy to understand. Lastly, it should be noted that industry inflows are associated with lower syndication rates. This suggests that in periods of easy money, there is less need for syndicate partners.

Table 6 examines the second-stage regressions, or the outcome equations. In general, the coefficients are similar to OLS, but stronger. For example, in the treatment effects model, the geographic heterogeneity measure's coefficient increases from .034 to .039, suggesting that geographically heterogeneous syndicates aren't necessarily more likely to be selecting better firms, but rather are adding value. The measure for age heterogeneity becomes statistically significant at the 10% level, and it should be noted that the measure for organizational structure heterogeneity (*1+ Independent VC and 1+ Non-Independent VC)* is much higher (0.011), albeit at a statistically insignificant level. Overall, it is comforting that the strongest result (geographic heterogeneity) is robust to selection effects.

6. Extensions and robustness checks

6.1 Do the results hold up across portfolio company regions?

Table 7 displays separate regressions for different portfolio company regions. Columns 1 and 2 examine coastal vs. interior portfolio companies, where coastal includes the following geographic regions: Mid-Atlantic, N. California, New England, New York Tri-State, Northwest, S. California, and Southeast. For coastal portfolio companies, the geographic heterogeneity of the VC firms plays a stronger role (the coefficient = .040). The coefficient for interior portfolio companies is less than half the size and not statistically significant. Looking at specific coastal regions yields some interesting results. For example, there is no effect for N. California (Silicon Valley) companies but rather strong effects for New England (Boston/Cambridge) and New York Tri-State. This could stem from the fact that the biggest VC ecosystem is Silicon Valley. Perhaps VCs there are in less need of outside help.

6.2. Do the results hold up across different first-round investment amounts?

Table 8 displays three separate regressions based on first-round investment amount. Although the results are not quite statistically significant, the strongest result in terms of economic significance is from the lowest quartile of first-round investment. This suggests that geographic heterogeneity is more important for the smallest portfolio companies. There are two important points here: syndications in the smallest companies are the least likely to be done for diversification purposes (Lockett and Wright (1999)). The second point is that the smallest investments are the least prone to endogeneity issues, i.e., VCs are less likely to be investing in sure things with small investments. Both points lead to the conclusion that these small-investment syndications are more likely to be for the purpose of adding value to the portfolio company, rather than for diversification or help with selection.

Table 9 is similar but looks at stage of the portfolio company. Results are strongest for both seed/startup firms and later-stage firms. The former result is consistent with the findings from Table 8, but the result concerning later-stage firms is much more prone to endogeneity issues, i.e., investments in later-stage companies are much more likely to be about selecting great companies that are close to going public or being acquired.

6.3. Do the results hold up across portfolio company industry?

The focus of this section is on whether the geographic heterogeneity inference holds up across portfolio company industries. In Table 10, I run six baseline models, one for each of the six main industries. The coefficient for geographic heterogeneity is economically significant for all industries save the computer industry. However, it is only statistically significant for the biotechnology and non-high-technology industries. This could be a power issue from slicing the sample thinner and thinner.

6.4. Are the results consistent across exit type?

Table 11 splits the dependent variable by exit type, IPO or acquisition. In the first three columns, success is defined more strictly as the portfolio company going public. In the last three columns, I exclude IPOs (due to the fact that it is usually the preferred route for high financial returns) and count success as the portfolio company being acquired. Interestingly, the geographic heterogeneity results are stronger for acquisitions whereas the age heterogeneity results are stronger for IPOs. If selection were an issue, it would more likely be an issue with the IPOs, i.e., investing in a sure thing would more likely result in an IPO than an acquisition. Thus, this is more evidence that the geographic heterogeneity results are robust to selection effects.

Finally, I examine whether the presence of a corporate venture capitalist impacts exit type. It seems reasonable that a corporate VC might influence the likelihood of an acquisition given the typical corporate VC's connections with other companies. However, I find no such evidence.

7. Conclusion

Most empirical studies of venture capital financing focus on the impact of the lead venture capitalist, thus ignoring a wealth of information about its syndicate partners. My study aims to fill this gap. Confirming Brander, Amit, and Antweiler (2002) and Tian (2008), I find that the number of syndicate partners in the first round of venture capital financing is strongly positively related to the success of the portfolio company. Part of the story is that bigger syndicates obviously provide more capital. Also, experience plays a role in that more seasoned VC firms have more success. However, I discover a novel finding as well: certain types of heterogeneity within the syndicate serve as a mechanism through which venture capital firms add value. In fact, after controlling for capital, VC experience, and heterogeneity, syndicate size is no longer a significant explanatory variable. I argue that these three mechanisms drive the positive correlation between syndication and success found in Brander, Amit, and Antweiler (2002) and Tian (2008).

I find that syndicates composed of venture capital firms from different geographic regions perform better than syndicates composed of venture capital firms from the same region, and I find evidence that syndicates that are more diverse in terms of age are more successful. However, I find that diversity of organizational structure does not matter. This is surprising given that different venture capital firm types employ people with different skills and knowledge bases. For example, corporate venture capitalists are experts in particular industries and technologies. In fact, Gompers and Lerner (1999) find a strong value-added effect from corporate venture capitalists. However, they examine all rounds of financing whereas I only look at the first round. It could be that corporate venture capitalists join the syndicate after investment prospects become clearer post-first round. I leave the exploration of this notion for future research.

Overall, my strongest result is consistent with the notion that syndicate partners add value through their access to different business networks rather than via their complementary skills. Venture capitalists are often former entrepreneurs themselves and are very familiar with their local business networks, which include customers, suppliers, investment bankers, and executives. It is intuitive that venture capitalists from different geographic regions could provide broader access to business networks, adding value for the portfolio company.

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Table 1 – Descriptive Statistics. The following table provides descriptive statistics for all dependent and independent variables. For indicator variables, the Mean column reports the frequency of observations, and the Standard Deviation is omitted. *Portfolio Company Success* is defined as the portfolio company either going public or being acquired. *First Round Syndicated?* is an indicator variable that takes the value 1 if there are two or more syndicate partners in the first round. *First-Round Syndicate Size* is the number of syndicate partners in the first round. *Average Age of 1st-Round Syndicate Members* is the average age of the syndicate partners at the time of the first-round investment. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested (2007 dollars) by the first-round partners. *Ln(Total VC Industry Annual Investment)* is the natural logarithm of the total VC industry amount (2007 dollars) invested in a given year. *Seed/Startup Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product under development. *Early stage?* is an indicator variable that takes the value 1 if the portfolio company has a product in testing or pilot production. *Expansion Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is in production and commercially available. *Later Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. *Geographic Heterogeneity - Entropy* is $-\Sigma$ pi * ln pi where i indexes the 18 geographic regions of the VC firms. *2+ VCs from Different Geo Region?* takes the value 1 if two or more first-round syndicate partners are from different geographic regions. *Std. Dev. Of Age of Syndicate Members* is the standard deviation of the ages of the syndicate partners at the time of the first-round investment. *Avg. Age Difference from Min.* measures the average age difference from the youngest first-round syndicate member. *1+ Independent VC and 1+ Non-Independent VC* is an indicator variable that takes the value 1 if there is at least one independent VC and one non-independent VC investing in the first round. *1+ Corporate VC and 1+ Non-Corporate VC* is an indicator variable that takes the value 1 if there is at least one corporate VC and one non-corporate VC investing in the first round. *1+ Bank VC and 1+ Non-Bank VC* is an indicator variable that takes the value 1 if there is at least one bank VC and one non-bank VC investing in the first round. *1+ Angel and 1+ Non-Angel* is an indicator variable that takes the value 1 if there is at least one angel and one non-angel investing in the first round.

Dependent Variables	Obs.	Mean	Std. Dev.	Min	25%	Median	75%	Max
Portfolio Company Success (IPO or Acquisition)?	10,191	0.521	-	0	0	1	1	1
First Round Syndicated?	10,191	0.539	-	0	0	1	1	1

Controls	Obs.	Mean	Std. Dev.	Min	25%	Median	75%	Max
First-Round Syndicate Size	10,191	2.257	1.806	1	1	2	3	21
Average Age of 1st-Round Syndicate Members	9,850	9.249	7.863	0	2.915	7.838	13.258	42.027
Ln(1st-Round Investment in Portfolio Company)	9,575	14.467	1.398	6.299	13.664	14.612	15.407	20.338
Ln(Total VC Industry Annual Investment)	10,191	22.661	0.846	18.955	22.447	22.589	23.202	23.794
Seed/Startup Stage?	10,191	0.384	-	0	0	0	1	1
Early Stage?	10,191	0.293	-	0	0	0	1	1
Expansion Stage?	10,191	0.270	-	0	0	0	1	1
Later Stage?	10,191	0.052	-	0	0	0	0	1

Heterogeneity Measures	Obs.	Mean	Std. Dev.	Min	25%	Median	75%	Max
2+ VCs from Different Geo Region?	10,191	0.277	-	0	0	0	1	1
Geographic Heterogeneity - Entropy	10,191	0.228	0.393	0	0	0	0.637	2.095
Std. Dev. of Age of Syndicate Members	10,191	3.136	5.034	0	0	0	5.639	30.956
Avg. Age Difference from Min.	10,191	1.556	3.463	0	0	0	0.122	24.517
1+ Independent VC and 1+ Non-Independent VC	10,191	0.170	-	0	0	0	0	1
1+ Corporate VC and 1+ Non-Corporate VC	10,191	0.051	-	0	0	0	0	1
1+ Bank VC and 1+ Non-Bank VC	10,191	0.098	-	0	0	0	0	1
1+ Angel and 1+ Non-Angel	10,191	0.059	-	0	0	0	0	1

Portfolio Company Industry	Percentage
Biotechnology	6.0%
Communications and Media	13.0%
Computer Related	31.8%
Medical/Health/Life Science	13.3%
Non-High-Technology	28.5%
Semiconductors/Other Elect	7.5%

Portfolio Company Geographic Region	Percentage
Alaska/Hawaii	0.1%
Great Lakes	5.3%
Great Plains	4.0%
Mid-Atlantic	3.9%
N. California	22.7%
New England	12.7%
New York Tri-State	9.8%
Northwest	3.7%
Ohio Valley	5.5%
Rocky Mountains	4.1%
S. California	9.7%
South	2.8%
Southeast	6.5%
Southwest	8.8%
US Territories	0.1%
Unknown	0.4%

Year of Initial VC Investment	Percentage
1975	0.4%
1976	0.3%
1977	0.5%
1978	1.1%
1979	1.5%
1980	2.2%
1981	4.3%
1982	4.2%
1983	5.9%
1984	5.3%
1985	4.2%
1986	4.9%
1987	5.6%
1988	5.0%
1989	4.4%
1990	3.4%
1991	2.5%
1992	3.8%
1993	3.4%
1994	4.1%
1995	8.7%
1996	11.2%
1997	12.7%

Table 2 - Baseline Probit Regressions, including First-Round Syndicate Heterogeneity Measures

The following table displays results from a probit regression where the dependent variable is *Portfolio Company Success?*, defined as the portfolio company going public or being acquired. The sample period is first-round US investments that occurred in 1975-1997. All coefficients are marginal effects. *First-Round Syndicate Size* is the number of syndicate partners in the first round. *Average Age of 1st-Round Syndicate Members* is the average age of the syndicate partners at the time of the first-round investment. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested (2007 dollars) by the first-round partners. *Ln(Total VC Industry Annual Investment)* is the natural logarithm of the total VC industry amount (2007 dollars) invested in a given year. *Seed/Startup Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product under development. *Early stage?* is an indicator variable that takes the value 1 if the portfolio company has a product in testing or pilot production. *Later Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. *2+ VCs from Different Geo Region?* takes the value 1 if two or more first-round syndicate partners are from different geographic regions. *Std. Dev. Of Age of Syndicate Members* is the standard deviation of the ages of the syndicate partners at the time of the first-round investment. *1+ Independent VC and 1+ Non-Independent VC* is an indicator variable that takes the value 1 if there is at least one independent VC and one non-independent VC investing in the first round.

Dept. Variable: Portfolio Company Success (IPO or Acquisition)?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
First-Round Syndicate Size	0.032***	0.009**	0.004	0.006*	0.008**	0.003	0.004
	[10.55]	[2.56]	[0.91]	[1.81]	[2.24]	[0.80]	[0.91]
Average Age of 1st-Round Syndicate Members		0.001*	0.001*	0.001	0.001*	0.001	0.001
		[1.85]	[1.80]	[1.51]	[1.85]	[1.56]	[1.14]
Ln(1st-Round Investment in Portfolio Company)		0.057***	0.055***	0.056***	0.057***	0.055***	0.055***
		[12.63]	[12.35]	[12.35]	[12.63]	[12.20]	[12.04]
Ln(Total VC Industry Annual Investment)		-0.056***	-0.055***	-0.057***	-0.056***	-0.055***	
		[8.31]	[8.14]	[8.42]	[8.29]	[8.20]	
Seed/Startup Stage?		-0.051***	-0.051***	-0.052***	-0.051***	-0.052***	-0.049***
		[3.63]	[3.66]	[3.69]	[3.63]	[3.70]	[3.48]
Early Stage?		-0.022	-0.022	-0.023	-0.022	-0.023	-0.021
		[1.49]	[1.53]	[1.55]	[1.49]	[1.56]	[1.41]
Later Stage?		0.078***	0.079***	0.078***	0.079***	0.079***	0.076***
		[3.08]	[3.12]	[3.07]	[3.08]	[3.10]	[2.97]
2+ VCs from Different Geo Region?			0.034**			0.030*	0.032**
			[2.22]			[1.84]	[1.98]
Std. Dev. of Age of Syndicate Members				0.002		0.001	0.001
				[1.57]		[0.92]	[0.74]
1+ Independent VC and 1+ Non-Independent VC					0.001	-0.005	-0.002
					[0.06]	[0.30]	[0.12]
Portfolio Company Industry Controls		x	x	x	x	x	x
Portfolio Company Region Controls		x	x	x	x	x	x
Year Controls							x
Observations	10,191	9,243	9,243	9,243	9,243	9,243	9,243

Robust z statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3 - Baseline Probit Regressions (Syndicated First-Round Investments Only)

The following table displays results from a probit regression where the dependent variable is *Portfolio Company* S*uccess?*, defined as the portfolio company going public or being acquired. The sample period is first-round US investments that occurred in 1975-1997. All coefficients are marginal effects. *First-Round Syndicate Size* is the number of syndicate partners in the first round. *Average Age of 1st-Round Syndicate Members* is the average age of the syndicate partners at the time of the first-round investment. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested (2007 dollars) by the first-round partners. *Ln(Total VC Industry Annual Investment)* is the natural logarithm of the total VC industry amount (2007 dollars) invested in a given year. *Seed/Startup Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product under development. *Early stage?* is an indicator variable that takes the value 1 if the portfolio company has a product in testing or pilot production. *Later Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. *2+ VCs from Different Geo Region?* takes the value 1 if two or more first-round syndicate partners are from different geographic regions. *Std. Dev. Of Age of Syndicate Members* is the standard deviation of the ages of the syndicate partners at the time of the first-round investment. *1+ Independent VC and 1+ Non-Independent VC* is an indicator variable that takes the value 1 if there is at least one independent VC and one non-independent VC investing in the first round.

Dept. Variable: Portfolio Company Success (IPO or Acquisition)?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
First-Round Syndicate Size	0.024***	0.006	0.003	0.005	0.006	0.003	0.004
	[6.28]	[1.44]	[0.57]	[1.25]	[1.31]	[0.57]	[0.81]
Average Age of 1st-Round Syndicate Members		0.001	0.001	0.001	0.001	0.001	0.001
		[1.37]	[1.31]	[0.85]	[1.37]	[0.92]	[0.53]
Ln(1st-Round Investment in Portfolio Company)		0.064***	0.062***	0.063***	0.064***	0.062***	0.060***
		[9.45]	[9.20]	[9.24]	[9.45]	[9.09]	[8.68]
Ln(Total VC Industry Annual Investment)		-0.053***	-0.051***	-0.054***	-0.053***	-0.052***	
		[5.84]	[5.60]	[5.96]	[5.80]	[5.68]	
Seed/Startup Stage?		-0.048***	-0.048***	-0.049***	-0.048***	-0.049***	-0.046**
		[2.59]	[2.59]	[2.63]	[2.59]	[2.62]	[2.44]
Early Stage?		-0.042**	-0.042**	-0.043**	-0.042**	-0.043**	-0.040**
		[2.13]	[2.15]	[2.16]	[2.13]	[2.17]	[2.04]
Later Stage?		0.092***	0.094***	0.093***	0.092***	0.094***	0.093***
		[2.81]	[2.88]	[2.83]	[2.81]	[2.88]	[2.84]
2+ VCs from Different Geo Region?			0.033**			0.029*	0.032*
			[2.10]			[1.80]	[1.95]
Std. Dev. of Age of Syndicate Members				0.002		0.001	0.001
				[1.48]		[0.99]	[0.72]
1+ Independent VC and 1+ Non-Independent VC					0.002	-0.003	0.000
					[0.12]	[0.16]	[0.02]
Portfolio Company Industry Controls		x	x	x	x	x	x
Portfolio Company Region Controls		x	x	x	x	x	x
Year Controls							x
Observations	5,495	5,376	5,376	5,376	5,376	5,376	5,376

Robust z statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4 - Baseline Probit Regressions - Alternate First-Round Syndicate Heterogeneity Measures. The following table displays results from a probit regression where the dependent variable is *Portfolio Company Success?*, defined as the portfolio company going public or being acquired. The sample period is first-round US investments that occurred in 1975-1997. All coefficients are marginal effects. *First-Round Syndicate Size* is the number of syndicate partners in the first round. *Average Age of 1st-Round Syndicate Members* is the average age of the syndicate partners at the time of the first-round investment. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested (2007 dollars) by the first-round partners. *Ln(Total VC Industry Annual Investment)* is the natural logarithm of the total VC industry amount (2007 dollars) invested in a given year. *Seed/Startup Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product under development. *Early stage?* is an indicator variable that takes the value 1 if the portfolio company has a product in testing or pilot production. *Later Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. *Geographic Heterogeneity - Entropy* is -Σ pi * ln pi where i indexes the 18 geographic regions of the VC firms. *Avg. Age Difference from Min.* measures the average age difference from the youngest first-round syndicate member. *1+ Corporate VC and 1+ Non-Corporate VC* is an indicator variable that takes the value 1 if there is at least one corporate VC and one non-corporate VC investing in the first round. *1+ Bank VC and 1+ Non-Bank VC* is an indicator variable that takes the value 1 if there is at least one bank VC and one non-bank VC investing in the first round. *1+ Angel and 1+ Non-Angel* is an indicator variable that takes the value 1 if there is at least one angel and one non-angel investing in the first round.

Dept. Variable: Portfolio Company Success (IPO or Acquisition)?

	(1)	(2)	(3)	(4)	(5)
First-Round Syndicate Size	0.004	0.006	0.008**	0.008**	0.010***
	[0.86]	[1.54]	[2.41]	[2.24]	[2.76]
Average Age of 1st-Round Syndicate Members	0.001*	0.001*	0.001*	0.001*	0.001*
	[1.84]	[1.71]	[1.86]	[1.85]	[1.80]
Ln(1st-Round Investment in Portfolio Company)	0.056***	0.056***	0.057***	0.056***	0.056***
	[12.43]	[12.56]	[12.63]	[12.61]	[12.57]
Ln(Total VC Industry Annual Investment)	-0.055***	-0.056***	-0.056***	-0.055***	-0.055***
	[8.16]	[8.34]	[8.30]	[8.24]	[8.28]
Seed/Startup Stage?	-0.051***	-0.051***	-0.051***	-0.051***	-0.051***
	[3.62]	[3.64]	[3.63]	[3.62]	[3.62]
Early Stage?	-0.022	-0.022	-0.022	-0.022	-0.022
	[1.52]	[1.50]	[1.50]	[1.50]	[1.49]
Later Stage?	0.080***	0.078***	0.079***	0.079***	0.078***
	[3.14]	[3.08]	[3.09]	[3.08]	[3.07]
Geographic Heterogeneity of Syndicate - Entropy	0.033*				
	[1.79]				
Avg. Age Difference from Youngest Syndicate Member		0.002			
		[0.86]			
1+ Corporate VC and 1+ Non-Corporate VC			0.005		
			[0.19]		
1+ Bank VC and 1+ Non-Bank VC				0.007	
				[0.38]	
1+ Angel and 1+ Non-Angel					-0.025
					[1.09]
Portfolio Company Industry Controls	x	x	x	x	x
Portfolio Company Region Controls	x	x	x	x	x
Observations	9,243	9,243	9,243	9,243	9,243

Robust z statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5 - Selection Equation - Treatment Effects and Heckman Models

The following table displays results of the selection equation from both a treatment effects model and a Heckman model where the dependent variable is *Syndicated in First Round?*, defined as the first round of VC investment involving two or more investors. The sample period is first-round US investments that occurred in 1975-1997. *Average Age of 1st-Round Syndicate Members* is the average age of the syndicate partners at the time of the first-round investment. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested (2007 dollars) by the first-round partners. *Ln(Total VC Industry Annual Investment* is the natural logarithm of the total VC industry amount (2007 dollars) invested in a given year. *Seed/Startup Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product under development. *Early stage?* is an indicator variable that takes the value 1 if the portfolio company has a product in testing or pilot production. *Later Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. The industry controls are indicator variables that take the value 1 if the portfolio company is in the specified industry.

Dept. Variable: First Round Syndicated?	
Average Age of 1st-Round Syndicate Members	-0.001
	[0.40]
Ln(1st-Round Investment in Portfolio Company)	0.410***
	[35.70]
Ln(Total VC Industry Annual Investment)	-0.129***
	[7.42]
Seed/Startup Stage?	0.499***
	[13.57]
Early Stage?	0.244***
	[6.47]
Later Stage?	0.220***
	[3.32]
<u>Portfolio Company Industry Controls</u>	
Biotechnology?	0.105***
	[3.66]
Communications and Media?	0.001
	[0.04]
Computers?	-0.011
	[0.50]
Medical/Health/Life Science?	-0.011
	[0.46]
Non-High-Technology?	-0.173***
	[7.39]
Constant	-3.123***
	[7.49]
Portfolio Company Region Controls	x
Observations	9,248

Absolute value of z statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6 - Outcome Equations - Treatment Effects and Heckman Models The following table displays results from a probit regression where the dependent variable is *Portfolio Company Success*, defined as the portfolio company going public or being acquired. The sample period is first-round US investments that occurred in 1975-1997. All coefficients are marginal effects. *First Round Syndicated?* is an indicator variable that takes the value 1 if there are two or more syndicate partners in the first round. *First-Round Syndicate Size* is the number of syndicate partners in the first round. *Average Age of 1st-Round Syndicate Members* is the average age of the syndicate partners at the time of the first-round investment. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested (2007 dollars) by the first-round partners. *Ln(Total VC Industry Annual Investment)* is the natural logarithm of the total VC industry amount (2007 dollars) invested in a given year. *Seed/Startup Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product under development. *Early stage?* is an indicator variable that takes the value 1 if the portfolio company has a product in testing or pilot production. *Later Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. *Std. Dev. Of Age of 1st-Round Syndicate Members* is the standard deviation of the ages of the syndicate partners at the time of the first-round investment. *1+ Independent VC and 1+ Non-Independent VC* is an indicator variable that takes the value 1 if there is at least one independent VC and one non-independent VC investing in the first round.

Selection Model	Treatment Effects	Treatment Effects	Treatment Effects	Heckman	Heckman	Heckman
Dept. Variable: Portfolio Company Success (IPO or Acquisition)?						
	(1)	(2)	(3)	(4)	(5)	(6)
First Round Syndicated? - instrumented	0.249*	0.244*	0.256*			
	[1.85]	[1.81]	[1.89]			
Average Age of 1st-Round Syndicate Members	0.001*	0.001	0.001*	0.001	0.001	0.001
	[1.82]	[1.45]	[1.88]	[1.26]	[0.71]	[1.33]
Ln(1st-Round Investment in Portfolio Company)	0.019	0.022	0.022	0.065**	0.072**	0.071**
	[1.00]	[1.15]	[1.15]	[2.04]	[2.25]	[2.22]
Ln(Total VC Industry Annual Investment)	-0.041***	-0.044***	-0.043***	-0.050***	-0.056***	-0.053***
	[4.84]	[5.26]	[5.07]	[3.97]	[4.46]	[4.23]
Seed/Startup Stage?	-0.088***	-0.086***	-0.086***	-0.04	-0.035	-0.036
	[3.41]	[3.33]	[3.33]	[0.99]	[0.86]	[0.89]
Early Stage?	-0.041**	-0.041**	-0.040**	-0.037	-0.035	-0.036
	[2.31]	[2.28]	[2.27]	[1.43]	[1.34]	[1.35]
Later Stage?	0.056**	0.055**	0.055**	0.091***	0.091***	0.090***
	[2.12]	[2.10]	[2.09]	[2.62]	[2.63]	[2.60]
2+ VCs from Different Geo Region?	0.039***			0.035**		
	[2.90]			[2.52]		
Std. Dev. of Age of Syndicate Members		0.002*			0.002*	
		[1.83]			[1.69]	
1+ Independent VC and 1+ Non-Independent VC			0.011			0.009
			[0.80]			[0.61]
Constant	1.115***	1.160***	1.121***	0.797*	0.829**	0.792*
	[6.49]	[6.72]	[6.52]	[1.92]	[1.99]	[1.91]
Inverse Mills Ratio	-0.149*	-0.142*	-0.144*	0.020	0.039	0.031
	[1.82]	[1.74]	[1.76]	[0.14]	[0.28]	[0.22]
Portfolio Company Industry Controls	x	x	x	x	x	x
Portfolio Company Region Controls	x	x	x	x	x	x
Observations	9,248	9,248	9,248	9,248	9,248	9,248

Absolute value of z statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7 - Probit Regressions, Portfolio Company Geographic Region Breakouts

The following table displays results from a probit regression where the dependent variable is *Portfolio Company Success*, defined as the portfolio company going public or being acquired. Separate regressions are displayed for each of five portfolio company geographic regions. The sample period is first-round US investments that occurred in 1975-1997. All coefficients are marginal effects. *First-Round Syndicate Size* is the number of syndicate partners in the first round. *Average Age of 1st-Round Syndicate Members* is the average age of the syndicate partners at the time of the first-round investment. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested (2007 dollars) by the first-round partners. *Ln(Total VC Industry Annual Investment)* is the natural logarithm of the total VC industry amount (2007 dollars) invested in a given year. *Seed/Startup Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product under development. *Early stage?* is an indicator variable that takes the value 1 if the portfolio company has a product in testing or pilot production. *Later Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. *2+ VCs from Different Geo Region?* takes the value 1 if two or more first-round syndicate partners are from different geographic regions.

	(1)	(2)	(3)	(4)	(5)
Portfolio Company Geo. Region	Coastal	Interior	N.Cali.	NE	NY Tri-St.
Dept. Variable: Portfolio Company Success (IPO or Acquisition)?					
First-Round Syndicate Size	0.005	0.002	0.005	-0.003	-0.001
	[0.95]	[0.22]	[0.76]	[0.22]	[0.08]
Average Age of 1st-Round Syndicate Members	0.001	0.002	0.001	-0.001	0.004**
	[1.08]	[1.55]	[0.80]	[0.46]	[2.00]
Ln(1st-Round Investment in Portfolio Company)	0.048***	0.070***	0.036***	0.057***	0.056***
	[8.89]	[8.65]	[3.63]	[4.23]	[4.14]
Ln(Total VC Industry Annual Investment)	-0.045***	-0.072***	-0.019	-0.038**	-0.044**
	[5.65]	[5.95]	[1.40]	[2.18]	[2.09]
Seed/Startup Stage?	-0.050***	-0.054**	-0.013	-0.071*	-0.069
	[2.95]	[2.20]	[0.41]	[1.79]	[1.57]
Early Stage?	-0.025	-0.018	0.036	-0.059	-0.054
	[1.39]	[0.73]	[1.07]	[1.40]	[1.18]
Later Stage?	0.079**	0.082*	0.103	-0.069	0.128*
	[2.48]	[1.95]	[1.31]	[0.93]	[1.91]
2+ VCs from Different Geo Region?	0.040**	0.019	-0.003	0.078*	0.080
	[2.21]	[0.67]	[0.11]	[1.83]	[1.55]
Portfolio Company Industry Controls	x	x	x	x	x
Portfolio Company Region Controls	x	x			
Observations	6,400	2,843	2,091	1,186	889

Robust z statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8 - Probit Regressions, Breakouts by First-Round Investment Amount

The following table displays results from a probit regression where the dependent variable is *Portfolio Company Success*, defined as the portfolio company going public or being acquired. Separate regressions are displayed for each of three first-round investment amount categories. The sample period is first-round US investments that occurred in 1975-1997. All coefficients are marginal effects. *First-Round Syndicate Size* is the number of syndicate partners in the first round. *Average Age of 1st-Round Syndicate Members* is the average age of the syndicate partners at the time of the first-round investment. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested (2007 dollars) by the first-round partners. *Ln(Total VC Industry Annual Investment)* is the natural logarithm of the total VC industry amount (2007 dollars) invested in a given year. *Seed/Startup Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product under development. *Early stage?* is an indicator variable that takes the value 1 if the portfolio company has a product in testing or pilot production. *Later Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. *2+ VCs from Different Geo Region?* takes the value 1 if two or more first-round syndicate partners are from different geographic regions.

	(1)	(2)	(3)
First-Round Investment Amount	Lower Quartile	Middle 50%	Upper Quartile
Dept. Variable: Portfolio Company Success (IPO or Acquisition)?			
First-Round Syndicate Size	0.001	-0.001	0.005
	[0.04]	[0.15]	[0.85]
Average Age of 1st-Round Syndicate Members	0.000	0.001	0.001
	[0.21]	[1.36]	[1.08]
Ln(1st-Round Investment in Portfolio Company)	0.035***	0.047***	0.051***
	[3.04]	[2.97]	[2.82]
Ln(Total VC Industry Annual Investment)	-0.041***	-0.063***	-0.056***
	[3.25]	[6.68]	[3.80]
Seed/Startup Stage?	-0.058**	-0.056***	-0.026
	[2.00]	[2.83]	[0.95]
Early Stage?	-0.007	-0.029	-0.018
	[0.22]	[1.41]	[0.68]
Later Stage?	0.095	0.070*	0.070*
	[1.64]	[1.75]	[1.86]
2+ VCs from Different Geo Region?	0.066	0.040*	0.015
	[1.50]	[1.93]	[0.60]
Portfolio Company Industry Controls	x	x	x
Portfolio Company Region Controls	x	x	x
Observations	2,250	4,614	2,354

Robust z statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9 - Probit Regressions, Breakouts by Portfolio Company Stage of Development

The following table displays results from a probit regression where the dependent variable is *Portfolio Company Success,* defined as the portfolio company going public or being acquired. Separate regressions are displayed for each of the four portfolio company stages of development. *Seed/Startup Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product under development. *Early stage?* is an indicator variable that takes the value 1 if the portfolio company has a product in testing or pilot production. *Expansion Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is in production and commercially available. *Later Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. The sample period is first-round US investments that occurred in 1975-1997. All coefficients are marginal effects. *First-Round Syndicate Size* is the number of syndicate partners in the first round. *Average Age of 1st-Round Syndicate Members* is the average age of the syndicate partners at the time of the first-round investment. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested (2007 dollars) by the first-round partners. *Ln(Total VC Industry Annual Investment)* is the natural logarithm of the total VC industry amount (2007 dollars) invested in a given year. *2+ VCs from Different Geo Region?* takes the value 1 if two or more first-round syndicate partners are from different geographic regions.

	(1)	(2)	(3)	(4)
First-Round Investment Amount	Seed/Startup	Early	Expansion	Later
Dept. Variable: Portfolio Company Success (IPO or Acquisition)?				
First-Round Syndicate Size	0.005	0.004	0.000	0.001
	[0.78]	[0.54]	[0.00]	[0.08]
Average Age of 1st-Round Syndicate Members	0.001	0.002	0.001	0.000
	[0.75]	[1.26]	[0.98]	[0.07]
Ln(1st-Round Investment in Portfolio Company)	0.058***	0.049***	0.061***	0.062***
	[7.76]	[5.70]	[7.21]	[3.47]
Ln(Total VC Industry Annual Investment)	-0.050***	-0.031**	-0.074***	-0.107***
	[4.49]	[2.37]	[6.05]	[3.55]
2+ VCs from Different Geo Region?	0.044*	-0.002	0.038	0.138**
	[1.87]	[0.08]	[1.21]	[2.21]
Portfolio Company Industry Controls	x	x	x	x
Portfolio Company Region Controls	x	x	x	x
Observations	3,624	2,642	2,471	486

Robust z statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10 - Probit Regressions, Portfolio Company Industry Breakouts

The following table displays results from a probit regression where the dependent variable is *Success*, defined as the portfolio company going public or being acquired. Separate regressions are displayed for each of the six portfolio company industries. The sample period is first-round US investments that occurred in 1975-1997. All coefficients are marginal effects. *First-Round Syndicate Size* is the number of syndicate partners in the first round. *Average Age of 1st-Round Syndicate Members* is the average age of the syndicate partners at the time of the first-round investment. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested (2007 dollars) by the first-round partners. *Seed/Startup Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product under development. *Early stage?* is an indicator variable that takes the value 1 if the portfolio company has a product in testing or pilot production. *Later Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. 2+ VCs from Different Geo Region? takes the value 1 if two or more first-round syndicate partners are from different geographic regions.

	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio Company Industry	Biotech	Coms/Media	Computer	Medical	Non-Hi-Tech	Semiconds.
Dept. Variable: Portfolio Company Success (IPO or Acquisition)?						
First-Round Syndicate Size	-0.009	0.007	0.002	0.003	0.006	0.006
	[0.53]	[0.58]	[0.29]	[0.24]	[0.83]	[0.52]
Avg Age of 1st-Round Syndicate Members	-0.001	0.002	0.003***	-0.006***	0.001	0.005*
	[0.49]	[1.04]	[2.65]	[2.89]	[0.91]	[1.88]
Ln(1st-Round Investment in Portfolio Company)	0.051***	0.046***	0.058***	0.056***	0.056***	0.045***
	[3.13]	[3.93]	[6.60]	[4.82]	[7.11]	[2.64]
Ln(Total VC Industry Annual Investment)	-0.074**	-0.031	-0.036***	-0.112***	-0.056***	-0.043**
	[2.28]	[1.64]	[2.96]	[4.79]	[5.19]	[1.97]
Seed/Startup Stage?	-0.051	-0.011	-0.064***	-0.011	-0.077***	-0.012
	[0.69]	[0.28]	[2.59]	[0.27]	[3.20]	[0.23]
Early Stage?	-0.012	-0.038	-0.006	0.059	-0.056**	-0.102*
	[0.15]	[0.96]	[0.25]	[1.41]	[2.22]	[1.86]
Later Stage?	-0.329*	0.061	0.061	0.221***	0.089**	0.005
	[1.66]	[0.78]	[1.22]	[2.97]	[2.38]	[0.05]
2+ VCs from Different Geo Region?	0.113*	0.045	-0.009	0.037	0.053*	0.045
	[1.78]	[1.09]	[0.33]	[0.90]	[1.80]	[0.88]
Portfolio Company Region Controls	x	x	x	x	x	x
Observations	540	1,194	2,943	1,240	2,633	680

Robust z statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 11 - Probit Regressions, Breakouts by Exit Type

The following table displays results from probit regressions where the dependent variable is either *IPO* or *M&A.* For the regressions with *M&A* as the dependent variable, IPOs are excluded since they typically deliver higher returns to the investor. The sample period is first-round US investments that occurred in 1975-1997. All coefficients are marginal effects. *First-Round Syndicate Size* is the number of syndicate partners in the first round. *Average Age of 1st-Round Syndicate Members* is the average age of the syndicate partners at the time of the first-round investment. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested (2007 dollars) by the first-round partners. *Ln(Total VC Industry Annual Investment)* is the natural logarithm of the total VC industry amount (2007 dollars) invested in a given year. *Seed/Startup Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product under development. *Early stage?* is an indicator variable that takes the value 1 if the portfolio company has a product in testing or pilot production. *Later Stage?* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. *2+ VCs from Different Geo Region?* takes the value 1 if two or more first-round syndicate partners are from different geographic regions. *Std. Dev. Of Age of Syndicate Members* is the standard deviation of the ages of the syndicate partners at the time of the first-round investment. *1+ Corporate VC and 1+ Non-Corporate VC* is an indicator variable that takes the value 1 if there is at least one corporate VC and one non-corporate VC investing in the first round.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	IPO	IPO	IPO	M&A	M&A	M&A
First-Round Syndicate Size	0.007***	0.004*	0.006**	-0.001	0.004	0.005
	[2.72]	[1.80]	[2.57]	[0.30]	[1.10]	[1.38]
Avg Age of 1st-Round Syndicate Members	-0.001	-0.001	-0.001	0.002**	0.002**	0.002***
	[0.97]	[1.33]	[1.01]	[2.54]	[2.38]	[2.62]
Ln(1st-Round Investment in Portfolio Co.)	0.028***	0.027***	0.028***	0.049***	0.050***	0.050***
	[7.89]	[7.57]	[7.86]	[9.87]	[10.02]	[10.22]
Ln(Total VC Industry Annual Investment)	-0.033***	-0.033***	-0.032***	-0.042***	-0.044***	-0.043***
	[6.93]	[7.00]	[6.87]	[5.85]	[6.08]	[6.00]
Seed/Startup Stage?	-0.025**	-0.026**	-0.025**	-0.045***	-0.045***	-0.044***
	[2.39]	[2.50]	[2.41]	[2.97]	[2.97]	[2.93]
Early Stage?	0.01	0.009	0.01	-0.035**	-0.035**	-0.035**
	[0.94]	[0.86]	[0.92]	[2.26]	[2.24]	[2.21]
Later Stage?	0.101***	0.101***	0.101***	0.03	0.028	0.028
	[5.04]	[5.04]	[5.05]	[1.02]	[0.95]	[0.97]
2+ VCs from Different Geo Region?	-0.01			0.047***		
	[0.96]			[2.86]		
Std. Dev. of Age of Syndicate Members		0.002*			0.001	
		[1.76]			[0.93]	
1+ Corporate VC and 1+ Non-Corporate VC			-0.005			0.011
			[0.28]			[0.39]
Portfolio Company Industry Controls	x	x	x	x	x	x
Portfolio Company Region Controls	x	x	x	x	x	x
Observations	9,208	9,208	9,208	7,588	7,588	7,588

Robust z statistics in brackets

Figure 1. Portfolio Company Success Rate (IPO or Acquisition) by First-Round Syndicate Size, 1975-1997

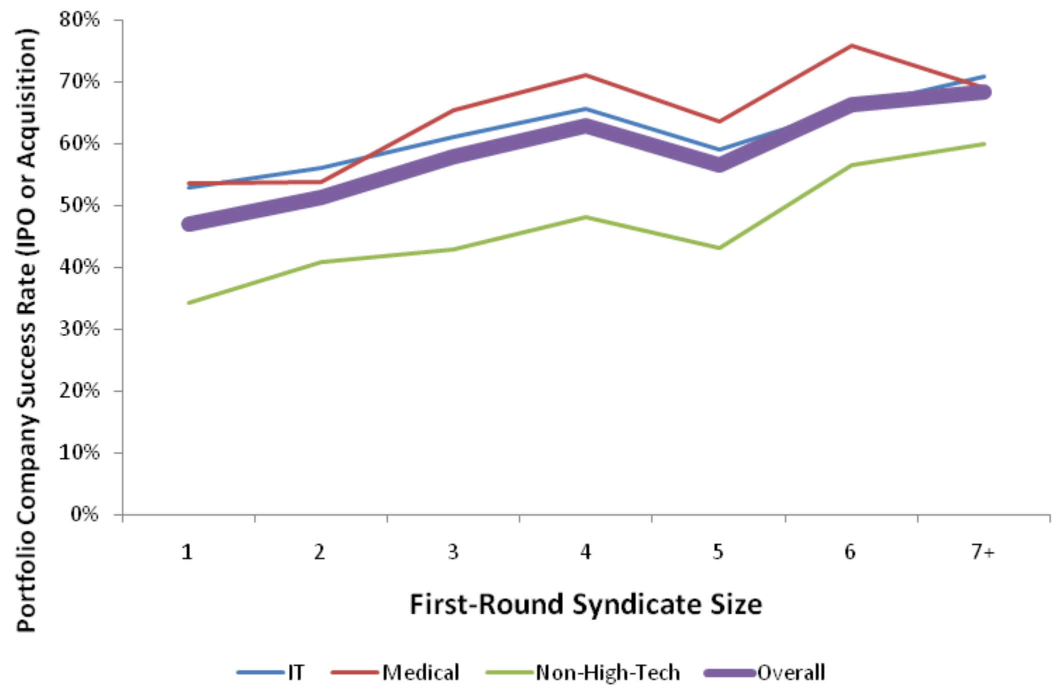
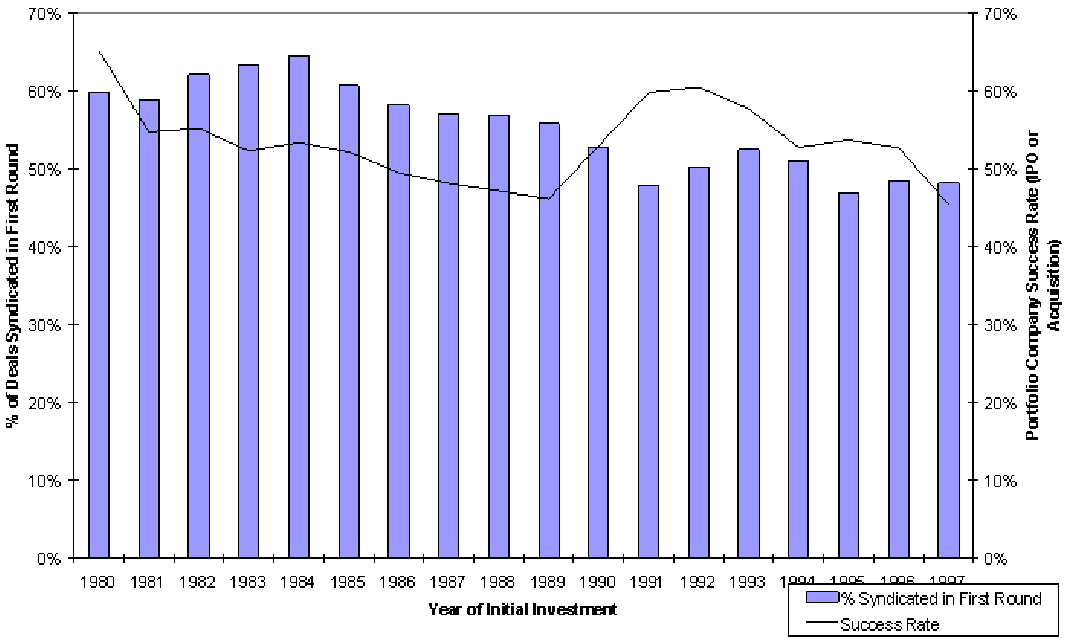


Figure 2. Portfolio Company Success Rates (IPO or Acquisition) and % of Deals Syndicated in First Round, 1980-1997



Chapter 2

The (d)Evolution of Venture Capital Syndication: Determinants and Outcomes

Abstract

The syndication of venture capital investments is a common but understudied phenomenon: more than 60% of all first-round investments from 1975-2007 involve two or more venture capitalists, though that fraction has fluctuated. The real value of the first-round investment is the strongest predictor of syndication, suggesting that portfolio diversification plays a role. In addition, younger entrepreneurial companies in more technologically complex industries are more likely to receive syndicated financing, offering support for the view that syndication pools information and reduces information asymmetries. After controlling for first-round investment values and industry effects, syndication is still more prominent in Boston, California, and the Pacific Northwest, suggesting either that heavy concentrations of venture capitalists increase the net benefits of syndication or that more challenging startups emerge in those areas. Intriguingly, after controlling for these factors, residual syndication rates are still cyclical, declining during the 1990s and increasing over the last decade. The period of low syndication was actually a time of more effective syndication, coinciding with strong financial markets and cohorts that had high realized rates of return. Arguably, recent high residual rates of syndication are a symptom of low expected returns, themselves a function of poor exit options and overinvestment in venture capital.

1. Introduction

Venture capital firms are financial intermediaries that invest in and nurture entrepreneurial companies with a high-risk, high-reward profile. Problems arise from the information asymmetries, lack of collateral, and agency costs inherent in these investments. To handle these problems, firms utilize a host of different mechanisms and strategies. For example, firms in the United States almost exclusively invest with convertible preferred shares; this protects their downside risk in the event of a failed venture but still allows the VC firm to share in the upside should the venture succeed, i.e. go public or be acquired. To deal with information problems, VCs stage, or mete out, their financing. This allows the VC firm to keep the entrepreneur on a short leash; should the entrepreneur not perform to the VC's satisfaction, it will cut off funding. Finally, the contracts venture capitalists write with entrepreneurs include a bevy of provisions designed to help with agency problems (see Appendix I for details).

Another strategy venture capital firms utilize is syndication: two or more firms taking an equity stake in a company for a joint payoff (Wilson, 1968). This occurs when one venture capitalist (the lead VC) invites another venture capitalist to co-invest.[1] More than 60% of first-round investments between 1975 and 2007 are syndicated, yet the process remains understudied in the finance literature. I seek to

[1] The lead venture capitalist typically invests more capital, is more likely to sit on the board of directors, and is usually more active in monitoring the entrepreneurial company (Gorman and Sahlman, 1989; Wright and Lockett, 2003).

establish facts and trends surrounding syndication, to examine the drivers of and motivations behind it, and to assess its effect on investment performance.

I find that the single strongest predictor of syndication is the dollar amount of the investment, consistent with the view that venture capital firms syndicate to diversify their portfolios. In a survey of VC firms, Lockett and Wright (1999) find this to be the most common reason cited for syndicating their investments. Syndication allows a capital-constrained VC fund to invest in more projects; indeed, Cumming (2006) finds that Canadian VC funds that actively syndicate manage portfolios with more companies. There are two ways this helps diversify risk. First, it allows the VC fund to avoid overweighting any one company in its portfolio. Second, it increases the odds of finding investments that covary less with current holdings, thus reducing overall portfolio risk (Markowitz, 1952). My finding that larger deals are syndicated more often is consistent with this diversification motive: should a portfolio company need a large amount of capital, a venture capitalist may choose to seek capital from other firms rather than overweight its own portfolio. I find that the strong positive relation between syndication and deal size is extremely consistent throughout my sample period.

Other forces also play a role, however. Entrepreneurial companies in high-technology industries (like biotechnology, medical devices, and software) actually tend to attract less venture capital in their first round of funding than non-high-technology companies (like retail and consumer goods). Despite this fact, I find that high-technology companies are syndicated at a much higher rate. This suggests syndication is not merely an attempt to diversify. High-technology industries are more difficult to understand; i.e. information asymmetries are higher. Sah and Stiglitz (1986) argue that groups are superior to individuals in their capacity to gather absorb, and process information. Bygrave (1987) finds that larger VC firms syndicate no more often than smaller firms; thus, he infers that sharing of information is a more important syndication motive than spreading financial risk. Lerner (1994) argues that gaining second opinions is a primary motive in syndicating investments. These notions are consistent with my finding that high-technology companies are syndicated more (despite their lower deal sizes), a relation that remains steady throughout my sample period.

Consistent with the information asymmetry motive, I find that seed stage investments are syndicated more often than expansion stage investments. Many companies receiving seed financing have no revenues, let alone positive net cash flows. By definition, these investments involve higher uncertainty and more information asymmetries; thus, venture capitalists derive more net benefits from the information sharing inherent in syndication. Interestingly, I find the association between stage and syndication lessens toward the end of my sample period. This appears to be driven by the fact that syndication rates don't rise for seed stage investments whereas they do for all other investments. A frequent complaint among entrepreneurs and policymakers is that venture capitalists don't provide as much seed stage financing as they used to. Indeed, I find that average deal sizes are relatively flat for seed stage investments and rising for the other stages. This appears to explain the flat syndication rates among seed stage investments and the rising rates among the other stages.

The economic geography of new ventures and venture capital also illuminate syndication. Sorenson and Stuart (2001) find that information about potential venture investment opportunities circulates within geographic spaces. This would suggest that syndication is more common in areas with high concentrations of venture capitalists – the likelihood of finding a knowledgeable partner and sharing information is higher. Indeed, I find that companies located in Boston, California, and the Pacific Northwest are more likely to receive a syndicated first round than companies from other parts of the country (oddly, New York City is average despite being the 3rd-largest venue for venture capital investment). This is true after controlling for deal size, industry, and stage, suggesting that the concentration of venture capitalists in these areas plays an independent role in the probability of an entrepreneurial company receiving syndicated financing. Of course, it could also indicate these areas generate or attract more complex businesses, even controlling for industry.

To recap, I find that four company-specific factors play a role in the probability of syndication: investment amount, industry, stage, and geographic region. But after controlling for these factors, I find that syndication is still cyclical; specifically, unexplained syndication declines from the mid-1980s up until the technology bubble of the late 1990s. Then it turns upward and stays at an elevated rate through 2007. Interestingly, this excess syndication is strongly negatively correlated with VC industry internal rates of return. For example, syndication rates bottomed out during the 1990s, a period considered the heyday for venture capital returns. In contrast, returns for more recent vintages are dismal while syndication rates have increased. Additionally, anecdotal evidence suggests that syndicates are breaking up at a record pace (see Venture Pools Begin to Show Some Fissures, Wall Street Journal, February 26, 2010).

Most of the extant literature focuses on the benefits of syndication (see Appendix II for details regarding a handful of exceptions). Given that, why might we see such a lack of performance during a time of high syndication rates? Brander, Amit, and Antweiler (2002) provide a model that potentially offers an explanation. In their paper, they attempt to dissect which of two motives for syndication is stronger: the selection hypothesis or the value-added hypothesis. The selection hypothesis, articulated in Lerner (1994), states that VCs syndicate in order to gain a second opinion from a trusted, competent source. The value-added hypothesis suggests that VCs syndicate in order to tap another VC's business network or industry knowledge and thus, increase the performance of its portfolio company (see Appendix III for details). Brander et al. (2002) construct two separate models, one for each hypothesis. In their model supporting the selection hypothesis, venture capitalists only syndicate when they themselves have mixed signals about an investment's prospects, i.e. encounter a lower expected-return project. The willingness of another VC to co-invest provides an additional and sufficient positive signal. In their model supporting the value-added hypothesis, venture capitalists syndicate in order to increase the expected return of the investment. Because they find that syndicated investments perform better, they conclude that the value-added hypothesis is stronger. However, I argue that the applicability of the two hypotheses depends on circumstances. For instance, during a time where more capital enters the industry than the inelastic managerial talent of the VC community can handle, there simply isn't as much capacity for venture capitalists to add value (Cumming and MacIntosh, 2004). In this case, syndicated investments would perform worse, and indeed I find this is the case post-bubble, a time of excess syndication. Some of this excess syndication appears to be in response to worsening liquidity options; specifically, a poor IPO market. Because it occurred during a flood of new capital, I argue that this excess syndication was a symptom of mixed signals amidst an increasing pool of lower-quality ventures.

2. Sources of data

I construct the sample spanning the 1975-2007 time period using Securities Data Corporation's VentureXpert (formerly Venture Economics). Kaplan, Sensoy, and Stromberg (2002) investigate the completeness of the database and find that it contains most VC investments. However, some of the older data are not considered as reliable (e.g., there are a disproportionate number of investment dates of January 1, 1960). Gompers and Lerner (2004) find data quality concerns for investments prior to 1975, so I exclude them. VC investment picked up considerably after ERISA changed its 'prudent man' rule in 1979 to explicitly allow pension funds to invest in venture capital. As such, excluding investments prior to 1975 is unlikely to make my data set unrepresentative. Finally, I exclude investments in international portfolio companies, also due to data quality concerns. I find that exits of international companies via acquisition are on the order of 5%, suggesting that not all exits are being captured.

I also restrict my analysis to the first round of funding. One reason for this is that VC investors in later rounds have more information to assess the strength of the venture. Also, VC firms often offer late-round investment opportunities to other VC firms hoping that those other VC firms will reciprocate for future ventures (Lerner (1994)). For both of these reasons, later investors are more likely to be passive investors that provide just financing and little advice or monitoring. Thus, their investment is more endogenous to the success of the venture.

I take great care to ensure that my data set does not contain leveraged buyouts. This is necessary because the VentureXpert database contains both VC financings and leveraged buyouts. It is not uncommon for VC firms to participate in these buyouts, so I cannot just include all activity by VC firms. As such, I only include portfolio companies that are classified as seed/startup stage, early stage, expansion stage, or later stage.

Finally, I eliminate any portfolio company whose first round of financing is of an unknown amount. In total, the data set contains 23,254 unique portfolio companies that received at least one round of VC financing from 1975 through 2007.

3. Primitive Empirics

3.1. Syndication Trends

Figure 1 displays two syndication measures over time: first-round syndicate size and percentage of first rounds syndicated, the latter measure being less prone to outliers. The first thing to note is that beginning around the mid-1980s, first-round syndication rates began a slow downward trend whose end corresponded roughly with the beginning of the Internet bubble. Specifically, in 1984, more than two-thirds of all first-round investments involved two or more venture capitalists. By 1998, this figure was just over one-half. Likewise, in the mid-1980s, average first-round syndicate size was roughly three. By the late 1990s, the average first-round syndicate numbered fewer than two members.

The syndication environment changed markedly during and after the Internet bubble. First-round syndication rates jumped back up to over two-thirds and have been roughly flat since. Average first-round syndicate sizes also increased during and after the Internet bubble, but not as sharply; they never returned to their historical levels. This suggests that the first-round syndicate size distribution is not as skewed as it was in the mid-1980s.

3.2. Syndication and First-Round Investments

Figure 2a displays real first-round investment amounts from 1975-2007. Deal sizes increased considerably through most of the 1990s and then even more during the Internet bubble. Post-bubble averages are similar to the 1990s. Figure 2b examines syndication trends by amount of the first-round investment in the portfolio company. Not too surprisingly, the more money required by the portfolio company, the higher the likelihood it will be funded by a syndicate. This stems from the fact that venture capital firms need to diversify their portfolios – if the entrepreneurial company needs more capital, a VC firm will recruit syndicate partners rather than over-weight its own fund's portfolio. The upper quartile, middle 50%, and lower quartile of first-round investment amount all exhibit the same syndication trend found globally: declining syndication rates from the 1980s up until the Internet bubble, a sharp increase during the bubble, and then a leveling off. It should be noted, though, that the trend is muted, suggesting that the mix of investment amounts is playing a strong role in the syndication spike around the bubble. In other words, if for 1999 and after, decidedly more investments were large ones (requiring more syndicate partners), that could be the source of the syndication spike. I include first-round real investment amounts in the regressions that follow.

3.3 Syndication by Industry

Figures 3a, 3b, and 3c investigate whether syndication trends were consistent across the industry of the portfolio companies (Figures 3b and 3c use rolling averages to smooth out noise). Generally speaking, they were. There is certainly a difference in the cross-section between industries, i.e., the information technology and medical companies are more likely to be syndicated due to the fact there are higher information asymmetries when investing in those companies (see Figures 3a and 3b). These industries also provide higher growth opportunities for investors. Figure 3c displays a finer breakout (six industries rather than three). All six industries generally follow the same familiar pattern: a downward trend in syndication from the mid-1980s through most of the 1990s. During the Internet bubble at the end of the 1990s (and after), all industries were syndicated more often. Regardless of cohort, all five high-technology industries are consistently syndicated more often than the non-high-technology companies (retail, consumer goods, etc.). Since more high-technology companies were being financed during the Internet bubble, industry mix could be the source of the spike in syndication. I include indicator variables for each industry in the regressions that follow.

3.4 Syndication by Life-cycle Stage of the Portfolio Company

Figure 4a displays syndication trends by stage of the portfolio company. Companies in the seed/startup stage have a product that is under development but not operational. Early-stage ventures have a product in testing or pilot production. Companies in the expansion stage have a product that is in production and commercially available. Finally, later-stage companies have a product that is widely available and are more likely to be profitable and near the point where they might go public or be acquired. These stages are listed in order of declining information asymmetry between the entrepreneurs and the investors. Roughly speaking, they are also listed in declining order of syndication rates, i.e., companies in the seed/startup stage are more likely to be syndicated while companies in the expansion stage are least likely[2]. This ordering starts to change around the time of the Internet bubble in that early-stage companies see the highest rates of syndication, while rates of companies in the seed/startup stage and the expansion stage roughly converge. Portfolio company stage is the only company characteristic where the ordering of syndication propensity seems to change over time. This appears to be driven by the fact that companies in the seed/startup stage weren't syndicated at an increasing rate during and after the Internet bubble. This could be a function of deal size, as shown in Figure 4b: expansion-stage deals became much larger post-bubble, while seed-stage deals remained relatively flat. This is consistent with the common complaint one hears from entrepreneurs and policymakers: venture capitalists don't provide as much seed-stage capital as they used to. Given the differences in syndication rates across stage, I include indicator variables in the regressions that follow, being particularly careful to examine any changes in the value of their coefficients over time.

3.5 Syndication by Region

Figures 5a and 5b indicate whether syndication trends were consistent across the geographic regions of the portfolio companies. Like with the industries, they generally were. But also consistent with the industry breakouts, there are differences in the cross section. Figure 5a breaks out coastal vs. interior portfolio companies. I consider companies from Northern California, Southern California, New England,

[2] A notable exception is later-stage companies, which make up roughly 5% of the sample. They are syndicated more often, but this is likely due to the fact that they need more capital and are likely to attract it from multiple VC firms given they are close to going public or being acquired.

New York Tri-State, the Pacific Northwest, the Mid-Atlantic, and the Southeast to be coastal companies; the rest I consider interior. As the figure shows, coastal companies are much more likely to be syndicated. This is not particularly surprising given that venture capital firms tend to cluster in coastal areas. A company looking to raise capital from multiple firms would be wise to locate its headquarters in one of these regions. Figure 5b shows that not all coastal regions are alike, though. While Northern California (Silicon Valley) and New England (Boston – Route 128) exhibit quite similar syndication patterns, New York portfolio companies are no more likely to be syndicated than companies from all other regions combined – this despite the fact that New York is the 3rd-largest venue for VC investment. Because syndication rates vary by region, I include indicator variables for sixteen different regions in the regressions that follow.

4. Regression Results

4.1. Baseline Probit Regressions

The previous four sets of figures (2 through 5) look at syndication trends broken out in a univariate fashion. Table 1 is a multivariate probit regression that simultaneously incorporates all of the variables from the previous four sets of figures. The first column is a regression over the entire time period: 1975-2007. The second column is identical but covers the period 1975-1998, while the third covers 1999-2007. These breakouts each contain roughly 50% of the data and can respectively be thought of as the pre-bubble and post-bubble periods (although this last period includes the bubble). This allows examination of any structural changes in syndication rates.

In terms of explanatory power, the size of the first-round investment is the strongest variable in the regression. Not surprisingly, bigger deals are much more likely to be syndicated. This is the case throughout the sample period, but its coefficient declines in value from before the bubble to after.

Next I look at the industry of the portfolio company. My base (omitted) case is computer companies (both software and hardware, but excluding semiconductors) since these make up 40% of my sample and are fairly representative in terms of syndication rates. I find that overall, biotechnology companies, medical/health/life science, and semiconductor companies are more likely to get venture capital from a first-round syndicate. This largely appears to be driven, however, by the post-Internet bubble period. I find that communications and media companies (includes Internet companies) are slightly less likely to get money from syndicates. In terms of statistical significance, this does not hold up in both time periods, but this appears to be from a lack of power. Not surprisingly, I find that non-high-technology (such as retail and consumer goods) companies are much less likely to get syndicated money in the first round. These companies involve lower information asymmetries between the founder and the investor, thus requiring lower rates of syndication.

I now turn to stage of the portfolio company and its association with syndication decisions. The base (omitted) case in my regressions is early-stage companies, which are companies farther along than seed stage/startup companies but younger than expansion-stage companies. Overall, I find that seed stage/startup companies are more likely to be syndicated, while expansion-stage companies are less likely. This is consistent with the notion that syndication helps out with information asymmetries between the entrepreneur and the investors. Seed stage/startup companies would have the most asymmetry, while expansion-stage companies would have the least, thus requiring fewer syndicate partners. This pattern does not hold up after the Internet bubble when seed-stage/startup companies are no more likely to be syndicated than early-stage companies. As noted in Figure 4a, this appears to be due to increased syndication rates among early-stage companies and expansion-stage companies while rates were relatively flat for seed-stage/startup companies. Expansion-stage companies are consistently syndicated less often than early-stage companies, consistent with the fact they contain fewer information asymmetries with their investors.

Finally, I examine syndication rates by geographic region and discover some interesting patterns. I verify that the Southeast region (includes the Research Triangle in North Carolina) has fairly representative syndication patterns over time and use it as my base (omitted) case. I consistently find that Northern California (includes Silicon Valley) and New England (includes Route 128 in Boston) companies receive syndicated money more often. Also, consistent with Figure 5b, I find that the New York Tri-Stage region sees less syndication (although this result is not statistically significant). Regardless, there is no doubt that New York sees lower syndication rates than the other venture capital hotbeds. Generally speaking, the only two other regions that see increased syndication rates on a consistent basis are Southern California (includes Los Angeles and San Diego) and the Pacific Northwest (includes Seattle and Portland). Post-Internet bubble, the Rocky Mountain region and the Great Plains region have experienced high levels of syndication. It appears elevated syndication is very much a West Coast phenomenon with the exception of Route 128 in Boston, the birthplace of venture capital. It could be that technology centers in appealing places to live attract a critical mass of venture capitalists, making syndication more common. Additionally, these regions may attract challenging companies, even after controlling for capital needs and industry.

4.2. Are Post-Bubble Syndication Rates Unusually High?

Syndication rates have not subsided post-bubble. In this section, I try to determine if recent elevated rates are unusually high. Figure 6a provides some evidence in the form of predicted vs. actual syndication rates, where the predicted rates are obtained from the baseline regression from the entire time period 1975-2007 (Column 1 of Table 1). Generally speaking, syndication rates were high during the 1980s, low during the 1990s, and high again post-bubble. I find that from the years 2001-2007, syndication rates were 4.1 percentage points higher than expected. Using the 1975-1998 regression (Column 2 of Table 1) to obtain predicted values, the gap is even larger (see Figure 6b). I calculate that rates were 6.1 percentage points higher than expected.

4.3. Examining Patterns in the Residuals

Figure 7 graphs unexplained syndication (the residuals from Figure 6a) with industry-wide internal rates of return. Intriguingly, the two variables appear to be highly negatively correlated; in other words, periods of excess syndication are accompanied by low rates of return while periods of minimal syndication coincide with strong returns. The extant literature mainly focuses on the benefits of syndication, suggesting that the post-bubble environment of high syndication rates combined with low returns represents a bit of a puzzle.

Brander, Amit, and Antweiler (2002) potentially offer an explanation. They construct two separate models, one for the selection hypothesis and one for the value-added hypothesis. A key facet of their model supporting the selection hypothesis is that if a project has high expected returns, a VC firm will be *less* likely to seek out a second opinion (and thus, less likely to syndicate) because it would prefer to keep the profits from the project to itself. Syndication occurs in their model when venture capitalists find lower expected-return opportunities and need the reassurance of a second informed player willing to make the same bet. Given that the syndicated investments in their sample perform better, they conclude that the value-added hypothesis is better supported by the data. It's important to note that their sample is based on Canadian VC firms during the highest-performing period in the history of venture capital: the early-to-mid-1990s.

Despite the fact that rudimentary statistics for a limited time period support the value-added hypothesis, Brander et al. allow that both the selection and the value-added hypotheses are at play. Indeed, Sorensen (2007) uses a two-sided matching model and finds that both factors matter but that the *selection* hypothesis is twice as important as the value-added hypothesis in explaining returns. It should be noted that his model assumes a single venture capitalist rather than a syndicate. Given that Brander et al. (2002) allow a possible role for selection and Sorensen (2007) finds its role to be twice as important, it seems reasonable to conclude that the relative influence of the two explanations is circumstance-dependent. Under what conditions might we expect the selection motive to be stronger than the value-added motive?

Cumming and MacIntosh (2004) provide some clues. They argue that during a boom cycle (a period marked by a rapidly increasing inflow of funds and seemingly promising projects), the short-run inelasticity of VC managerial talent prevents the VC community from adequately adjusting to the flood of new money. Venture capitalists possess a lot of pragmatic skills and specialized industry knowledge that can't be taught in school; in other words, a VC firm can't just run out and hire the smartest business school graduates to successfully help manage the new money. This means VC firms must manage more deals per partner, as Cumming (2006) empirically finds. Given the fact that there are only 24 hours in a day, this necessarily means that each VC is adding less value to any given portfolio company, as predicted theoretically by Kanniainen and Keuschnigg (2003) and found empirically by Cumming and Johan (2007) and Cumming and Walz (2009). Consistent with this, Kortum and Lerner (2000) and Lerner (2002) find that venture capitalists contribute 15% less to innovation during boom periods. All of these findings indicate that venture capitalists add less value during a boom period. So if we were to see an upward spike in syndication during a rapid increase in the supply of venture capital, then we would expect that to be explained by something other than the value-added hypothesis, like help with selecting investments. Brander et al.'s selection hypothesis predicts that sketchy deals are more likely to be syndicated. Indeed, returns for deals funded since 2000 have been low, and many observers argue that there has been too much money chasing too few good prospects. I argue that since an excess of venture capital during this period made syndication less likely to be explained by the value-added hypothesis and more likely to be explained by the selection hypothesis, increasing syndication served as a signal that the venture capital community was entering a period of low returns.

4.4. Does the Efficiency of Syndication Change over Time?

It is important to note that just because aggregate syndication rates move inversely with industry rates of return doesn't mean that syndication is always ineffective. Periods of low syndication can still be periods of effective syndication. In fact, Table 2 provides evidence that on average, syndication adds value. It contains probit regressions where the dependent variable is *Portfolio Company Success?*, which takes the value 1 for an IPO or acquisition, and 0 otherwise. There is no publicly available, comprehensive database of specific VC fund performance due to the fact that VC firms are hesitant to disclose their funds' return data. Thus, the VC literature is forced to rely on noisy proxies of fund performance, i.e., exits. Following

Gompers and Lerner (1999), I denote success as the occurrence of one of the two most profitable exits, IPOs and acquisitions. Of course, these proxies don't incorporate investment costs or ownership stakes, but Cochrane (2005) and Kaplan and Schoar (2005) examine proprietary return data and conclude that most of the returns are comprised of the returns from these two exits.

Table 2 contains all the same control variables as Table 1, but also includes the main variable of interest: *First Round Syndicated?*, which takes the value 1 if the first round of investment involves two or more financiers, and 0 otherwise. A positive coefficient would indicate better performance by syndicated investments. I find that on average, syndicated investments have a 3.3 percentage-point higher probability of succeeding (see column 1). Column 1 is the only regression that doesn't include partially censored data. Measuring exits is tricky due to the fact that it takes time for venture capitalists to nurture their portfolio companies. VCs are nearly always contractually required to return capital to their limited partners (pensions, endowments, insurance companies, etc.) within ten years, which means a venture capitalist could be 'succeeding' after, say, seven years despite the fact that no exit has been obtained. Columns 2, 3, and 4 only allow 7, 5, and 3 years to exit, respectively (exit data was collected during 2008). Thus, their coefficients should be interpreted with caution. It is interesting to note that the coefficient for *First Round Syndicated?* declines from columns 1 to 4, suggesting that the efficiency of syndication is dropping over the end of the sample period. I analyze this in more depth in Table 3.

Table 3 displays *First Round Syndicated?* coefficients from the specification in Table 2, but on a 5-year rolling basis. This allows tracking of the efficiency of syndication over time. Figure 8 is a graphical representation of the coefficients. It is clear that the overall results that indicated syndication adds value are driven by the 1990s (the only period with statistically significant positive coefficients). The other main finding is that the post-bubble period is marked by lower, even apparently negative, outcomes of syndication, the only period where the coefficients are negative and statistically significant. From this, it's reasonable to suggest that Brander et al.'s value-added hypothesis was stronger in the 1990s (the time period of their sample) but that their selection hypothesis is stronger post-bubble (syndicated investments are those with lower returns), the same conclusions reached in the prior section.

4.5. Other Factors that could be Contributing to Excess Syndication Post-Bubble

Given the rise and fall of unexplained syndication over time, there could be exogenous factors that are contributing to VC firms' syndication behavior. One such possible factor is liquidity conditions of the exit markets at the time of investment. Venture capitalists earn a substantial majority of their returns by taking their companies public via an initial public offering (IPO) or by selling them to another company. Historically, IPOs have been the preferred exit in terms of financial returns. Cumming, Flemming, and Schwienbacher (2005) theorize that venture capitalists are less likely to syndicate when these exit markets are relatively liquid. They argue that more liquid exit markets mean lower investment risk and thus, less need to syndicate for other risk-reducing reasons such as screening (Lerner, 1994) or adding value (Brander, Amit, and Antweiler, 2002).

Another possible exogenous factor is the total amount of money invested by the entire venture capital community. While venture capitalists invest their own money in entrepreneurial companies, the vast majority of their capital comes from other investors: pensions, endowments, foundations, insurance companies, financial institutions, wealthy individuals, etc. If these investors would like to increase their allocation of high-risk, high-reward investments, one can think of their investing in a venture capital fund as increased demand for entrepreneurship. If the supply of entrepreneurial opportunities remains relatively constant, then at the margin, a given venture capitalist will invest in a project already discovered by another venture capitalist rather than invest in a new entrepreneurial opportunity. Numerous observers believe that there is currently ‘too much money chasing too few deals’ in the VC industry, and it is possible that syndication is a symptom of this phenomenon.

Another possible exogenous factor is general investment conditions. It is possible that during times of investor excitement, venture capitalists are less concerned about risks stemming from investing by themselves, leading to lower syndication rates. I also include the eventual annual IRR realized by investors in the VC industry.

Table 4 builds on the specification from Table 1 and contains regression coefficients after including the four previously mentioned exogenous factors: number of IPOs, total VC inflows, and general investment conditions (proxied by NASDAQ levels and realized IRR). The most consistent result is that liquidity conditions (proxied by IPOs) has a negative effect on syndication. This is consistent with Cumming, Flemming, and Schwienbacher (2005), suggesting that venture capitalists are more likely to syndicate when they are worried about exiting their investments. It appears this can partially explain the excess syndication exhibited by the VC community post-bubble.

I also find that excess syndication is strongly negatively correlated with industry returns. What causes what is an open question, but it appears safe to say that excess syndication is a symptom of a low-return environment. Interestingly, after controlling for liquidity conditions and investment conditions, the total amount invested by the VC community is positively correlated with syndication. This is consistent with the notion that too much money led to too much syndication. Perhaps the expression 'too much money chasing too few deals' has a close cousin: 'too many syndicates chasing too few deals'.

5. Conclusion

Venture capital syndication is a response to a spectrum of forces, and I find empirical support for many of the theories that have been advanced. The most common survey response given by venture capitalists is that they syndicate to diversify their portfolios, and I find evidence consistent with that in the fact that bigger investments are more likely to be syndicated. VCs also syndicate to reduce information asymmetries, and I find evidence of this in the fact that investments in seed-stage, high-tech companies are more likely to be syndicated, even though they typically receive less capital in the first round relative to other types of investments. Finally, I find that syndication rates are negatively correlated to VC industry rates of return. This does not necessarily mean syndication is ineffective, as I find that syndicated investments perform better during the 1990s – superior performance that is consistent with Brander et al.'s value-added hypothesis. However, the post-bubble environment arguably had poorer exit options, allowing support for the selection hypothesis, which states VCs would only syndicate their lower expected-return investments. Syndicated investments have performed worse post-bubble, and I find that part of the reason they are syndicated more is a response by venture capitalists to poor liquidity conditions. Arguably, current excess syndication is a symptom of overinvestment in the venture capital industry. Since the success of syndication depends on circumstance and because most research has focused on benefits of syndication, it may bear fruit to examine the effects of syndications gone bad. For instance, when syndicates dissolve, are the partners less likely to syndicate in the future? Are the firms less likely to survive? If they do survive, do they invest at lower valuations or with more adverse terms in their contracts? There are multiple opportunities for the enterprising researcher to advance our knowledge of this important phenomenon, particularly the negative aspects.

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Table 1 - Baseline Probit Regressions

The following table displays results from a probit regression where the dependent variable is *First Round Syndicated?*, defined as the portfolio company receiving venture capital from two or more unique financiers in the first round. The sample period is first-round investments that occurred in 1975-2007. All coefficients are marginal effects. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested by the first-round partners. Five indicator variables are used for the six different industries of the portfolio companies (the omitted base case is *Computer-Related*). *Startup/Seed* is an indicator variable that takes the value 1 if the portfolio company has a product under development. The omitted base case stage is *Early*, when the portfolio company has a product in testing or pilot production. *Expansion* is an indicator variable that takes the value 1 if the portfolio company has a product that is in production and commercially available. *Later* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. Fifteen indicator variables are used for the sixteen geographic regions of the portfolio companies (*Southeast* is the omitted base case).

Dependent Variable: First Round Syndicated?	(1)	(2)	(3)
	1975-2007	1975-1998	1999-2007
Ln(1st-Round Inv't - 2007 $)	0.149***	0.156***	0.135***
	[50.24]	[35.14]	[33.71]
Industry of Portfolio Company			
Biotechnology	0.045***	0.005	0.085***
	[3.02]	[0.21]	[4.43]
Comms and Media	-0.023**	-0.022	-0.020
	[2.23]	[1.36]	[1.59]
Medical/Health/Life Science	0.043***	0.029*	0.066***
	[3.76]	[1.71]	[4.21]
Non-High-Technology	-0.065***	-0.054***	-0.073***
	[6.76]	[4.02]	[5.18]
Semiconductors/Other Electronics	0.030**	0.008	0.055***
	[2.15]	[0.38]	[3.05]
Stage of Portfolio Company			
Startup/Seed	0.054***	0.107***	0.010
	[6.47]	[8.73]	[0.87]
Expansion	-0.130***	-0.104***	-0.132***
	[14.77]	[7.69]	[11.43]
Later	-0.059***	0.002	-0.108***
	[3.19]	[0.09]	[4.00]
Region of Portfolio Company			
Alaska/Hawaii	-0.037	0.116	-0.090
	[0.34]	[0.74]	[0.72]
Great Lakes	0.014	0.042	-0.013
	[0.70]	[1.44]	[0.46]
Great Plains	0.039*	0.018	0.073**
	[1.74]	[0.56]	[2.36]
Mid-Atlantic	0.021	0.023	0.012
	[1.11]	[0.73]	[0.52]

N. California	0.094***	0.113***	0.078***
	[6.71]	[5.26]	[4.33]
New England	0.081***	0.103***	0.063***
	[5.26]	[4.43]	[3.08]
New York Tri-State	-0.008	-0.018	-0.001
	[0.48]	[0.71]	[0.03]
Northwest	0.075***	0.066**	0.081***
	[3.73]	[2.10]	[3.16]
Ohio Valley	-0.007	0.007	-0.019
	[0.34]	[0.25]	[0.74]
Rocky Mountains	0.041**	0.036	0.051*
	[1.97]	[1.14]	[1.88]
S. California	0.058***	0.077***	0.043**
	[3.57]	[3.13]	[2.00]
South	0.000	0.038	-0.048
	[0.01]	[1.09]	[1.22]
Southwest	0.018	0.048*	-0.008
	[1.02]	[1.87]	[0.35]
US Territories	-0.199**	-0.405***	-0.028
	[2.06]	[2.91]	[0.24]
Observations	23,254	10,969	12,285
Pseudo R-squared	0.131	0.132	0.122

Robust z statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2 - Probit Regressions - Syndication Effectiveness

The following table displays results from a probit regression where the dependent variable is *Portfolio Company Success?*, defined as the portfolio company either going public or being acquired. The sample period is first-round investments that occurred in 1975-2007. All coefficients are marginal effects. *First Round Syndicated?* is an indicator variable that takes the value 1 if the portfolio company receives venture capital from two or more unique financiers in the first round. *Ln(Total 1st-Round Investment)* is the natural logarithm of the total amount invested by the first-round partners. Five indicator variables are used for the six different industries of the portfolio companies (the omitted base case is *Computer-Related*). *Startup/Seed* is an indicator variable that takes the value 1 if the portfolio company has a product under development. The omitted base case stage is *Early*, when the portfolio company has a product in testing or pilot production. *Expansion* is an indicator variable that takes the value 1 if the portfolio company has a product that is in production and commercially available. *Later* is an indicator variable that takes the value 1 if the portfolio company has a product that is widely available. Fifteen indicator variables are used for the sixteen geographic regions of the portfolio companies (*Southeast* is the omitted base case).

Dependent Variable: Portfolio Company Success (IPO or Acquisition)?

	(1) 1975-1997	(2) 1975-2000	(3) 1975-2002	(4) 1975-2004
First Round Syndicated?	0.033***	0.031***	0.023***	0.013*
	[2.90]	[3.53]	[2.78]	[1.68]
Ln(1st-Round Inv't - 2007 $)	0.053***	0.024***	0.024***	0.024***
	[12.57]	[7.72]	[8.03]	[8.39]
Industry of Portfolio Company				
Biotechnology	0.113***	0.149***	0.097***	0.067***
	[4.79]	[7.80]	[5.57]	[4.13]
Comms and Media	0.003	0.008	-0.001	0
	[0.17]	[0.70]	[0.13]	[0.02]
Medical/Health/Life Science	0.001	0.070***	0.054***	0.033***
	[0.06]	[4.99]	[4.12]	[2.65]
Non-High-Technology	-0.178***	-0.077***	-0.078***	-0.078***
	[12.87]	[7.19]	[7.68]	[8.10]
Semiconductors/Other Electronics	0.019	0.062***	0.033**	0.006
	[0.89]	[3.74]	[2.20]	[0.40]
Stage of Portfolio Company				
Startup/Seed	-0.013	0.033***	0.051***	0.071***
	[1.04]	[3.45]	[5.60]	[8.13]
Expansion	0.026*	0.061***	0.068***	0.081***
	[1.86]	[6.02]	[7.17]	[8.89]
Later	0.106***	0.163***	0.168***	0.163***
	[4.19]	[7.68]	[8.32]	[8.53]

<u>Region of Portfolio Company</u>				
Alaska/Hawaii		-0.344**	-0.194	-0.199*
		[2.26]	[1.50]	[1.65]
Great Lakes	-0.059*	-0.045*	-0.026	-0.019
	[1.93]	[1.94]	[1.20]	[0.91]
Great Plains	-0.028	-0.024	-0.015	-0.016
	[0.85]	[0.94]	[0.63]	[0.72]
Mid-Atlantic	-0.034	-0.021	-0.009	-0.022
	[1.02]	[0.94]	[0.44]	[1.09]
N. California	0.024	0.01	0.022	0.01
	[1.02]	[0.58]	[1.41]	[0.67]
New England	0.036	0.040**	0.044**	0.039**
	[1.42]	[2.14]	[2.50]	[2.33]
New York Tri-State	-0.012	-0.03	-0.017	-0.019
	[0.44]	[1.60]	[0.99]	[1.15]
Northwest	0.017	0.005	0.02	0.006
	[0.51]	[0.19]	[0.88]	[0.30]
Ohio Valley	-0.038	-0.036	-0.025	-0.023
	[1.26]	[1.60]	[1.17]	[1.15]
Rocky Mountains	0.021	0.023	0.040*	0.039*
	[0.64]	[0.94]	[1.74]	[1.78]
S. California	-0.002	-0.015	0.005	0.007
	[0.07]	[0.80]	[0.28]	[0.43]
South	0.006	0.004	0.021	0.022
	[0.17]	[0.15]	[0.76]	[0.81]
Southwest	-0.037	-0.022	-0.012	-0.01
	[1.36]	[1.12]	[0.63]	[0.57]
US Territories	-0.246*	-0.256**	-0.256***	-0.242**
	[1.72]	[2.44]	[2.61]	[2.55]
Observations	9569	16550	18469	20024

Robust z statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3 - First-Round Syndication Efficiency Trends

The following table displays results from probit regressions where the dependent variable is *Portfolio Company Success?*, defined as the portfolio company either going public or being acquired. The sample periods are 5-year rolling windows from 1975-2007. All coefficients are marginal effects. *First Round Syndicated?* is an indicator variable that takes the value 1 if the portfolio company receives venture capital from two or more unique financiers in the first round. The rest of the control variables are identical to Table 2 and are omitted for brevity. As detailed in Table 2, investments made after 1997 are susceptible to censored outcomes and should be interpreted with caution.

End of 5-Year Rolling Window	*First Round Syndicated?* Coefficient
1979	0.063
1980	0.066
1981	-0.02
1982	0.018
1983	0.027
1984	0.017
1985	-0.004
1986	0.016
1987	0.004
1988	-0.008
1989	-0.01
1990	-0.011
1991	-0.03
1992	-0.029
1993	0.006
1994	0.045
1995	0.049**
1996	0.053***
1997	0.050***
1998	0.042***
1999	0.027**
2000	0.005
2001	0.005
2002	-0.005
2003	-0.015
2004	-0.022*
2005	-0.025**
2006	-0.029***
2007	-0.016**

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4 - Additional Explanatory Variables

The following table displays results from a probit regression where the dependent variable is *First Round Syndicated?*, defined as the portfolio company receiving venture capital from two or more unique financiers in the first round. The sample period is first-round investments that occurred in 1981-2006 (due to incomplete IRR data), and the 2nd and 3rd blocks split this. All coefficients are marginal effects. *Annual # of IPOs / 100* is the number of companies that went public in a given year, divided by 100. *Nasdaq Level / 100* is the average value of the Nasdaq index in a given year, divided by 100. *Ln(Annual Total VC Investment)* is the natural logarithm of the total amount invested by the VC community in a given year. *Annual VC Industry IRR* is the annual internal rate of return realized by investors in the venture capital industry. The rest of the control variables are identical to Table 1 and are omitted for brevity.

Dependent Variable: First Round Syndicated?	(1)	(2)	(3)	(4)	(5)
1981-2006					
Annual # of IPOs / 100	-0.026***				-0.005**
	[13.10]				[1.98]
Nasdaq level / 100		-0.003***			-0.009***
		[7.81]			[5.47]
Ln(Annual Total VC Investment - 2007 Dollars)			-0.027***		0.039**
			[8.08]		[2.50]
Annual VC Industry IRR				-0.128***	-0.191***
				[11.73]	[11.28]
Observations	21,501	21,501	21,501	21,501	21,501
1981-1998					
Annual # of IPOs / 100	-0.029***				-0.005
	[9.74]				[1.22]
Nasdaq level / 100		-0.013***			-0.019***
		[15.06]			[6.76]
Ln(Annual Total VC Investment - 2007 Dollars)			-0.107***		0.077***
			[14.38]		[3.12]
Annual VC Industry IRR				-0.197***	-0.142***
				[12.95]	[6.53]
Observations	10,412	10,412	10,412	10,412	10,412
1999-2006					
Annual # of IPOs / 100	-0.024***				-0.025**
	[7.89]				[2.46]
Nasdaq level / 100		-0.006***			-0.001
		[7.70]			[0.20]
Ln(Annual Total VC Investment - 2007 Dollars)			-0.054***		-0.011
			[7.04]		[0.35]
Annual VC Industry IRR				0.783***	-1.059***
				[2.90]	[2.62]
Observations	11,089	11,089	11,089	11,089	11,089

Robust z statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

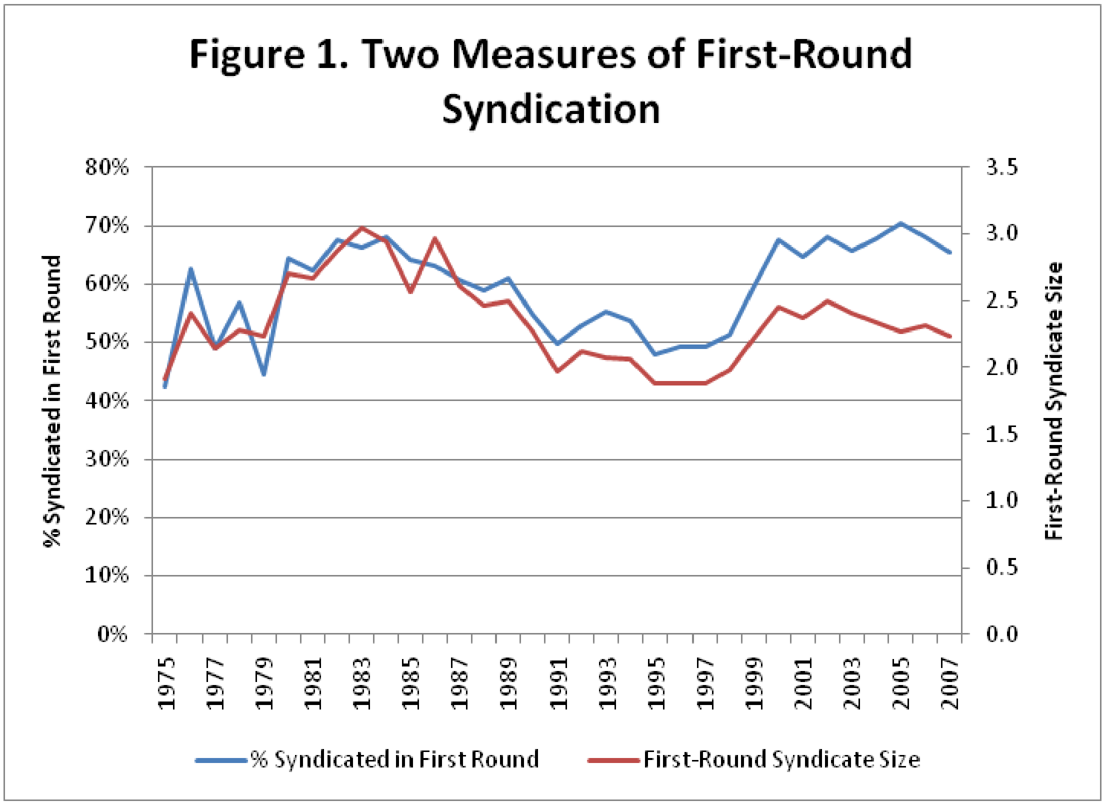


Figure 1. Two Measures of First-Round Syndication
% Syndicated in First Round
First-Round Syndicate Size
80%
70%
60%
50%
40%
30%
20%
10%
0%
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
% Syndicated in First Round
First-Round Syndicate Size

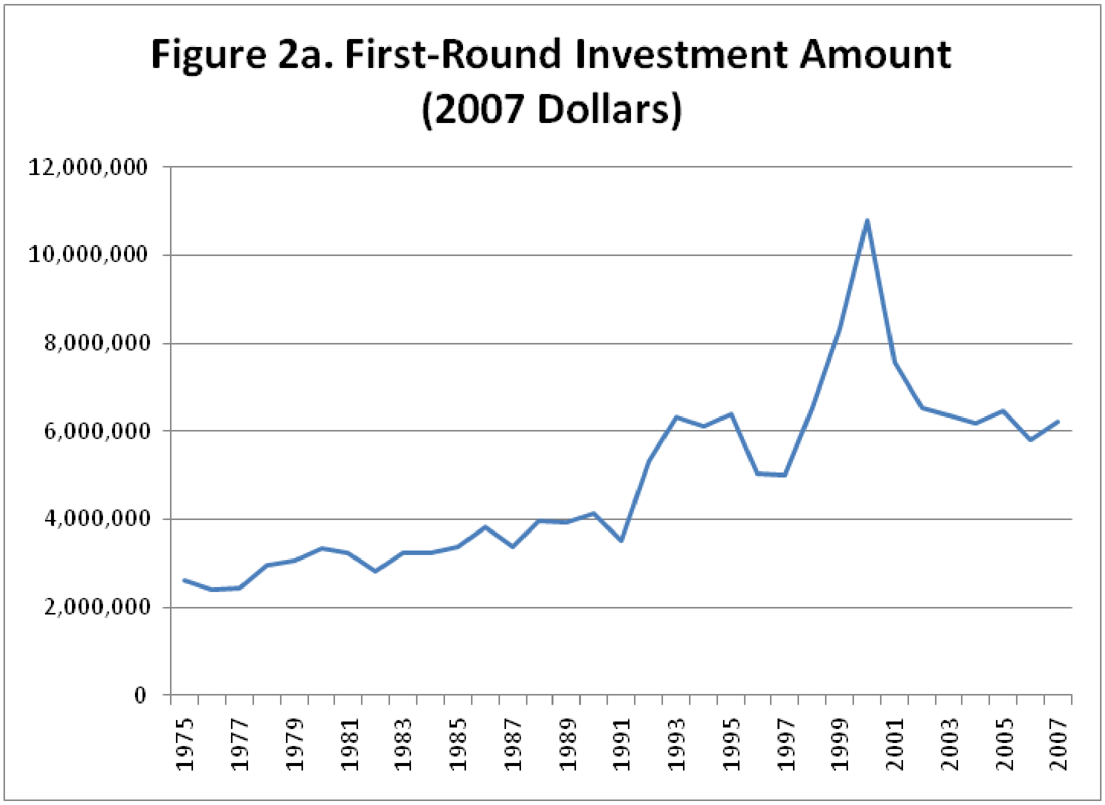


Figure 2a. First-Round Investment Amount (2007 Dollars)
12,000,000
10,000,000
8,000,000
6,000,000
4,000,000
2,000,000
0
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007

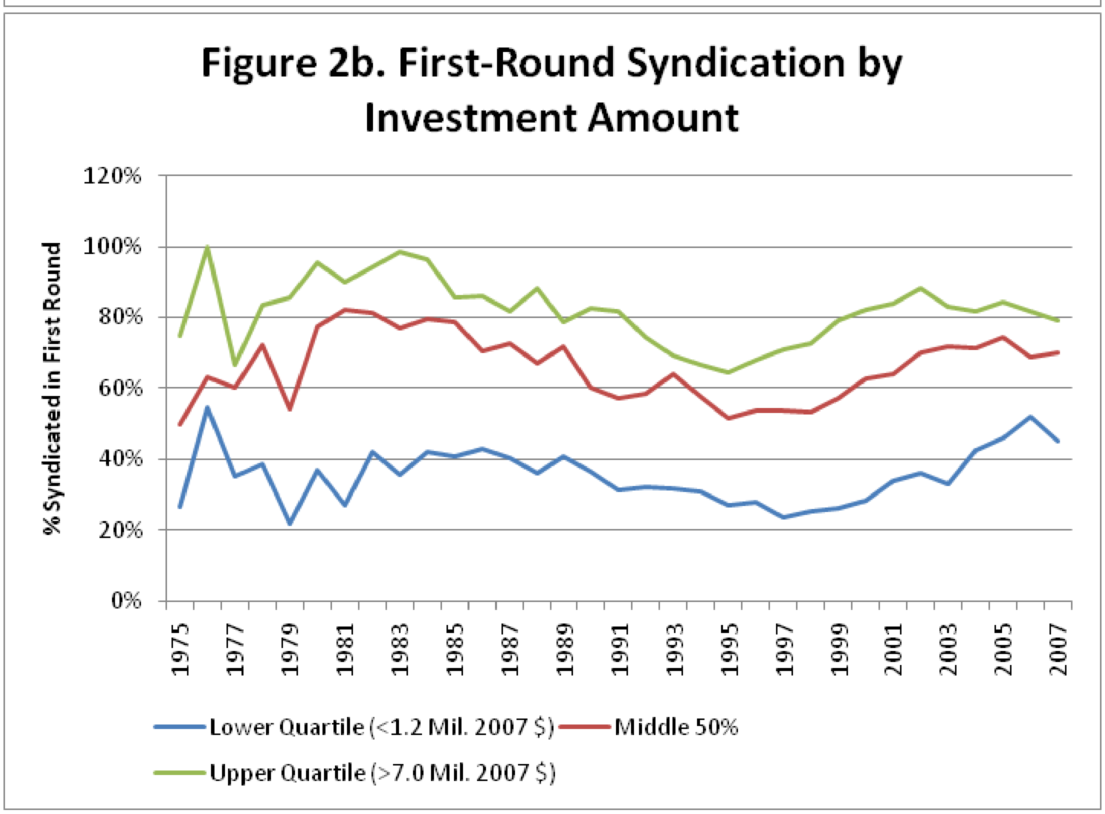


Figure 2b. First-Round Syndication by Investment Amount
% Syndicated in First Round
120%
100%
80%
60%
40%
20%
0%
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
Lower Quartile (<1.2 Mil. 2007 $)
Middle 50%
Upper Quartile (>7.0 Mil. 2007 $)

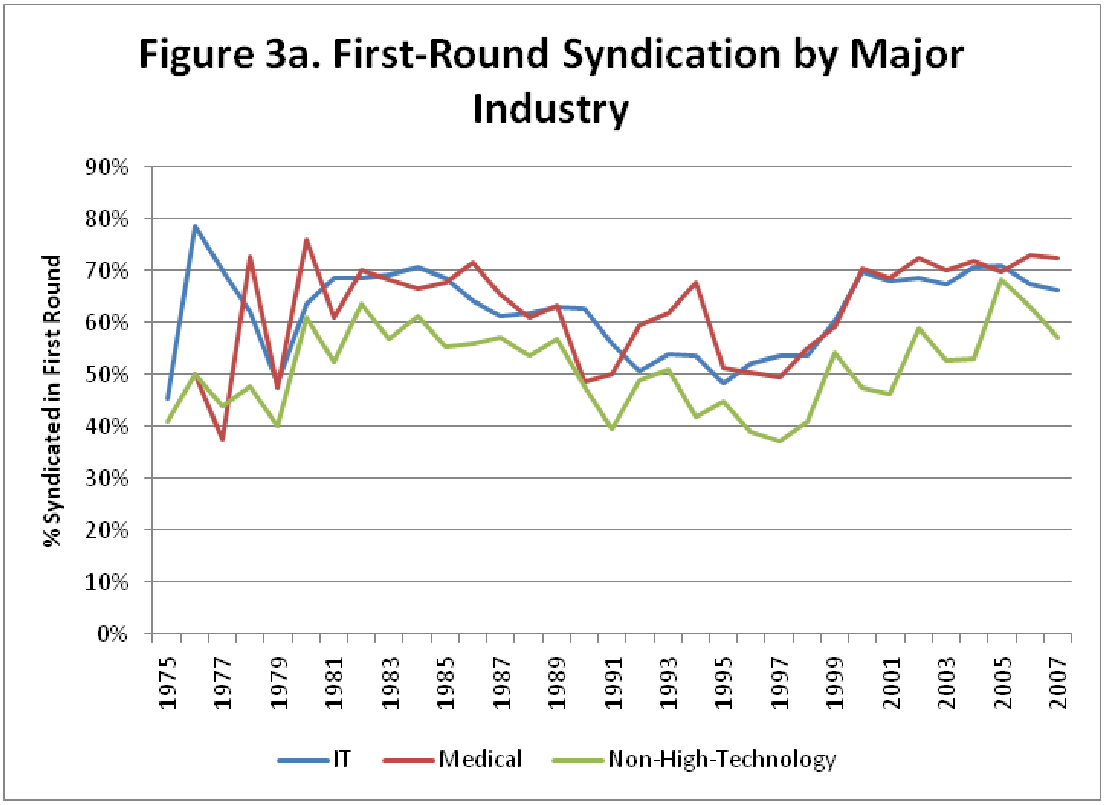


Figure 3a. First-Round Syndication by Major Industry
% Syndicated in First Round
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
IT
Medical
Non-High-Technology

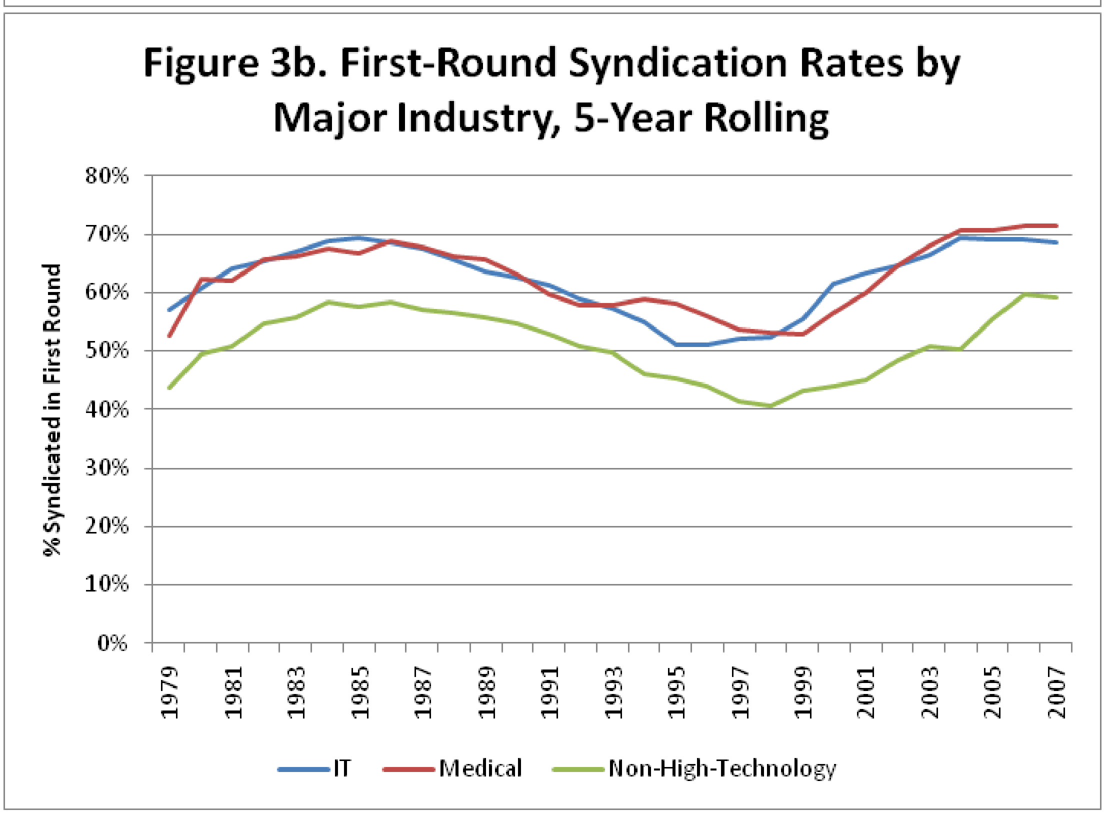


Figure 3b. First-Round Syndication Rates by Major Industry, 5-Year Rolling
% Syndicated in First Round
80%
70%
60%
50%
40%
30%
20%
10%
0%
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
IT
Medical
Non-High-Technology

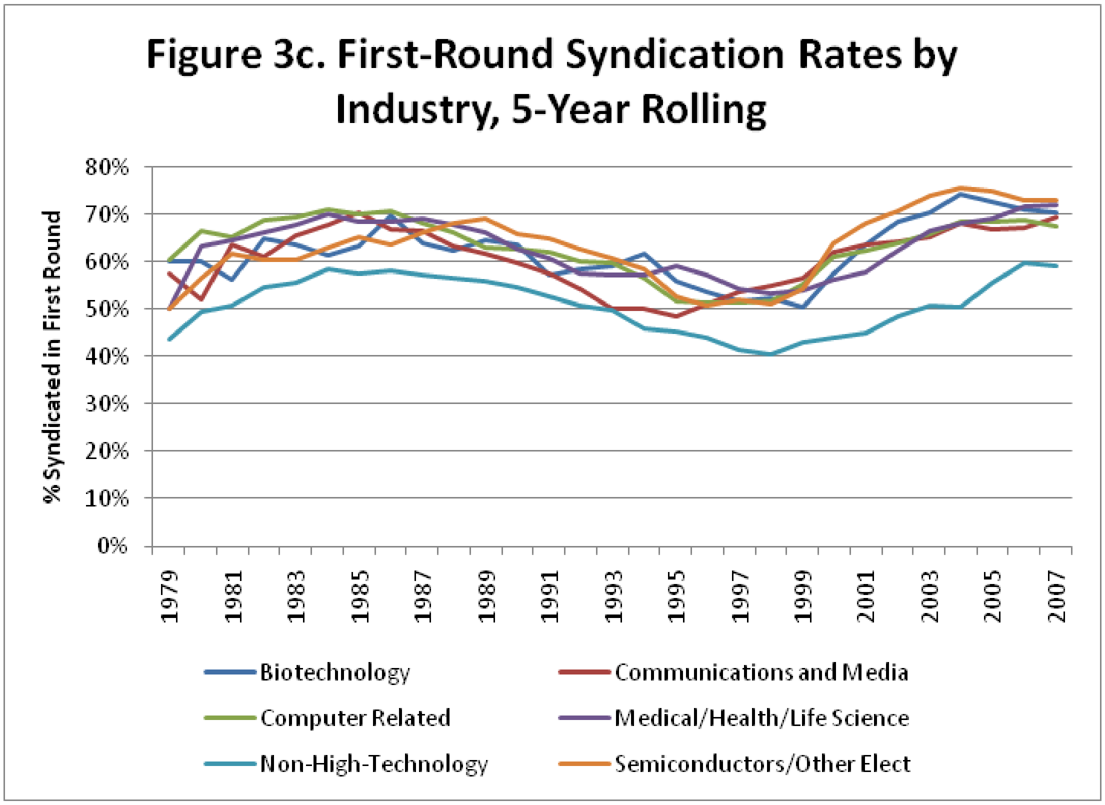


Figure 3c. First-Round Syndication Rates by Industry, 5-Year Rolling
% Syndicated in First Round
80%
70%
60%
50%
40%
30%
20%
10%
0%
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
Biotechnology
Communications and Media
Computer Related
Medical/Health/Life Science
Non-High-Technology
Semiconductors/Other Elect

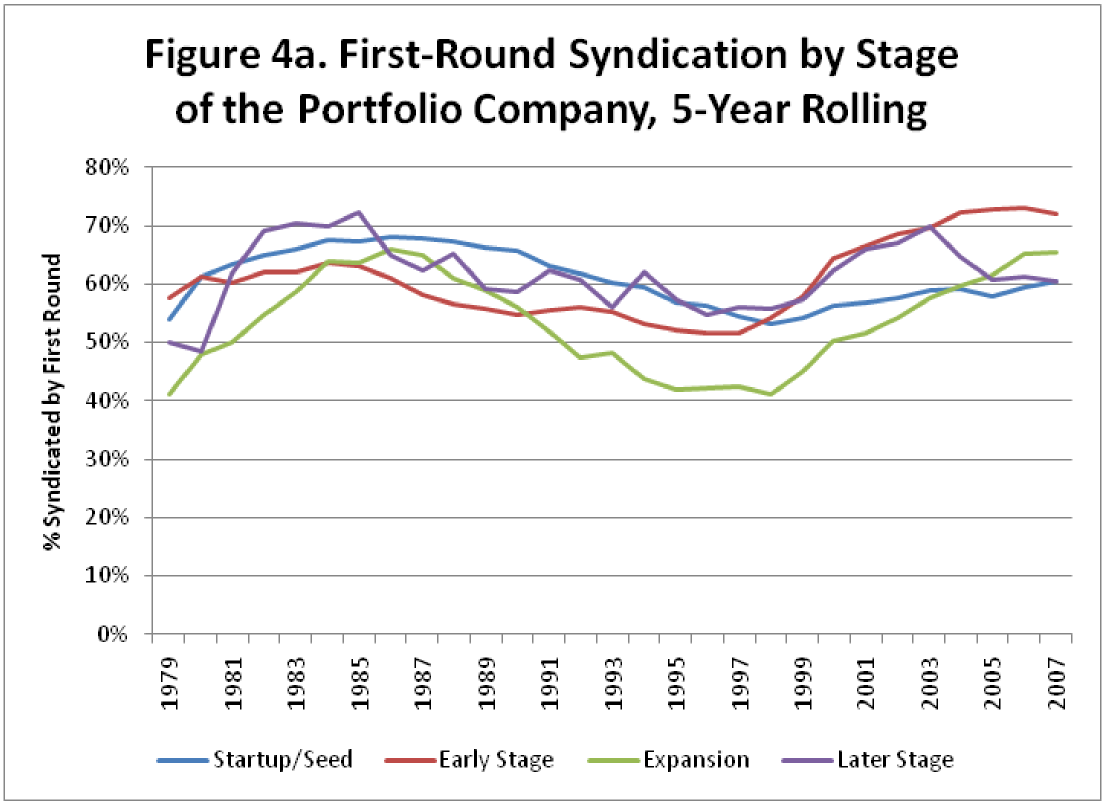


Figure 4a. First-Round Syndication by Stage of the Portfolio Company, 5-Year Rolling
% Syndicated by First Round
80%
70%
60%
50%
40%
30%
20%
10%
0%
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
Startup/Seed
Early Stage
Expansion
Later Stage

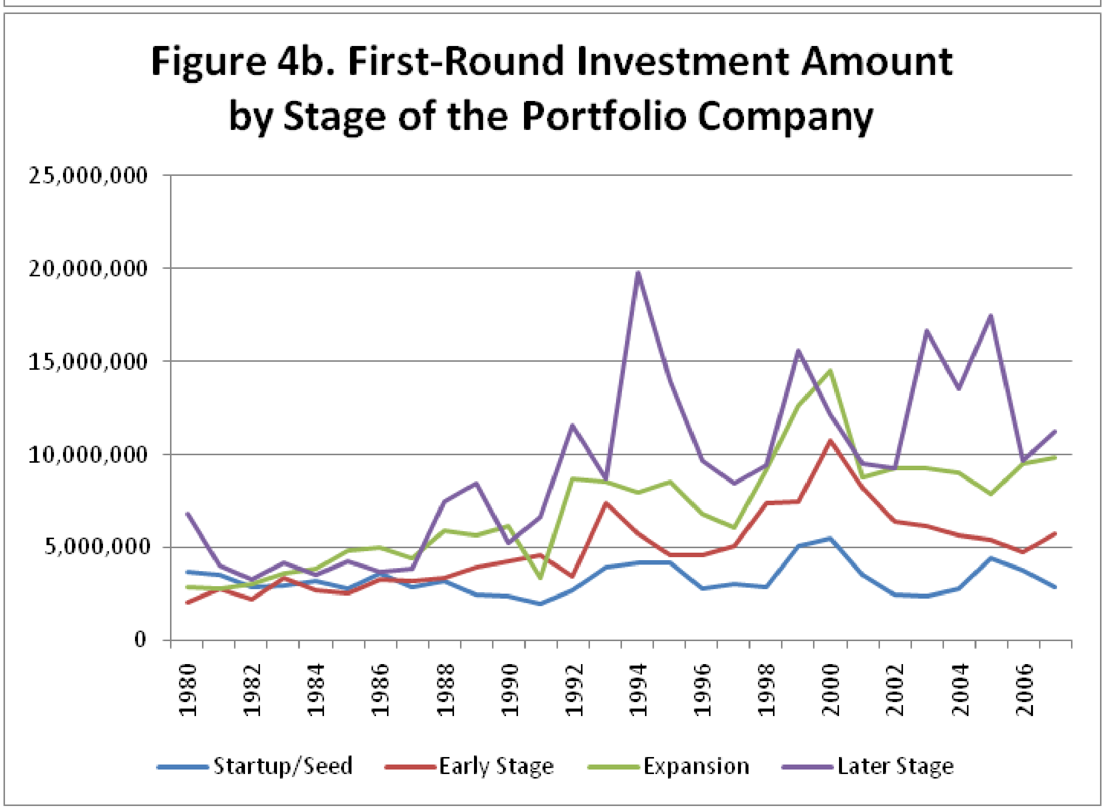


Figure 4b. First-Round Investment Amount by Stage of the Portfolio Company
25,000,000
20,000,000
15,000,000
10,000,000
5,000,000
0
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
Startup/Seed
Early Stage
Expansion
Later Stage

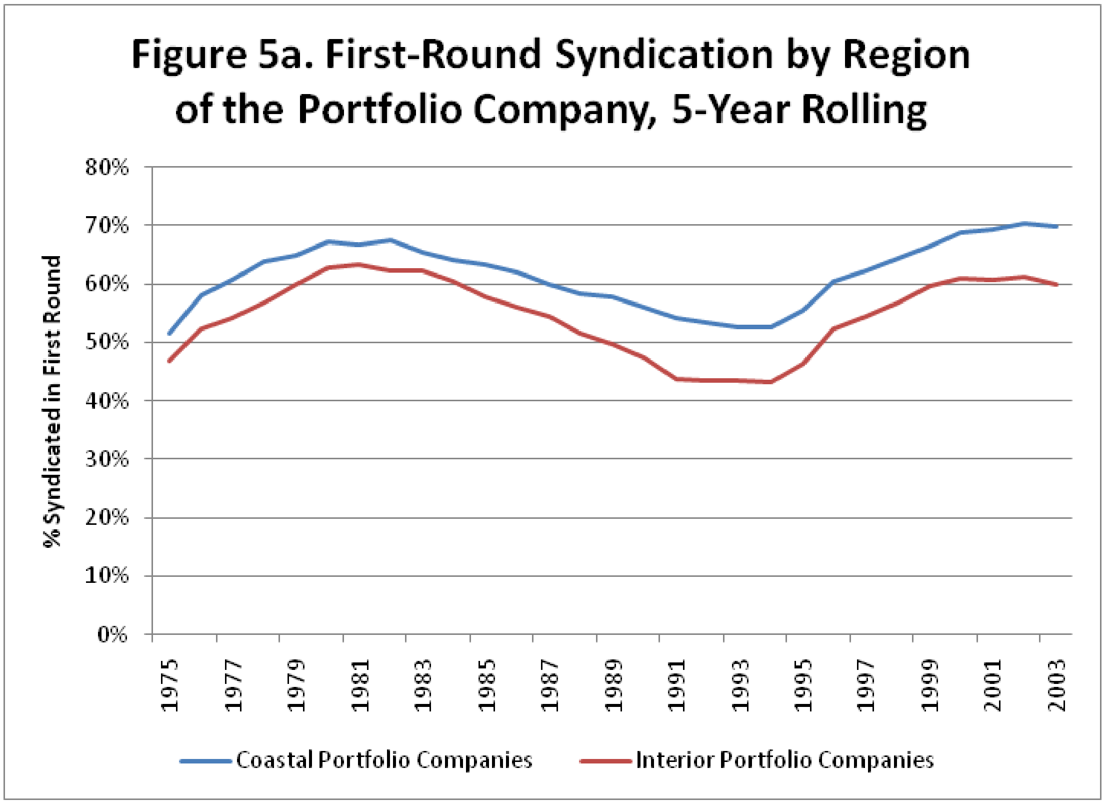


Figure 5a. First-Round Syndication by Region of the Portfolio Company, 5-Year Rolling
80%
70%
60%
50%
40%
30%
20%
10%
0%
% Syndicated in First Round
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
Coastal Portfolio Companies
Interior Portfolio Companies

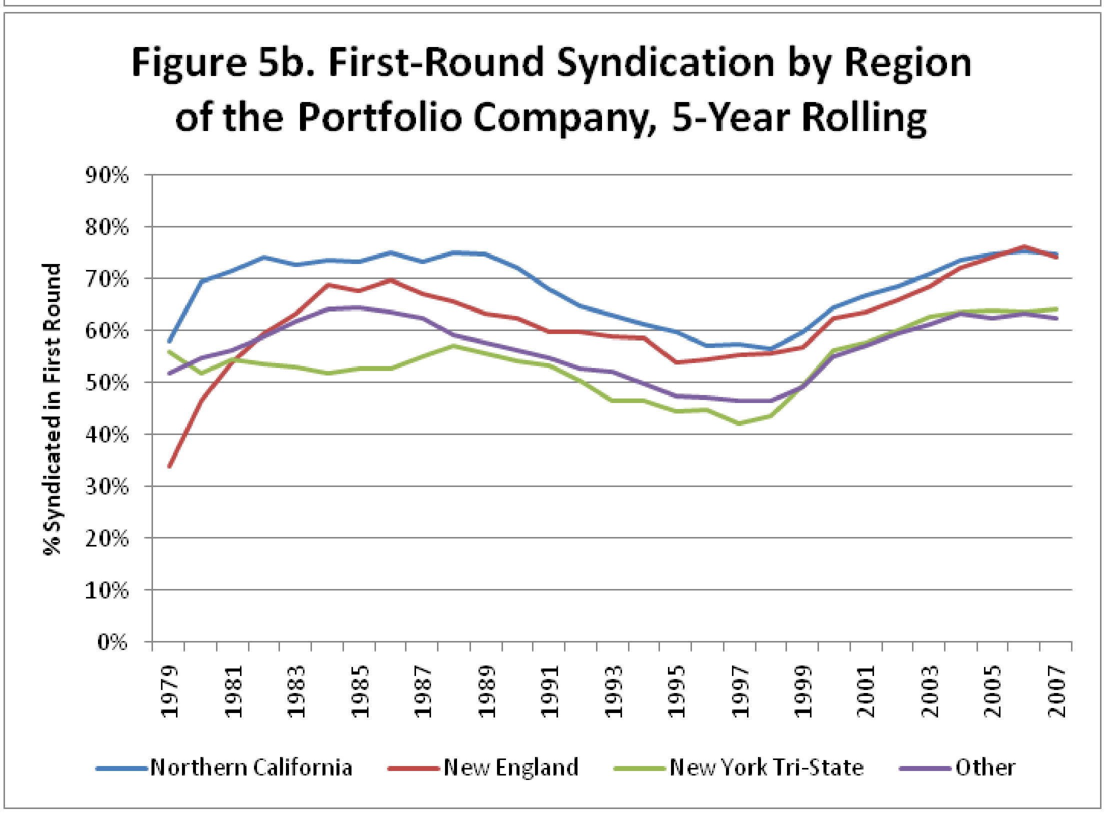


Figure 5b. First-Round Syndication by Region of the Portfolio Company, 5-Year Rolling
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
% Syndicated in First Round
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
Northern California
New England
New York Tri-State
Other

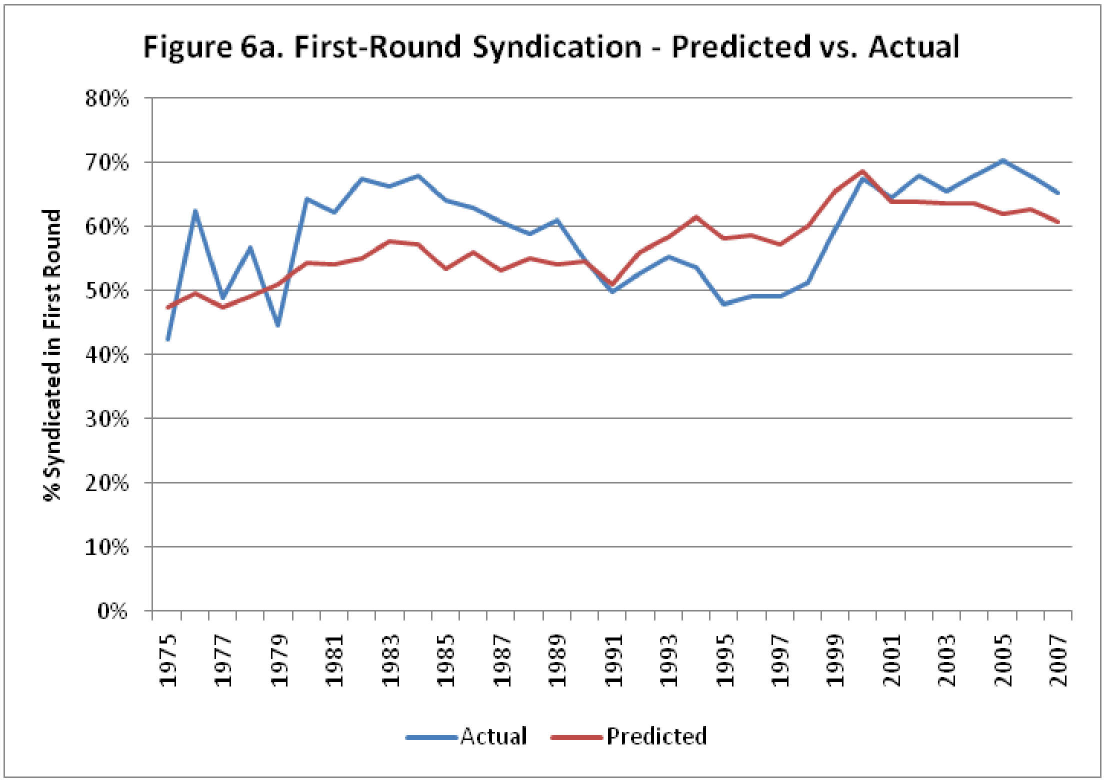


Figure 6a. First-Round Syndication - Predicted vs. Actual
80%
70%
60%
50%
40%
30%
20%
10%
0%
% Syndicated in First Round
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
Actual
Predicted

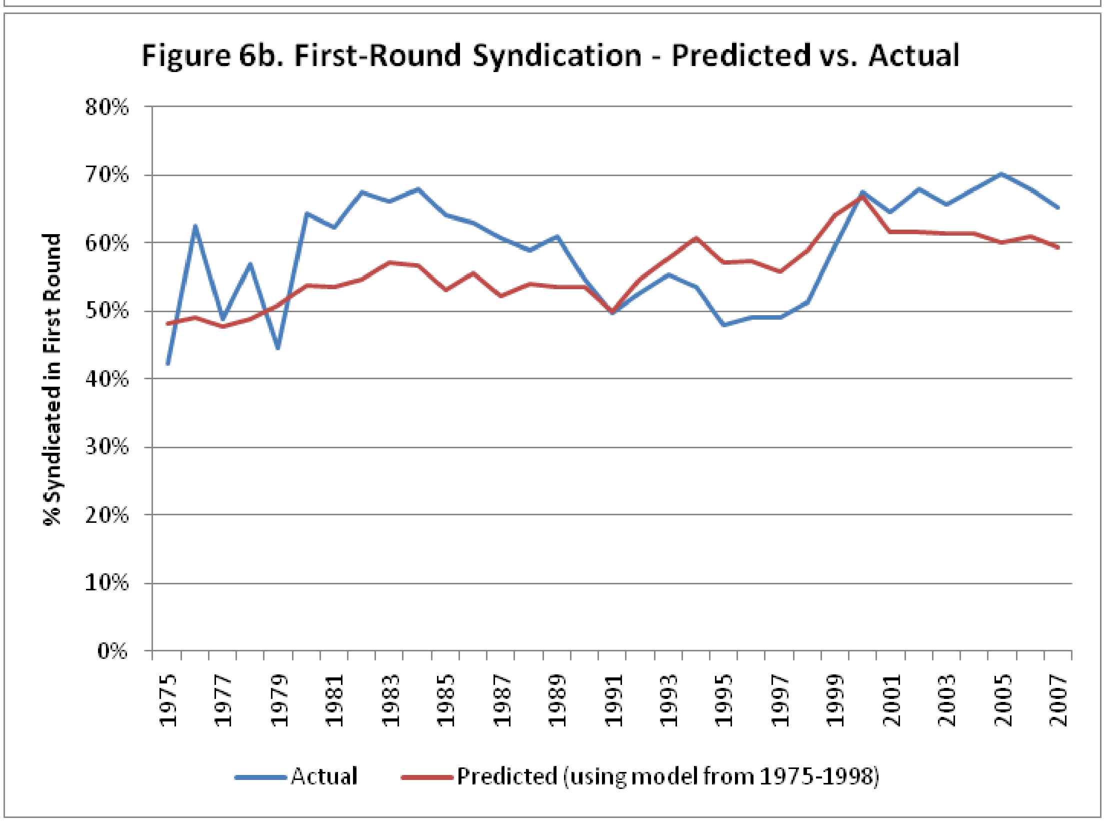


Figure 6b. First-Round Syndication - Predicted vs. Actual
80%
70%
60%
50%
40%
30%
20%
10%
0%
% Syndicated in First Round
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
Actual
Predicted (using model from 1975-1998)

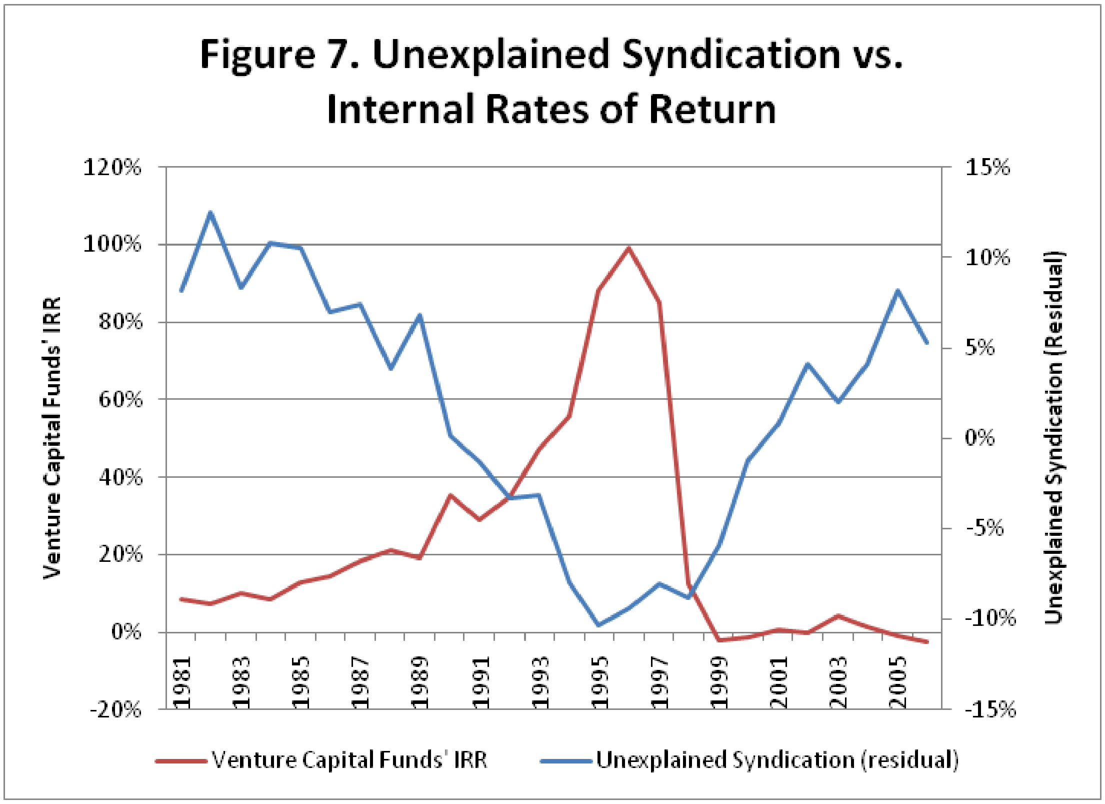
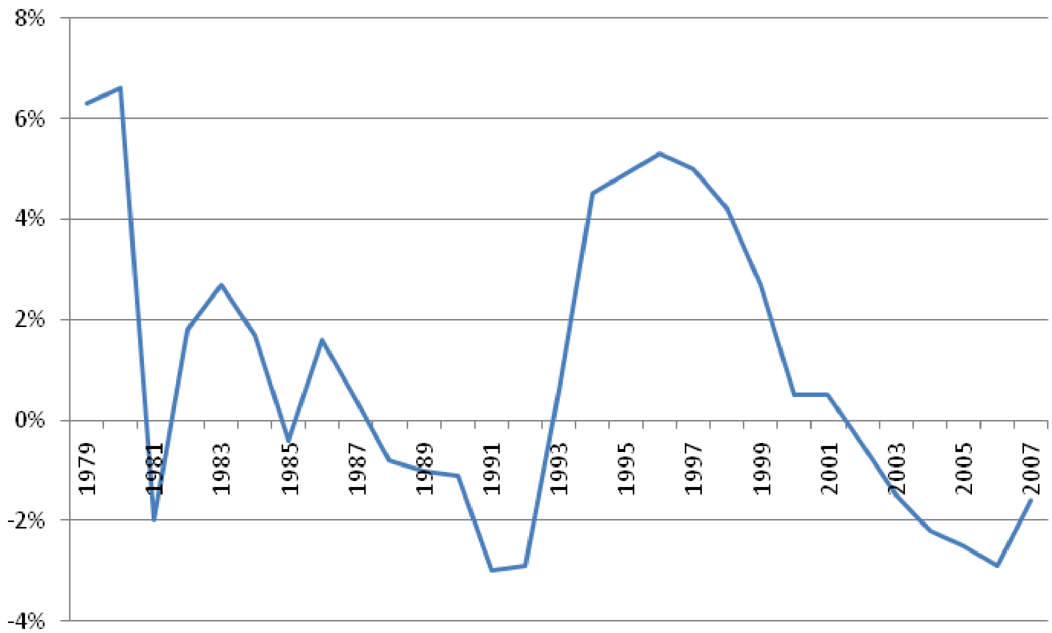


Figure 7. Unexplained Syndication vs. Internal Rates of Return
Venture Capital Funds' IRR
Unexplained Syndication (Residual)
120%
100%
80%
60%
40%
20%
0%
-20%
15%
10%
5%
0%
-5%
-10%
-15%
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
Venture Capital Funds' IRR
Unexplained Syndication (residual)

Figure 8. Coefficient of *First Round Syndicated?*, 5-year Rolling



Appendix I

According to Kaplan and Stromberg (2004), there are four agency problems that concern venture capitalists. The first is that the entrepreneur will shirk post-investment. The second related agency problem is that the entrepreneur knows his or her ability and/or company better than the venture capitalist does. Third, venture capitalists worry about future disagreements with entrepreneurs about uncertain topics. Finally, an entrepreneur can "hold up" the venture capitalist with a threat to leave at an inopportune time; i.e. when the entrepreneur's special human capital is particularly in demand.

The first two agency problems (lack of knowledge about the entrepreneur's skill, work ethic, or motives) can be remedied with pay-for-performance incentives. The most common of these is stock options, which allow the entrepreneur to increase his or her equity stakes if certain performance benchmarks are hit. These benchmarks can be tied to sales, profits, the development of a patent, or the acquisition of a large customer. Redemption rights may also be used to combat the first two agency problems. These allow the VC to demand repayment of the VC's claim at a stated liquidation value at a stated time post-investment. This claim may even exceed the VC's cumulative investment. Finally, antidilution provisions can remedy the first two agency problems. These increase the amount of shares owned by the VC in the event that the entrepreneur raises future capital at a lower valuation.

The third agency problem (potential future disagreements) can be negated with strong control rights. The most common of these allow the VCs more seats on the board in negative states of the world.

The final agency problem ('hold-up') can be diminished via time vesting of the entrepreneur's shares, making it less likely that he or she will choose to leave at a critical time.

Appendix II

Dimov and De Clerq (2006) examine the portfolios of roughly 200 venture capitalists from 1990-2001 and find that heavier syndication rates are associated with lower performance. They put forward two possible reasons for this. The first is that syndication may lead to a reduction in each VC's perceived responsibility for the success of the investment. In these situations, there may be less incentive to escalate commitment to the venture. The second reason is social loafing, or free riding. Venture capitalists may be less likely to exert effort if they believe it is possible that another venture capitalist may provide it.

Guler and McGahan (2007) also cite social loafing as a potential downside of syndication along with two others. First, more venture capitalists mean higher dilution of ownership. This may lead to higher coordination costs and a more complicated decision-making process. The second reason they cite is an increased risk of expropriation of the entrepeneur's idea. The more venture capitalists are involved, the better the chance one may leave the syndicate to start a company with a similar product.

Guler (2007) mainly examines downsides to staging, but a few of these relate directly to syndication. Her study documents reasons that venture capitalists may 'throw good money after bad'. In her extensive survey of venture capitalists, she finds that syndicate partners often drive this negative phenomenon. One way is through coercive pressure applied through contractual provisions. Specifically, venture capitalists can structure subsequent rounds of funding so as to dilute the shares of the ‘defecting’ venture capitalist in what is termed a ‘washout round’. Another pressure to continue co-investing comes from the fear that future syndication opportunities could dry up. A representative quote reported by Guler (2007) was “There’s a little bit of reputation involved, and you want to show good faith to your co-investors.”

Appendix III

Venture capitalists add value to syndicates (and thus their portfolio companies) in multiple ways. A local corporate venture capitalist I spoke with believed he was invited to join syndicates because he had more detailed knowledge about the industries and products relevant to the entrepreneurial companies in which he was investing. Similarly, a separate local venture capitalist told me that when seeking syndicate partners, the first thing he sought was ‘somebody who knows the space’, i.e. the industry. Echoing this point, a venture capitalist from the Southeast indicated that bringing in an investor with experience in the industry may have a positive impact on the company’s valuation that round. But if the VC’s experience was mainly in another industry, it may have a neutral (or even negative) impact on the valuation.

Venture capitalists also add value via their business networks. Gompers and Reitz (2000) provide an intriguing example. In October 1998, Battery Ventures invested in Akamai Technologies, knowing that two of the three founders were short on business experience. One founder was a computer scientist from academia, while the other was a PhD student. Loosely speaking, they were ‘idea men’ rather than businessmen. One member of the founding team did have a few years of business experience before getting his MBA, but this wasn’t nearly enough. Battery Ventures was able to remedy the situation by bringing in a business partner who had served as president and editor of Time Inc. News Media to become Akamai’s president and Chief Operating Officer. Battery Ventures also brought in another venture capitalist, Polaris Venture Partners, to join the syndicate. One of their partners, who had years of operating experience at GTE and IBM, was willing to serve as chairman and CEO of Akamai. Today, Akamai brings in nearly $1 billion in revenues as a dominant player in the global Internet content and application delivery business.

Chapter 3

What Does the Corporate Bond Market Know?

Abstract

Do smaller, less liquid markets reveal information about larger and more liquid related markets? Using TRACE bond data, we investigate this question for the period July 2002 through December 2008 for 1,167 bonds issued by 442 firms. A firm's traded corporate bonds partially anticipate its stock price movements by one to three months. A decline of 10% over three months of a firm's bonds is associated with an ensuing cumulative stock-price decline of 3% to 6%. Estimates that take into account stock reversal increase the size and stability of the effect. Stocks with the lowest prior bond returns and highest prior stock returns have the lowest current stock returns. Bond categories with greater volatility (high-yield, greater trading volume, high coupons, and volatile associated stock) show the largest stock price declines in the wake of a large bond price decline. The effect is non-linear, with bond price declines signaling lower future stock prices, but bond price increases having no effect once stock reversal is taken into account. Possible explanations for the lead of bond prices over stocks include the focus of bond analysts on negative results, the use of credit-default swaps as venues for informed trading (including insider trading), and the influence of noise traders on equity prices.

1. Introduction

Do smaller side markets anticipate returns in a larger, related market? Surprisingly, a growing body of research suggests they often do.

Zitzewitz (2006) provides an intriguing example. He finds that a relatively obscure prediction market for short-term changes in the Dow Industrial Average helps explain actual short-term volatility in the Dow incrementally to actual historical volatility and CBOE options. In the same vein, and perhaps less surprisingly, Pan and Poteshman (2006) report that stocks with low ratios of put-to-call volume outperform stocks with high put-to-call ratios. In a recent paper more closely related to our topic, Altman, Gande and Saunders (2010) offer evidence on the ability of the market for traded bank loans to predict bond price movements around defaults and other "information intensive events."

We investigate whether "smaller-anticipates-bigger" holds for two related markets in which, at first glance, it would seem unlikely that the smaller, less-intensively followed and often quite illiquid market would convey any additional information not already impounded in the larger market. Corporate bond trading is in fact notoriously spotty, illiquid and confined to less transparent over-the-counter markets. For our sample of bonds already sifted for liquidity, the median number of trades per day is 1.7 and no trades occur at all on 47 percent of trading days. Given such sparse trading, it would seem unlikely that a firm's bond price would contain information about that firm's prospects not already incorporated in its stock price. In fact, the bulk of existing research on bond-stock interaction finds that a corporation's bonds are less efficiently priced and lag its stock price.[3]

That presumption and evidence aside, bond markets may nevertheless reflect information before stock markets for three reasons. First, bond traders and analysts may be better attuned to negative news and to what is happening with a company's balance sheet. Second, a company's stock, though more liquid, may nonetheless be more subject to noise trading and implausibly optimistic assessments, as well as practical limits on short selling. Lastly, and perhaps most importantly, the advent of credit default swaps for corporate bonds has generated markets in corporate credit risk that are not only more liquid than the bond market but quite likely a venue for informed and insider trading. The CDS market effectively allows short sales; its synthetic nature results in low transactions costs; and insider trading in credit default swaps has only been prosecuted once and may in fact be legal. Also, a theoretical arbitrage relationship exists between a corporation's corporate bonds and credit default swaps written on the same bonds. While arbitrage trades may not be possible in most cases, CDS prices provide very direct information on the "right price" of corporate bonds and may do so before the stock market fully reflects that information.

Our work examines the ability of a company's bonds to predict what will happen to its stocks by using recently available TRACE bond data for 1,167 bond-stock pairs for the period July 2002 through December 2008. We regress current stock returns on lagged bond and lagged stock returns to assess whether past bond

[3] Kwan (1996), Hotchkiss and Ronen (2002) and Gebhardt et al. (2005). We emphasize below that these studies look at comparatively short lags.

price movements partially anticipated stock price movements. It turns out they do. A firm's traded corporate bonds partially anticipate its stock price movements by one to three months. A 10% decline in bond prices over twelve weeks has an estimated cumulative effect on stocks in the range of -3% to -6%. There is substantial evidence of an asymmetric effect, with bond price declines more powerful than bond price increases. The effect appears consistently across different bond characteristics, including different maturities, coupon yields, trading frequencies of the bonds, and volatility of the associated stock. Bond categories with greater bond return volatility (high yield, greater trading volume, high coupons, and volatile associated stock) show the largest stock price declines in the wake of a large bond price decline.

One very important conditioning variable is the concomitant lagged change in a company's own stock price. We find substantial reversal in our sample, admittedly heavily weighted toward the financial crisis year of 2008, and including lagged stock price changes increases the stability and typical size of our lagged bond coefficients.

It bears emphasis that regressions using lagged bond returns constitute weak tests of the proposition that "bonds predict stocks." If bonds sometimes anticipate stock price movements, they will do so episodically and with varying lags, and not gradually. For some bonds, a major decline associated with, say, premonitions of financial distress may come a week before the stock decline, and in other cases a month earlier. Also, given a corporation's capital structure and expected volatility of its cash flows, there is an equilibrium theoretical relationship between its bond and stock price. Thus, it may be possible to construct more powerful tests of violations of the equilibrium relationship of the bond and stock prices of a corporation that does not impose a functional form on the lag structure.[4]

Our findings add to recent work on the flow of information between related markets. For example, industry portfolios help predict stock market movements in major stock markets [Hong, Torous and Valkanov (2007)], and oil price shocks appear to anticipate general market movements world wide [Driesprong, Jacobsen and Maat (2008)]. Because we focus on the relationship between trading in a firm's fixed income instruments and its stock, our work is most closely related to recent research on the influence of the credit default swaps written on a firm's bonds and its stock price [e.g., Berndt and Ostrovnaya (2008)]. However, that work, which finds that CDS markets lead bonds and stocks, is typically based on a relatively small number of bonds and corporations, and a relatively short time period. The small sample size seems to be a function of the difficulty or expense of obtaining credit default swap data.

While we do not include CDS data, we bring more information to bear in two dimensions. We use substantially more bonds and firms, and we cover a longer time period that includes the financial crisis that began in 2007. The interaction with prior stock returns suggests that lagged bond returns have their biggest effects for stocks subject to price-pressure and illiquid trading, consistent with the work of Avramov, Chordia and Goyal (2006) on the origins of short-term stock reversal.

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[4] We are thinking of the literature spawned by Merton (1974). For recent empirical work, see Eom, Helwege and Huang (2004).

2. Previous Research

In a classic efficient markets framework, past information is irrelevant for future returns. However, a growing body of research supports the notion that asset prices sometimes react to new information with a lag. The best-known and now-classic examples include the momentum effect (stocks exhibit momentum over medium-term intervals of several months to a year) and the continued positive drift of stock prices after earnings announcements. Other work documents instances in which prices in one market appear to anticipate prices in another related market. A key issue is the length of the lag between the recognition of new information and its incorporation in asset prices. Some studies focus on lags of a minute, others several months or a year. Our work focuses on cross-market lags of several weeks to several months. Another important task involves reconciling such findings with our understanding of what moves markets. We will first review the empirical literature and then the relevant theoretical work.

Return Anticipation in Related Markets. Pan and Poteshman (2006) find that relative put/call options volume predicts stock price movements, consistent with the view that informed traders use the options markets. A deeper link with our paper comes from their observation that informed traders may prefer to trade in the increasingly important derivatives market rather than the reference asset. They site the higher leverage available with options. Indeed, Pan and Poteshman find that non-public signals have a stronger and more lasting lagged effect, which plays itself out over several weeks. There may be other institutional or regulatory reasons for some informed trades to take place in the options market. For example, acquirers have an incentive to purchase call options on a target in advance of a takeover, thus internalizing some of the run-up in stock price that occurs with an announcement. An acquirer can capture some of the increase in a target's price by purchasing call options before crossing the 5% disclosure hurdle.

At a higher level of aggregation, Hong, Torous and Valkanov (2007) report that past industry-level returns help predict aggregate market returns at lags of one to two months, both in the U.S. and in foreign markets. They appeal to a possible lag between the recognition of new realities at the industry-level and when those realities become reflected in broader indices. In addition, they suggest that many investors may not be able to extract information from asset markets they do not follow closely. Finally, they point out that few investors trade in all assets; rather, investors specialize. Related work by Driesprong, Jacobsen and Maat (2008) shows that increases in oil prices result in lagged effects on equity prices worldwide, with the strongest lag at one month. They appeal to theories in which private information diffuses gradually [e.g., Hong and Stein (1999)].

Perhaps the most surprising finding along these lines comes from Zitzewitz (2006), who finds that the relatively small prediction market for short-term Dow stock-index changes adds extra explanatory power to a model that predicts realized volatility of the index based on past volatility and standard traded options. A possible explanation comes from a study by Tetlock (2007), who looks at sports betting markets and finds that increased liquidity often decreases the accuracy of sports betting markets, consistent with the view that noise traders play a bigger role in more liquid markets and may slow the incorporation of relevant information in asset prices.

Good News and Bad News. Equity markets do not seem to digest good and bad news the same way. The classic study by Bernard and Thomas (1989) found post-announcement drift when announced earnings come in below expectations. Chan (2003) finds strong drift after bad news but not good news, with the effect stronger among firms with lower capitalization and less liquid stocks. This is relevant for our study since we find – once the effect of stock reversal is taken into account – that a bond price decline results in a substantial future decline in stock prices, but bond price increases do not result in future stock price increases. A good-news bias may be at work, though other factors, notably the inherent focus of bond markets on downside risk and the intrinsic non-linear relationship between bond and stock prices may also play a role.[5]

Return Anticipation by Bond Markets and Related Venues (other credit markets). Most work relating bond and stock markets focuses on the ability of a company's relatively liquid stock market to predict bond price movements. The lead of stocks over bonds tends to be quite strong. Research that looks at the ability of bond returns

[5] Along the same lines, DeFond and Zhang (2009) find that bond markets anticipate bad news earnings surprises, but not good news earnings surprises. Johnston, Markov and Ramnath (2009) report that companies in distress receive more debt research.

to predict stock returns offers mixed results. It is also based on substantially less data than we use here.

Kwan (1996) represents an early study. He looks at 702 bonds for 327 firms for 1986 to 1990, regressing current weekly bond yield changes on lagging, current, and leading stock changes. Lagged stock returns have a negative effect on yields (hence positive effect on bond prices), while leading stock returns are not statistically significant, indicating that bond prices do not anticipate new developments in the stock market. It bears emphasis that this period pre-dates the development of credit default swaps, which we discuss below.

Hotchkiss and Ronen (2002) look at 55 high-yield bonds for twenty firms on NASD's Fixed Income Pricing System (FIPS) and focus on short-term, hourly and daily results for January – October 1995. They find similar efficiency across stocks and bonds at intraday frequencies in reacting to earnings news. The relatively small sample size and possibly unrepresentative nature of the sample preclude confident generalization to all bonds or other periods. They also do not examine weekly or monthly lags, understandable given the nature of their data.

Gebhardt, Hvidkjaer and Swaminathan (2005) look at much longer frequencies and find evidence of spillover from equities to bonds at annual intervals (companies whose stocks do well have bonds that do well the following year), based on data from 1973 through 1996. Their Table 2 forms portfolios of firms on the basis of the previous six-months' bond returns and various bond characteristics (rating, trading volume, face value and variance), and tracks the stock returns over the ensuing two to seven months after portfolio formation. There is no apparent relationship. Again, their period predates the advent of the CDS market for corporate bonds, and they focus on returns over very long periods and longer lead-lag relationships than we examine here.

Downing, Underwood and Xing (2009) take up both hourly and daily returns with the same TRACE data we use, but for a more limited period, October 2004 through December 2005 (rather than December 2008). They focus on 3,000 bonds issued by 439 firms and the associated stocks, and run Granger temporal-correlation tests using hourly and daily returns, with a maximum daily lag of five days. Their focus is on the influence of stocks on bonds, and they find that stock returns predict returns on BB- and junk-rated bonds at daily and hourly frequencies. They do test influence in the other direction, and their tests of cross-effects of bonds on stocks for individual bonds reject the null hypothesis of no effect for a slightly larger fraction of bonds than would be expected by chance, at least for BBB and Junk-rated bonds (Table 5, p. 1093). However, their lags are quite short and their data do not include later years, when many more bonds came to be included in TRACE and the bond markets experienced a burst of volatility.

Altman, Gande and Saunders (2010) show that fluctuations in traded bank loans anticipate fluctuations in bonds around defaults for a sample of 176 firms. The reverse is not true: bond price changes do not anticipate changes in the price of traded bank loans. They examine lag lengths of ten days, and their coverage runs from November 1999 through October 2007. The authors find confirmation for the view that traded bank loans reflect more informed trading because banks have a continued incentive to monitor the borrowers.

We have already alluded to the prior research showing that stocks lead bonds, and do so in a robust fashion. Nonetheless, some evidence exists that bond analysts contribute to a more efficient equity market. Gurun, Johnston and Markov (2009) look at the effect of bond sell-side reports for 921 companies over the period July 2002 through December 2004, and find that bond prices lag stock prices less in the presence of sell-side reports.

The Increasing Role of Credit Default Swaps. Credit default swaps constitute a major and largely hidden force affecting the corporate bond market over the past decade. A credit default swap is an insurance contract written on a bond, and importantly for the purpose at hand, the CDS market is plausibly the preferred venue for informed and insider trading. First, the CDS market makes it possible to sell a bond short, in effect. Second, CDS's are synthetic, making long and short sales relatively frictionless. They are simply side bets. Third, they take place on the over-the-counter market and are largely unregulated. The status of insider trading with CDS's is contested, and the SEC filed its first insider trading case against CDS trades only in 2010.[6]

[6] Kara Scannell, Serena Ng and Alistair MacDonald, "Can Anyone Police the Swaps?" Wall Street Journal, August 31, 2006. The industry trade group, the International Swaps and Derivatives Association, contends the U.S. Securities and Exchange Commission has no jurisdiction. The article was occasioned by several instances in which, "prices of swaps climbed in the weeks before news of major acquisitions became public." The first insider-trading case based on trading in credit default swaps went to trial in April 2010. Thom Weidlich, "Rorech Testifies in First

Finally, there is a theoretical arbitrage relationship between the CDS premium and the credit spread on a bond. [See Blanco, Brennan and Marsh (2005).] While bonds are not typically sold short, the CDS spread nonetheless offers signals about the underlying value of the bond.

It bears emphasis that the volume of credit default swaps has grown by leaps and bounds over the last decade. According to the International Swaps and Derivatives Association, the notional amount of credit default swaps increased from $919 billion in 2001 to $30.4 trillion in 2009.[7] Although the notional amounts are misleading guides to net positions because investors often hedge (say going long the CDS on a five-year bond and shorting the CDS on the ten-year), these statistics likely convey an accurate sense of the growth of the market.

Not surprisingly, a growing body of research supports the idea that the CDS market is the venue for informed trading in corporate bonds. Blanco, Brennan and Marsh (2005), using a sample of 33 corporations for January 2001 through June 2002, find that credit default swaps lead corporate bonds and thus contribute to price discovery in the corporate bond market. Acharya and Johnson (2007) take up the question of insider trading in credit derivatives for a sample of large firms over the

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Insider-Trading Credit-Default-Swap Case," Business Week, June 12, 2010. http://www.businessweek.com/news/2010-04-21/rorech-testifies-in-first-insider-trading-default-swap-case.html

[7] International Swaps and Derivatives Association, ISDA Market Survey, http://www.isda.org/statistics/historical.html. The ISDA data begin with 2001, but are consistent with Longstaff, Mithal and Neis (2005, p. 2214), who report notional amounts of $180 billion in 1997 and $2.0 trillion by 2002 (close to the $2.1 trillion reported by ISDA).

period January 2001 through October 2004. They find that credit default swaps anticipate market movements and that this ability to anticipate is stronger the greater the number of bank relationships a firm has and the greater its financial stress.

Additional evidence on the strong role played by the CDS market in informed trading comes from Berndt and Ostovnaya (2008) in a study based on 144 firms over the period January 2002 through November 2006. They find, intriguingly, that while both CDS and options markets anticipate stock price movements, only those signals also confirmed by the CDS market result in stock price changes.[8]

The Question of Lags. In our summary above of previous work on the link between bond and stock markets we emphasized the lag length and noted that nearly all of the work to date looks at relatively short lags: hourly to one week [Kwan (1996), Hotchkiss and Ronen (2002), Downing, Underwood and Xing (2009).] One study goes to the other extreme and looks at cross-relationships at six-month to annual intervals [Gebhardt, Hvidkjaer and Swaminathan (2005).] This leaves a gap, especially since in other contexts it is clear that asset prices reflect certain types of information with a lag of several weeks to several months. Bernard and Thomas

[8] In addition to research on the effects of the CDS market, there have been many recent studies regarding the introduction of TRACE and its impact on the corporate bond market. Edwards, Harris and Piwowar (2007) find that the introduction of TRACE reduced transactions costs on corporate bonds. Goldstein, Hotchkiss and Sirri (2005) similarly find that the introduction of TRACE increased transparency and liquidity (in terms of bid/ask spreads) within the corporate bond market. Lastly, Bessembinder, Maxwell and Venkataraman (2005) report decreased transactions costs, increased liquidity, and increased competition in the corporate bond market post-TRACE. All three of these papers provide support for the hypothesis that the corporate bond market has become more transparent.

(1989) found continued post-earnings-announcement drift up to and perhaps beyond sixty days. An even more extreme manifestation comes from Dichev & Piotroski (2001), who find that bond downgrades mark the beginning of several years of stock price declines. Similarly, Karpoff & Lou (2009) show that for stocks of companies that reveal mis-stated earnings, short interest not only anticipates the restatement and stock price drop, but does so as far as 19 months in advance. Finally, Hong, Valkanov and Torous (2007) and Driesprong, Jacobsen and Maat (2008) find significant lags at monthly intervals.

Thus, lags of several weeks to several months have been neglected in the literature on the bond-stock relationship, and other research suggests that this a plausible interval for further investigation.

Short-Term Stock Reversals. In the work below, we find significant negative autocorrelation of stock returns. In our sample, a 10% increase in stocks over three months is associated with a 2% to 3% cumulative decline in stocks. The magnitude may be specific to our sample of companies with traded bonds, but the general finding is consistent with work by others. Avramov, Chordia and Goyal (2006) find reversals at weekly and monthly intervals. Far from representing a violation of market efficiency, they conclude that these reversals occur in high-turnover, low-liquidity stocks in response to price-pressure and do not represent a tradable opportunity for a contrarian strategy. In our setting, stocks subject to reversal may be those whose prices are determined by transitory, non-fundamental factors. These are plausibly also the stocks for which price changes in the bond market lead changes in the stock market.[9]

Conceptual Framework. Under what conditions do asset prices reflect information with a lag? In our context, when is there a significant lagged cross-correlation between related markets?

One line of theory emphasizes the slow spread or realization of information in markets that appear for all intents and purposes to be liquid. Hong and Stein (1999) develop a model in which information spreads slowly among informed traders, leading to short-term momentum and long-term reversal. (Their stylized facts do not take into account the short-term reversal we and others have found.) Theirs is the framework adopted by Hong, Torous and Valkanov (2007) and by Dreisprong, Jacobsen and Maat (2008) to explain why aggregate stock markets react with a lag to developments in major sectors such as energy. Thus, participants in the lagging market have limited ability to evaluate the information generated in the leading market. Note in the current context, each market – bond or stock – could lead in recognizing one type of information such as the likelihood of default and lag in recognizing another type of information such as an uptick in revenue.

An alternative theory to explain why one market would lag the other appeals to investor sentiment that takes stocks from fundamentals. For example, Baker and

[9] Consistent with this finding, Chordia et al. (2009) find that post-earnings-announcement drift takes place predominantly with illiquid stocks and transactions costs would nullify much of the gain from the implied long-short strategy.

Wurgler (2007) propose that small companies, companies in growth industries and others that may be subject to investor sentiment may be pulled from true value. These are also stocks that are hard to arbitrage and hard to value. One might argue that the bond markets for these companies are relatively less susceptible – though clearly not immune – to these waves of sentiment.

3. Data Description

In an effort to bring much-needed transparency to the over-the-counter (OTC) corporate bond market, the National Association of Securities Dealer (NASD) began a real-time price dissemination service called the Trade Reporting and Compliance Engine (TRACE) on July 1, 2002. As a result, 100% of OTC activity representing over 99% of total U.S. corporate bond market activity can be accessed through the TRACE system today. This unique dataset allows us to assess the informational efficiency of the corporate bond market relative to the stock market on a scale much larger than past research allowed (NASD – TRACE Fact Book (2006)).

Of course, the TRACE system has evolved since its start date. Phase I of TRACE was launched on July 1, 2002, at which time it only included Investment Grade debt securities that had an initial issue of $1 billion or more (along with 50 FIPS securities). By the end of 2002, NASD was disseminating information through TRACE on roughly 520 securities (NASD – TRACE Fact Book (2006)).

On April 14, 2003, TRACE implemented Phase II, which brought in all Investment Grade securities of at least $100 million par value that were rated A3/A-or higher, a group of 120 Investment Grade securities rated Baa/BBB, and 50 High-Yield bonds. This extended the total number of bonds covered to roughly 4,650 (NASD – TRACE Fact Book (2006)).

The last phase (Phase III) began on October 1, 2004, and was fully effective on February 7, 2005. Post-Phase III, TRACE now captures 100% of OTC transactions (roughly 99% of all public transactions). During the introduction of TRACE, the time in which transactions are required to be reported has been reduced gradually. On July 1, 2002, that requirement was 75 minutes. It declined first to 45 minutes on October 1, 2003, next to 30 minutes on October 1, 2004, and finally to 15 minutes on July 1, 2005 (NASD – TRACE Fact Book (2006)).

A typical day of bond trading is characterized by large intra-day price differences that are correlated with trade size, as documented by Bessembinder, Maxwell, and Venkataraman (2006). Because of this fact, small trades may not reflect the efficient price of the underlying bond. Hence, we eliminate all trades whose value is less than $500,000, as in Ronen and Zhou (2009). Additionally, the TRACE system does not indicate whether the trade was initiated with a buy or a sell. This leads to bias from bid-ask bounce. To remedy this, we capture the midpoint of all daily trades.[10] This means nearly every daily bond price in our data set reflects trades that happened before the last daily stock transaction.

Additionally, we eliminate any bond trade that's been canceled, corrected, or halted. We also eliminate any trade marked as irregular, when-issued, or special price.

[10] Bessembinder, Kahle, Maxwell, and Xu (2009) suggest a similar strategy of using the daily weighted average price to address these two issues.

We also drop trades with prices containing dealer commissions. It is well known that the corporate bond market is markedly less liquid than the market for corporate equities. For this reason, we only include bonds in our sample that trade on average once per day over the sample period, following Downing, Underwood and Xing (2009).

We utilize a sample period from July 1, 2002 (the day Phase I started) to December 31, 2008 so as to maximize the total types of bonds in our sample. Many of the high-yield bonds were not included in Phases I or II. During the sample period, approximately 38,000 bonds from roughly 3,300 companies traded. However, since many of these bonds are extremely illiquid, our final sample consists of 1,167 bonds from 442 companies.

We then take our sample of bond prices and merge it to stock prices from CRSP by company. Because of the fact that bonds don't trade every day, we impute a zero return for the bond on those days. It should be noted that this biases our results against finding a relationship where bonds lead stocks.

As shown in Table 1, the mean coupon rate is 5.8%, while the median is 6.0%, indicating there is not a great amount of skewness. The upper quartile is 7.125%, and the lower is 4.875%. In terms of grade, 58% of the bonds are considered investment grade, while the other 42% are high-yield. Turning to liquidity measures, the mean bond in our sample trades on 53% of possible trading days, while the median is 51%. The upper quartile is 65%, and the lower is 42%.

The other liquidity measure displays a bit more right skewness. The mean bond in our sample trades 2.3 times per day, while the median is 1.7. The upper quartile is 2.5, and the lower is 1.2. Keep in mind that our sample is filtered so as to only include bonds that trade at least once per day (on average). At the end of the sample period, the mean bond's years to maturity is 10.6. The median is 6.7, so there's substantial right skewness here, as expected. The upper quartile is 15.1, while the lower is 4.0.

Table 2 provides summary statistics for the weekly return for each of the relevant bond characteristic measures. Besides grade and year, these measures are broken into quintiles. Because our sample includes 2008, the year of the global financial crisis, the typical weekly corporate bond return is negative 14 basis points, and the standard deviation is 3.2 percent. Higher coupon and higher-yield bonds exhibit lower returns and higher volatility. Liquidity (measured by trades per day) does not appear to be associated with returns but does appear to be associated with higher volatility. Longer-term bonds don't appear to be associated with either returns or volatility. Lastly and not surprisingly, the corporate bonds of the most volatile stocks exhibited the lowest returns and the highest volatility.

4. Econometric Specification

Consider bond-stock pair i in a pooled regression model. The return of stock i in week t, rs_{it}, is represented as a function of the lagged returns on bonds over the three previous four-week periods, $r\bar{b}_{i,t-k}$, ending in weeks t-1, t-5 and t-9, and also as a function of the lagged returns on stocks in the same three previous four-week periods,

$\bar{rs}_{i,t-k}$, again ending in weeks t-1, t-5 and t-9. In addition, to allow for non-linearities, we add an interaction with an indicator variable $D_{i,t-k}$, k = 1, 5 or 9, that takes on the value of one if the four-week bond return ending with week t-1, t-5 or t-9, respectively, was negative. Thus:

$$rs_{it} = a + \sum_{k=1,5,9} \delta_{i,k} \bar{rb}_{i,t-k} + \sum_{k=1,5,9} \gamma_{i,k} D_{i,k} \bar{rb}_{i,t-k} + \sum_{k=1,5,9} \phi_{i,k} \bar{rs}_{i,t-k} + \varepsilon_{it} \qquad (1)$$

Note that the estimated cumulative effects will be four times the sum of the estimated coefficients. Thus the cumulative effect of lagged *positive* bond changes over weeks t-1 through t-12, will be

$$4 \bullet \sum_{k=1,5,9} \delta_{i,k} \, .$$

The cumulative effect of all lagged bond price changes (both positive and negative) will be

$$4 \bullet \sum_{i=1,5,9} (\delta_{i,k} + \gamma_{i,k}).$$

In the work below, we report the three estimated four-week coefficients for a few base cases in Tables 3 and 4, and then in subsequent tables provide only the summed effects.

5. Empirical Results

Table 3 shows the results for Equation (1) for our entire sample of 1,167 bond-stock pairs over the period July 2002 through December 2008. In a simple model that includes only lagged bond returns over the previous twelve weeks (Column 1), the cumulative effect sums to 0.12. Thus, a 10 percent decline in bond prices is associated with a subsequent decline of stocks of 1.2%. Note that for this simple case the effect for Weeks 1-4 and Weeks 5-8 is strongly positive, and the effect for Weeks 9-12 is strongly negative.

In a model that also includes the indicator variable for declines in bond prices (Column 2), the results suggest an inverted-V, with negative coefficients summing to less than zero for bond price increases and a positive sum of coefficients for bond price declines. The net effect on stock prices in a sustained down market for bonds (the base effect from the regression plus the effect if the bond market is in decline) is still negative, with a coefficient again of 0.12. However, the net effect of sustained bond-price increases is negative.

The last two columns show the effect of including prior stock returns. In the sample here, which is restricted to stocks with traded bonds and which includes disproportionately the crisis year 2008, the cumulative effect of lagged stock returns is -0.30. Thus, a 10 percent increase in stocks over the previous twelve weeks is associated with a cumulative subsequent decline of 3%. The value of the estimated effect of lagged bond changes is strongly affected by the addition of lagged stock changes, however. The effect of past bond returns is now much more strongly positive and confined to down markets. Without dummy variables for negative past bond returns, the cumulative coefficient is 0.53. With those dummy variables, the effect is 0.59, but only for the down market. Prior bond price increases, once lagged own-stock-price effects are accounted for, have no effect on current stock prices.

Table 4 repeats the estimates in Table 3 for bond-stock pairs restricted to each company's most liquid bond. This addresses the heavy weighting of certain companies. For example, General Electric issued 31 of the bonds in our sample, and Ford issued 20 bonds. Implementation of this filter brings our sample down to 442 bond-stock pairs, each representing a distinct company. With this restricted sample of more liquid bonds, we find the effect of past bond returns is lower, roughly half as strong, though still substantial.

Column 2 shows the same inverted-V we found in Table 3, but a lower and now insignificant net cumulative effect of 0.07. We again get the largest effect for the last two specifications, which include lagged stock returns. In Column 4, the cumulative effect of bond price changes in the base case is close to zero (-0.04), while the effect in a down bond market is strong and positive (0.35), with a net effect of 0.31. Note that for this sample of most-liquid bonds, the cumulative coefficient of past stock returns is substantially less, -0.16.

Tables 3 and 4 are based on all firms in our sample. In the work that follows, we investigate the stability of the positive lagged effect of corporate bond price changes on stock prices. One aim in these breakouts is to look for influential observations or influential circumstances. If the results in Tables 3 and 4 are stable for plausible partitions of our sample, it should strengthen the conclusion that they are not to due to outliers or the special circumstances of a particular crisis, for example. If there are variations across subsamples, we expect the effect to be largest in instances where bond trading (and in the background, CDS trading) attracts informed investors; and where stocks are, in effect, influenced by the opposite, where they are most likely to move away from fundamentals for weeks and months at a time.

Table 5a breaks down our sample in three dimensions: by year, by rating, and by coupon quintile. The first panel shows the results for the years 2005 through 2008. (We omit years 2002 through 2004 because sample sizes were relatively small. In reporting the summed coefficients for lagged stock returns, we only report the results for the full model, with an indicator variable for negative past bond returns, what we call the "splined" specification.) Two features stand out. The effect was substantially positive in all years, except 2005, and stock reversals, as evidenced by negative lagged stock effects, was very strong in 2008. Also note that for 2006 increases in lagged bond effects raise stock prices, but declines in bond prices have little or no additional effect. (In other words, the relationship is linear for 2006.) The strong bond market and arguable "credit bubble" of 2006 may have contributed to this effect.[11] It bears emphasis that panel regressions for single years are "short and fat," heavily weighted toward cross-section results and reflect the bond and stock market dynamics of a particular year.

[11] "Off the Run: Risk Concerns Falter Before Need For Yield," Wall Street Journal, March 1, 2006.

The middle panel of Table 5a shows the results broken down by bond rating, either high yield or investment grade. The simple lagged effects, without consideration of stock reversals, is positive for high-yield bonds and negative for investment grade bonds. However, once we control for lagged stock returns, the net effect is positive for both categories of bonds. Perhaps surprisingly, the effect is larger for the less volatile investment grade bonds. Perhaps investment grade bonds have more informed trading; perhaps in this sample, heavily weighted toward the crisis years 2007 and 2008, those investment-grade firms (often firms like Citibank and Morgan Stanley) moved farthest from fundamentals.

Finally, the bottom panel of Table 5a breaks down our regression by coupon yield quintile. Again, we find largely consistent results: for all but the fourth quintile (coupon of 6.515% to 7.50%), the lagged coefficient is positive. In three of the five quintiles, the effect is large for negative bond returns by a wide margin. Consistent with our findings for bond ratings, low-coupon and presumably original-issue investment-grade bonds have the largest coefficients. One possibility for the lower coefficients on high-yield and high-coupon bonds is the inherent volatility and uncertainty about what constitutes "right price." Thus, the estimates for these bonds may be subject to an errors-in-variable problem and attenuation bias. (Unusually high or unusually low bond returns may reflect, in part, the noisiness of their return series.)

Table 5b provides parallel results, but broken down by maturity, trades per day, and the standard deviation of the associated stock return. Except in one case, the net coefficient for a decline in bond prices is significantly positive, falling in the range of 0.35 to 1.01. In all cases, there is pronounced short-term stock reversal, with coefficients ranging from -0.14 to -0.56. In all cases, adding lagged stock returns results in a large, more positive sum of coefficients for lagged bond returns.

Given the non-linear nature of the relationship between lagged bond returns and current stock returns, scatter-plot representations provide compact summaries of the data. The scatter plots also serve as a check on the regression results. In each case for Figures 1- 8, we sort the bond-stock pairs into deciles based on the prior four-week bond return, and compute the mean lagged four-week bond return and the current weekly stock return.

Figures 1a shows the results for all 1,167 bond-stock pairs. The scatter plot is based on the most recent four-week bond and stock return used in the Table 3 regressions. Thus, it captures only the immediate four weeks and not the full twelve weeks used there. The scatter plot shows the inverted V-relationship we found in Column 2 of Table 3. For the eight lowest bond-return deciles, there is a pronounced positive relationship between prior bond returns and current stock returns. For the very top bond-return decile, the relationship appears negative. Recall, these results do not control for mean reversion in stocks. (Recall also, an estimate of the full cumulative effect requires multiplication of the weekly stock return by four. Thus, for the bottom bond-return decile, bonds declined -11.22% over the previous four weeks, and stocks declined -1.43% over one week. The cumulative effect is -1.43% x 4 = -5.72%.)

Figure 1b shows the same scatter plot based on the most liquid bond for each company. The same pattern still emerges, though the plot does not have the same strictly linear relationship. Declines in bonds presage declines in stocks. The situation is a bit more ambiguous for increases in bonds, with very large bond price increases taking place ahead of slight declines in stock prices.

The scatter plots in Figure 2 address the role of prior stock movements. We sort the bond-stock pairs into quintiles based on the stock price movement over the previous four weeks and then within each quintile create portfolios based on the bond-return deciles. For all quintiles, the positive relationship of prior bond price changes and current stock price changes remains evident.

We do find some unusual behavior for the stocks with the greatest decline. If both bonds and stocks had strong drops (bottom decile in Figure 2a), the current weekly stock return is in fact close to zero. For the other four quintiles, the scatter plots present a tidy picture. Substantial bond-price declines subsequently result in lower average stock prices. Note that for the top two quintiles, this is true only for companies with the most troubled bonds.[12] It is worth noting that the inverted-V pattern is essentially absent in the middle three quintiles. This supports the notion

[12] Our results on lagged own-stock effects mirror those found in Lo and MacKinlay (1990), who report that individual stock returns show reversal, but portfolios show positive auto-correlations, the result of cross-correlations. Thus, we find negative lagged effects of a company's own stock returns, but the one week return of the quintiles is strictly increasing, except for the last quintile (-0.60%, -0.36%, -0.06%, 0.02% and -0.27%).

that the inverted-V stems from a reversal effect: strong bond returns are correlated with strong stock returns, but reversal of stock prices predicts a future decline.

Arguably the strongest test for the proposition that bond-price declines predict stock price declines comes from year-by-year results. Is this a result that holds up during different financial conditions? Ideally, we would want to look at a few decades of material. Given the recent origins of our TRACE database, we are only able to examine the four years 2005 through 2008. As we saw in Table 5, for one year, the twelve-week lagged effects of bond price changes are in fact negative.

Scatter plot results by year are shown in Figure 3. The basic positive relationship does hold across years, though the implied effect at this lag (previous four weeks only) is quite variable. Note that in three of the four years (2005, 2006 and 2008) the bottom bond-return decile does not have the worst stock returns. For 2005 stock returns for the deciles formed on prior bond returns fall in a relatively narrow band. (Recall that our cumulative regression results over twelve weeks showed a negative relationship.) All years have plots that suggest non-linearity, or other, omitted factors. This shows up especially strongly in the crisis year 2008, where the very bottom decile (a lagged four-week bond return of -20.53%) has a weekly stock return of only -1.68%, much closer to zero than implied by deciles two through seven.

Figure 4 shows that relationship between lagged bond and current stock returns is, perhaps surprisingly, very similar for investment grade and high-yield bonds. The latter have substantially more volatility, but in both cases, a non-linear relationship summarizes the results.

Figure 5 provides a breakdown by coupon, showing remarkable stability and the now-familiar lopsided inverted-V (negative effect of lagged strongly positive changes and a positive effect of lagged intermediate or strongly negative changes).

Figure 6 shows that the basic positive and non-linear relationship also holds across maturities, perhaps most strongly for the intermediate maturities. Indeed, that was the finding in our earlier regressions (Table 5b, top panel). Short-term maturities will be less prone to bankruptcy risk because of the short horizon, and creditors are less likely to lend on very long terms to troubled companies. Hence, the strongest effects come from the intermediate maturities.

Figure 7 shows very similar effects across our liquidity measure, trades per day. If one takes liquidity as an indicator of informed trading, this suggests that the ability of the bond market to anticipate stock price movements does not come from the bond side.

Figure 8 breaks down the data on the basis of stock volatility during our sample period. As stock volatility increases, so does the dispersion of bond-return deciles. However, the basic relationship holds.

6. Conclusions

We have used a newly available, comprehensive bond database (TRACE) to examine whether past bond prices can provide information about future stock prices. Our study represents a step forward in several dimensions. First, we bring to bear a much larger dataset than previous studies. The TRACE data are new and the number of bonds included has increased substantially each year. Second, we include the crisis year 2008, when both the stock and bond markets experienced unusually large changes. Third, we examine lags of several weeks to several months, which other studies have not yet addressed. Cross-market lagged effects at those frequencies have been found in other markets, but no study has addressed them in the bond market.

We find that lagged bond returns do in fact provide incremental information about the future course of stock returns. The effect is evident both in our regressions, which include lagged bond returns over twelve weeks, and in our scatter plots, which are based on the previous four weeks. We find evidence of an asymmetric, inverted-V relationship between bonds and stocks, with bond price increases being related to future stock price declines, though declines that are not as strong as those resulting from bond price decreases. However, the evidence strongly suggests that this is an artifact of short-term stock reversal. Including lagged stock returns in our regressions results in a lagged "up market" bond coefficient of essentially zero, and stratification by prior stock return in our scatter plots suggests the effect is minimal or non-existent for stocks with moderate price changes (Figure 2).

The apparent ability of past bond returns to help predict future stock returns is remarkably stable across subsamples. It holds up for investment grade and high-yield bonds, and for quintiles based on coupon rates, maturity, liquidity and stock volatility. The major exception is the year 2005, when the regressions based on bond returns over the previous twelve weeks show a negative effect. However, as the scatter plot based on bond returns over four weeks shows (Figure 3a), the relationship over a shorter period is in fact positive, though muted in comparison to the years 2006-2008.

Our work provides support for a new and important stylized fact: bond prices partially anticipate stock prices. The relatively small and illiquid over-the-counter market for a corporation's bonds contains information about the future course of its stocks. We are agnostic on whether this represents a tradable strategy. Implementing such a strategy would involve taking positions in a large number of stocks, many of them conceivably subject to large price-pressure effects. Hedge fund lore holds that theoretically profitable strategies are in fact not profitable for CRSP deciles one through six. However, these results do support the notion that price discovery and information flows may not take place instantaneously, perhaps taking weeks or months to fully reveal themselves.

Much remains to be done, in particular explaining the source of this effect and in explaining possible variations in its magnitude. If bonds predict stocks, it seems plausible that the effect will be greater for bonds characterized by relatively more informed trading and for stocks characterized by less informed trading. Thus, it might be possible to invoke measures of informed trading for both bonds and stocks.

Also, as we emphasized in the introduction, the phenomenal growth of credit default swaps written against corporate bonds, and the presumption and growing evidence that the CDS market is the venue for informed trading, even insider trading, point to an alternative research strategy of examining the links among CDS trading, bond prices and stocks. Acharya and Johnson's (2007) study of insider trading for credit default swaps takes a step in this direction. It has the limitation that it covers the years 2001 through 2004 and has a median of 46 observations per day based on 79 large corporations. Moreover, they examine lags of only five days between the CDS market and the stock market.

Another line of inquiry would examine notable historical episodes. A leading example involves telecom bonds and stocks over the period 1995-2005. Telecom underwent a boom and bust, and it was heavily financed with bonds. Did the bond market anticipate the collapse of the telecom market? If so, where was this ability strongest? A study along these lines depends on securing historical bond data from a source other than TRACE.

Finally, many of the commercial and investment banks that have storied roles in the financial crisis of 2007 and 2008 issued large amounts of traded debt – much of it insured with CDS contracts. Did the CDS and bond markets anticipate the financial crisis and its arguably rocky and incomplete resolution ahead of the stock market?

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Table 1 - Summary Statistics for Corporate Bonds

These statistics are calculated for the 1,167 corporate bonds already sifted for liquidity, i.e., at least one trade per day.

Bond Characteristic	Obs.	Mean	Std. Dev.	Min	25%	Median	75%	Max
Coupon (%)	1,167	5.8	2.3	0.0	4.875	6.0	7.125	13.5
% High-Yield	1,167	41.8		0.0	0.0	0.0	100.0	100.0
Trades per Day	1,167	2.3	1.9	1.0	1.2	1.7	2.5	14.0
% Days Traded	1,167	53.2	17.4	1.5	41.9	50.7	64.6	100.0
Years to Maturity	1,167	10.6	10.1	0.1	4.0	6.7	15.1	78.3

Table 2 - Statistical Summary of Weekly Bond Returns (%). The following statistics are weekly bond returns of the 1,167 corporate bonds already sifted for liquidity, i.e., at least one trade per day. Besides year and grade, the other bond characteristics below are sorted into quintiles.

	Obs.	Mean	Std. Dev.	Min	25%	Median	75%	Max
All bonds	142,781	-0.14	3.22	-97.01	-0.56	0.00	0.52	335.71
Year								
2002	2,276	0.34	3.23	-39.02	-0.44	0.35	1.17	35.34
2003	6,382	0.09	1.56	-15.56	-0.64	0.10	0.87	17.53
2004	10,529	0.08	1.40	-23.10	-0.39	0.00	0.54	46.82
2005	19,438	-0.08	1.63	-21.40	-0.59	0.00	0.43	27.68
2006	25,839	0.05	1.27	-17.74	-0.35	0.00	0.41	20.57
2007	34,470	-0.05	1.67	-35.01	-0.45	0.00	0.41	58.25
2008	43,847	-0.44	5.28	-97.01	-1.03	0.00	0.70	335.71
Coupon (%)								
0-4.25	28,735	-0.11	3.38	-77.08	-0.60	0.00	0.61	89.00
4.3-5.65	28,700	-0.05	2.60	-97.00	-0.44	0.00	0.45	154.55
5.7-6.5	28,533	-0.10	3.63	-63.64	-0.61	0.00	0.55	335.71
6.515-7.5	28,705	-0.15	2.68	-95.77	-0.55	0.00	0.50	58.00
7.5-13.5	28,108	-0.27	3.64	-72.13	-0.65	0.00	0.55	100.81
Grade								
High-yield	61,992	-0.29	4.08	-97.01	-0.74	0.00	0.56	335.71
Investment-grade	80,789	-0.02	2.33	-66.41	-0.47	0.00	0.50	154.55
Years to Maturity								
0.1-2.8	28,529	-0.05	2.40	-77.08	-0.33	0.00	0.33	89.00
2.8-4.4	28,466	-0.12	2.72	-55.37	-0.49	0.00	0.48	82.83
4.4-6.8	28,328	-0.25	3.33	-97.01	-0.61	0.00	0.51	100.81
6.8-17.6	28,338	-0.14	3.48	-95.77	-0.72	0.00	0.65	154.55
17.6-78.3	28,358	-0.11	3.32	-63.64	-0.87	0.00	0.82	94.04
Stock Return - St. Dev. (%)								
0.1-3.6	27,659	-0.04	2.01	-50.30	-0.42	0.00	0.47	58.00
3.6-4.7	29,483	0.00	1.76	-27.93	-0.47	0.00	0.50	30.75
4.8-5.9	28,380	-0.09	2.16	-45.09	-0.57	0.00	0.53	40.11
5.9-8.2	28,756	-0.16	4.30	-66.41	-0.71	0.00	0.61	335.71
8.2-25.1	28,502	-0.39	4.61	-97.01	-0.74	0.00	0.53	100.81

Table 3 - All Bond-Stock Pairs. Estimated coefficients from regression of current weekly stock returns on lagged bond returns and lagged stock returns for 1,167 bond-stock pairs from July 2002 through December 2008. The dependent variable is the current weekly stock return. *Prior Bond Returns* are the cumulative bond returns from the specified weeks. *Negative Bond Return?* is an indicator variable that takes the value 1 if the cumulative bond return was negative over the specified weeks. *Prior Stock Returns* are the cumulative stock returns from the specified weeks. The cumulative results at the bottom of the table are sums of the lags multiplied by 4 due to the fact that the dependent variable is weekly while the dependent variables are cumulative 4-week returns.

	(1)	(2)	(3)	(4)
Intercept	-0.002***	-0.001***	-0.002***	-0.001***
Prior Bond Return (Weeks 1-4)	0.035***	-0.031***	0.083***	0.006
Prior Bond Return (Weeks 1-4) * Negative Bond Return?		0.102***		0.126***
Prior Bond Return (Weeks 5-8)	0.032***	-0.012	0.068***	0.006
Prior Bond Return (Weeks 5-8) * Negative Bond Return?		0.047***		0.075***
Prior Bond Return (Weeks 9-12)	-0.036***	-0.005	-0.019***	0.009
Prior Bond Return (Weeks 9-12) * Negative Bond Return?		-0.072***		-0.075***
Prior Stock Return (Weeks 1-4)			-0.040***	-0.044***
Prior Stock Return (Weeks 5-8)			-0.021***	-0.023***
Prior Stock Return (Weeks 9-12)			-0.008***	-0.008***
Observations	127,406	127,406	127,238	127,238
Adjusted R^2	0.0015	0.0025	0.0055	0.0072
Sums of Bond Lags (Weeks 1-12)				
Simple (Only Prior Bond Returns)	**0.12*** **			
Splined				
Positive (or zero) Bond Return		**-0.19*** **		
Negative Bond Return		**0.31*** **		
Net		**0.12*** **		
Simple plus Prior Stock Returns			**0.53*** **	
Splined plus Prior Stock Returns				
Positive (or zero) Bond Return				**0.09**
Negative Bond Return				**0.50*** **
Net				**0.59*** **
Sum of Stock Lags (Weeks 1-12)			**-0.28*** **	**-0.30*** **

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4 - Bond-Stock Pairs - Each Stock's Most Liquid Bond. Estimated coefficients from regression of current weekly stock returns on lagged bond returns and lagged stock returns for 442 bond-stock pairs from July 2002 through December 2008. The dependent variable is the current weekly stock return. *Prior Bond Returns* are the cumulative bond returns from the specified weeks. *Negative Bond Return?* is an indicator variable that takes the value 1 if the cumulative bond return was negative over the specified weeks. *Prior Stock Returns* are the cumulative stock returns from the specified weeks. The cumulative results at the bottom of the table are sums of the lags multiplied by 4 due to the fact that the dependent variable is weekly while the dependent variables are cumulative 4-week returns.

	(1)	(2)	(3)	(4)
Intercept	-0.003***	-0.002***	-0.003***	-0.001***
Prior Bond Return (Weeks 1-4)	0.055***	0.010	0.089***	0.044***
Prior Bond Return (Weeks 1-4) * Negative Bond Return?		0.067***	0.022**	0.070***
Prior Bond Return (Weeks 5-8)	0.010	-0.033**	-0.047***	-0.029*
Prior Bond Return (Weeks 5-8) * Negative Bond Return?		0.055***		0.067***
Prior Bond Return (Weeks 9-12)	-0.055***	-0.037**		-0.026
Prior Bond Return (Weeks 9-12) * Negative Bond Return?		-0.044**		-0.050**
Prior Stock Return (Weeks 1-4)			-0.027***	-0.028***
Prior Stock Return (Weeks 5-8)			-0.004	-0.005
Prior Stock Return (Weeks 9-12)			-0.006	-0.006
Observations	40,049	40,049	40,049	40,049
Adjusted R^2	0.0030	0.0036	0.0044	0.0052
Sums of Bond Lags (Weeks 1-12)				
Simple (Only Prior Bond Returns)	**0.04**			
Splined				
Positive (or zero) Bond Return		**-0.24*** **		
Negative Bond Return		**0.31*** **		
Net		**0.07**		
Simple plus Prior Stock Returns			**0.26*** **	
Splined plus Prior Stock Returns				
Positive (or zero) Bond Return				**-0.04**
Negative Bond Return				**0.35*** **
Net				**0.31*** **
Sum of Stock Lags (Weeks 1-12)			**-0.15*** **	**-0.16*** **

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5a - Sums of Lags. The following tables display sums of lags identical to those at the bottom of tables 3 and 4. The detailed regressions are omitted for brevity. Each panel represents a different bond characteristic (year, grade, coupon, maturity, trades per day, and standard deviation of associated stock.

Sums of Bond Lags (Weeks 1-12)	2005	2006	2007	2008
Simple (Only Prior Bond Returns)	-0.20**	0.38***	0.75***	0.32***
Splined				
Positive (or zero) Bond Return	0.08	0.39***	0.14	-0.60***
Negative Bond Return	-0.54***	-0.02	1.04***	0.22*
Net	-0.47***	0.37***	1.18***	-0.37***
Simple plus Prior Stock Returns	-0.19*	0.53***	0.74***	0.49***
Splined plus Prior Stock Returns				
Positive (or zero) Bond Return	0.10	0.52***	0.16	-0.18
Negative Bond Return	-0.55***	0.01	1.05***	0.71***
Net	-0.44***	0.53***	1.21***	0.53***
Sum of Stock Lags (Weeks 1-12) - Full Model	-0.01	-0.09***	-0.03	-0.675***

Sums of Bond Lags (Weeks 1-12)	Hi-Yield	Inv't-Grade	-	-
Simple (Only Prior Bond Returns)	0.12**	0.05		
Splined				
Positive (or zero) Bond Return	-0.17**	-0.07		
Negative Bond Return	0.36***	-0.15*		
Net	0.19***	-0.23***		
Simple plus Prior Stock Returns	0.32***	0.77***		
Splined plus Prior Stock Returns				
Positive (or zero) Bond Return	0.01	0.20**		
Negative Bond Return	0.39***	0.55***		
Net	0.40***	0.75***		
Sum of Stock Lags (Weeks 1-12) - Full Model	-0.14***	-0.53***		

			Coupon (%)		
Sums of Bond Lags (Weeks 1-12)	0-4.25	4.3-5.65	5.7-6.5	6.515-7.5	7.5-13.5
Simple (Only Prior Bond Returns)	-0.002	0.32***	0.22***	-0.37***	0.31***
Splined					
Positive (or zero) Bond Return	-0.17*	-0.04	0.01	-1.15***	-0.25*
Negative Bond Return	0.19*	0.29*	0.1	0.73***	0.64***
Net	0.02	0.24**	0.11	-0.42***	0.40***
Simple plus Prior Stock Returns	0.51***	1.28***	0.71***	-0.04	0.41***
Splined plus Prior Stock Returns					
Positive (or zero) Bond Return	0.32***	0.27*	0.22**	-0.87***	-0.15
Negative Bond Return	0.20*	1.40***	0.57***	0.83***	0.67***
Net	0.52***	1.67***	0.79***	-0.04	0.52***
Sum of Stock Lags (Weeks 1-12) - Full Model	-0.36***	-0.71***	-0.39***	-0.21***	-0.09***

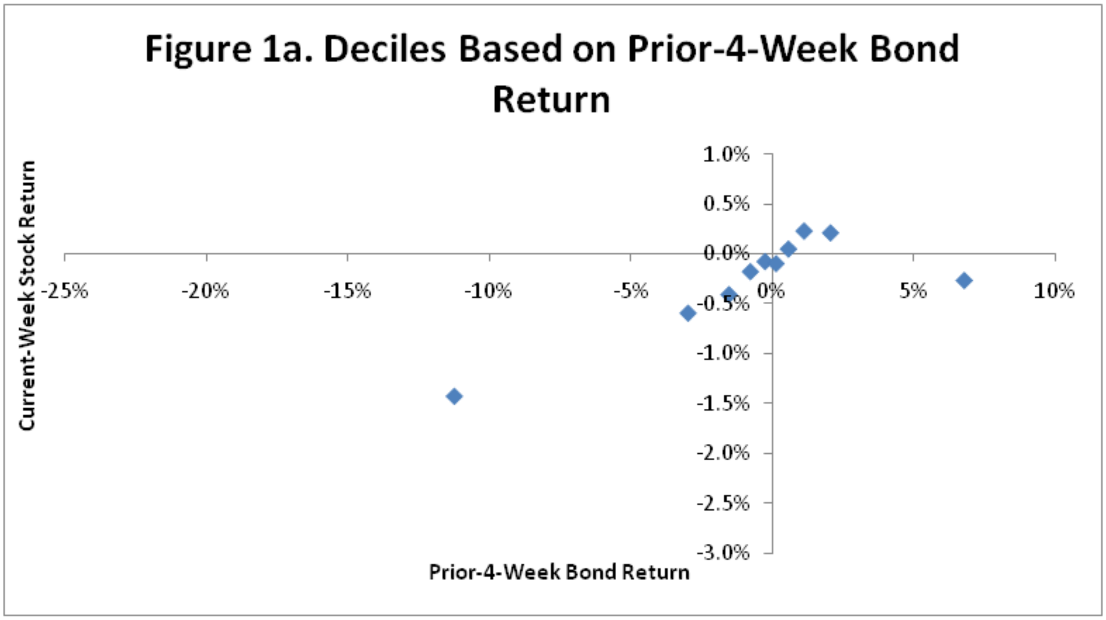
Table 5b - Sums of Lags. The following tables display sums of lags identical to those at the bottom of tables 3 and 4. The detailed regressions are omitted for brevity. Each panel represents a different bond characteristic (year, grade, coupon, maturity, trades per day, and std. deviation of associated stock.

	Years to Maturity				
Sums of Bond Lags (Weeks 1-12)	0.1-2.8	2.8-4.4	4.4-6.8	6.8-17.6	17.6-78.3
Simple (Only Prior Bond Returns)	0.01	-0.001	0.38***	-0.02	0.03
Splined					
Positive (or zero) Bond Return	-0.03	-0.61***	-0.52***	-0.06	-0.21**
Negative Bond Return	-0.15	0.64***	1.05***	-0.06	0.22**
Net	-0.19*	0.02	0.53***	-0.13	0.01
Simple plus Prior Stock Returns	0.50***	0.55***	0.52***	0.57***	0.46***
Splined plus Prior Stock Returns					
Positive (or zero) Bond Return	0.32**	-0.19	0.39***	0.27**	0.12
Negative Bond Return	0.04	0.81***	1.13***	0.31**	0.36***
Net	0.35***	0.62***	0.74***	0.58***	0.48***
Sum of Stock Lags (Weeks 1-12) - Full Model	-0.28***	-0.36***	-0.14***	-0.41***	-0.34***

	Trades per Day				
Sums of Bond Lags (Weeks 1-12)	1.00-1.14	1.15-1.36	1.36-1.75	1.75-2.39	2.40-14.01
Simple (Only Prior Bond Returns)	0.16**	-0.04	0.08	0.31***	0.09
Splined					
Positive (or zero) Bond Return	-0.13	-0.07	0.31***	-0.17	-0.18
Negative Bond Return	0.26*	-0.06	0.48***	0.50***	0.22*
Net	0.13	-0.12	0.16**	0.33***	0.04
Simple plus Prior Stock Returns	0.65***	0.51***	0.37***	0.66***	0.48***
Splined plus Prior Stock Returns					
Positive (or zero) Bond Return	0.25*	0.27**	-0.12	0.12	0.05
Negative Bond Return	0.44***	0.24*	0.62***	0.62***	0.46***
Net	0.69***	0.51***	0.51***	0.74***	0.50***
Sum of Stock Lags (Weeks 1-12) - Full Model	-0.31***	-0.40***	-0.23***	-0.26***	-0.30***

	Standard Deviation (%) of Stock Returns				
Sums of Bond Lags (Weeks 1-12)	0.1-3.6	3.6-4.7	4.8-5.9	5.9-8.2	8.2-25.1
Simple (Only Prior Bond Returns)	0.41***	0.16**	0.13*	0.05	0.02
Splined					
Positive (or zero) Bond Return	0.06	-0.07	-0.43***	0.19**	-0.38***
Negative Bond Return	0.37***	0.22*	0.49***	-0.25**	0.41***
Net	0.43***	0.15*	0.06	-0.06	0.03
Simple plus Prior Stock Returns	0.55***	0.62***	0.99***	0.17**	0.65***
Splined plus Prior Stock Returns					
Positive (or zero) Bond Return	0.15	0.29***	0.21	0.21**	0.17
Negative Bond Return	0.45***	0.39***	0.80***	-0.19*	0.51***
Net	0.60***	0.68***	1.01***	0.02	0.68***
Sum of Stock Lags (Weeks 1-12) - Full Model	-0.16***	-0.36***	-0.56***	-0.06*	-0.42***

Figure 1 – Trading Strategies. The following graphs display trading strategies based on observing bond returns for four weeks and then investing in stocks for one week. Deciles are formed based on prior-4-week bond returns, which are plotted on the x-axis. The current weekly stock return for each decile is plotted on the y-axis. Figure 1a includes all bond-stock pairs, whereas Figure 1b only includes the most liquid bond for each stock in the sample.



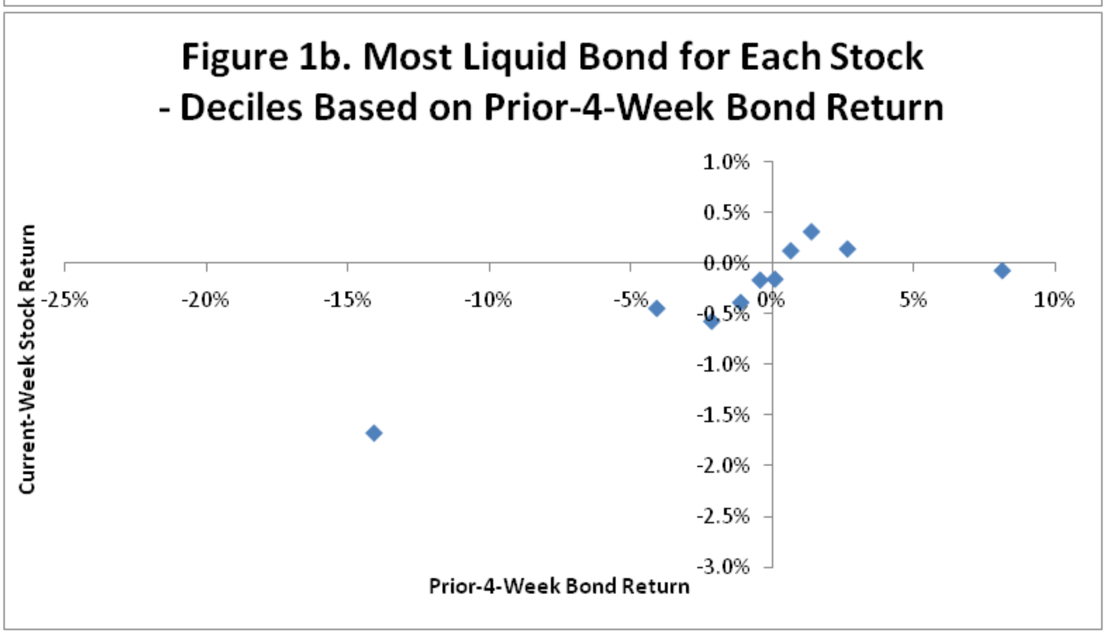


Figure 2 – Trading Strategies by Prior-4-Week Stock Return. The following five charts represent trading strategies identical to Figure 1, but broken out by quintiles based on the stock's performance in the prior four weeks. For example, Figure 2a displays the quintile with the lowest prior-4-week stock returns. Within that subset, deciles are formed based on prior-4-week bond returns, which are plotted on the x-axis. The current weekly stock return for each decile is plotted on the y-axis.

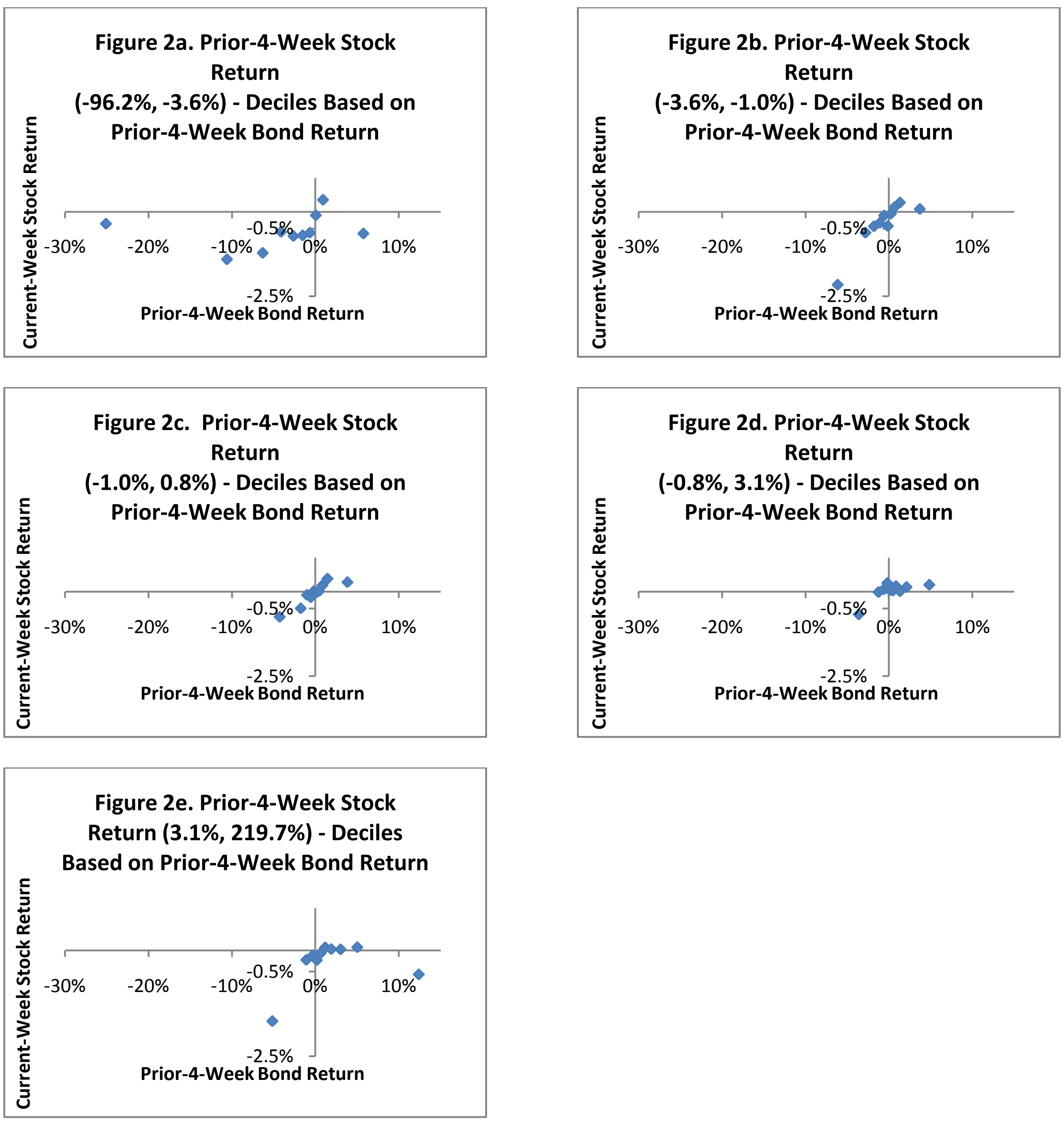


Figure 3 – Trading Strategies by Year. The following four charts represent trading strategies identical to Figure 1, but broken out by calendar year. For example, Figure 3a displays bond-stock pairs from 2005. Within that subset, deciles are formed based on prior-4-week bond returns, which are plotted on the x-axis. The current weekly stock return for each decile is plotted on the y-axis.

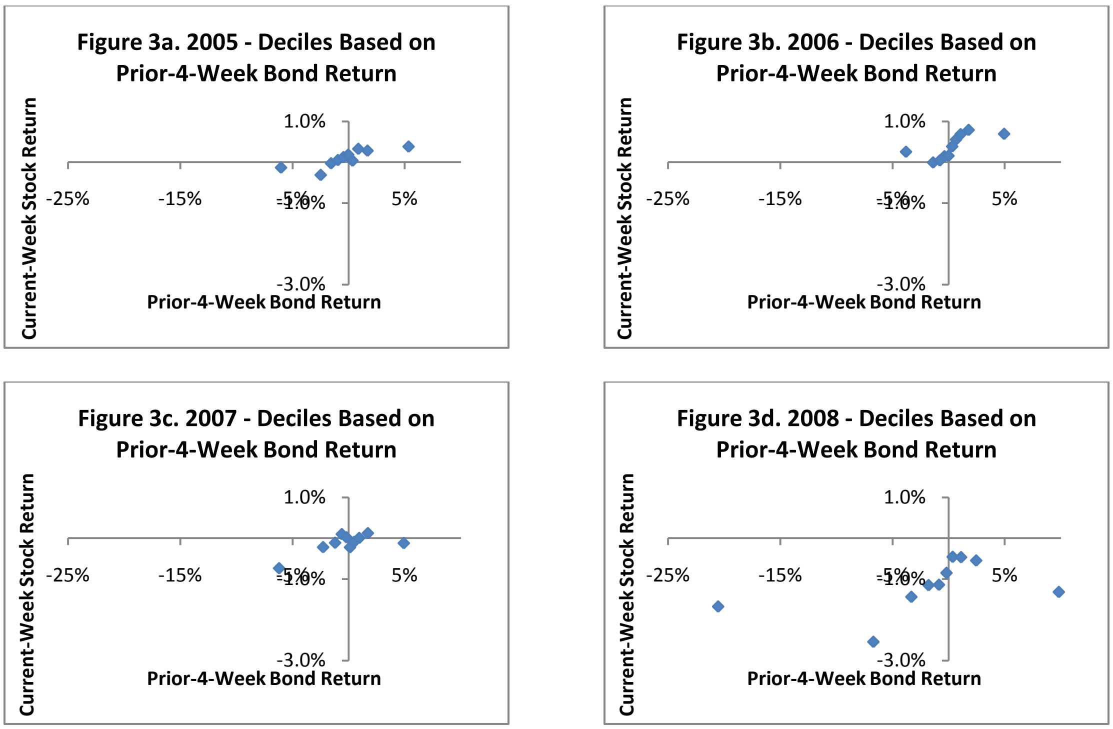
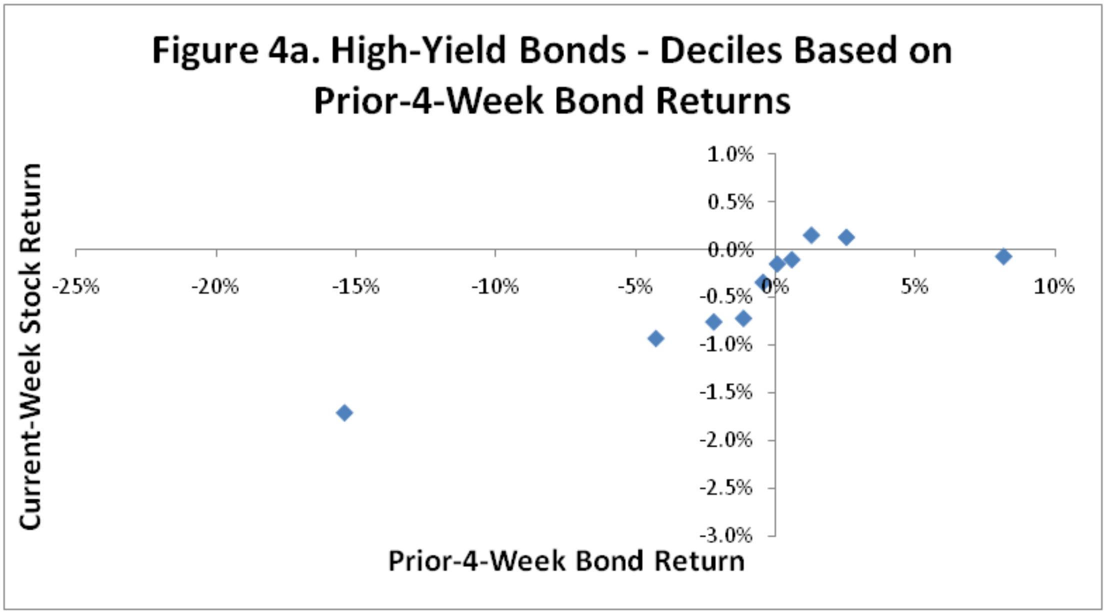


Figure 4 – Trading Strategies by Grade. The following two charts represent trading strategies identical to Figure 1, but broken out by bond grade. For example, Figure 4a displays bond-stock pairs for only high-yield bonds. Within that subset, deciles are formed based on prior-4-week bond returns, which are plotted on the x-axis. The current weekly stock return for each decile is plotted on the y-axis.



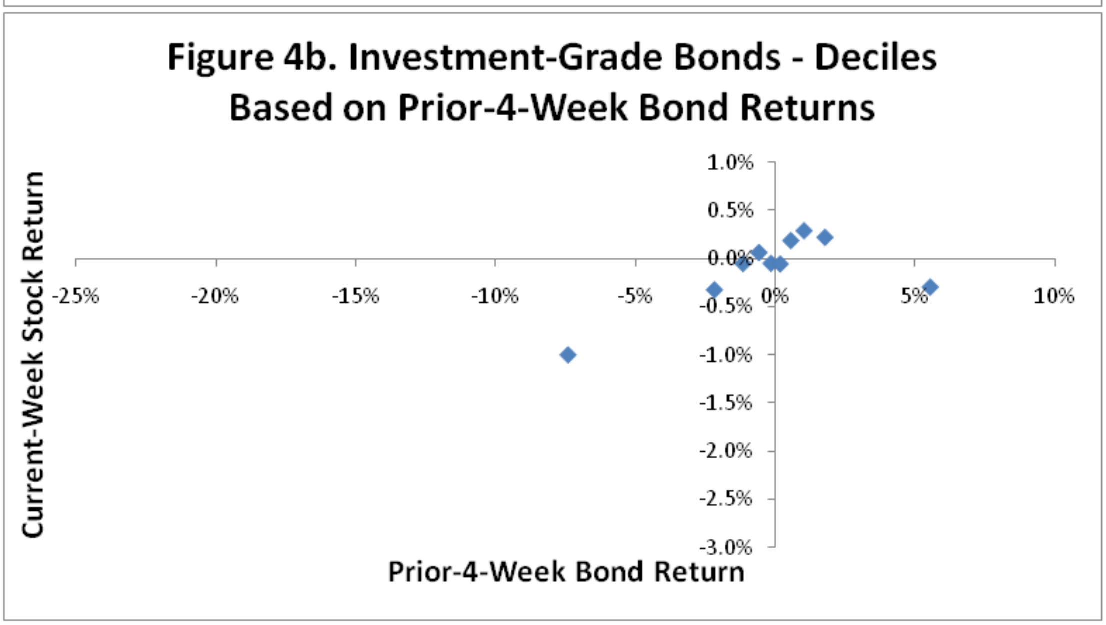


Figure 5 – Trading Strategies by Coupon. The following five charts represent trading strategies identical to Figure 1, but broken out by bond coupon quintiles. For example, Figure 5a displays the quintile with the lowest coupons. Within that subset, deciles are formed based on prior-4-week bond returns, which are plotted on the x-axis. The current weekly stock return for each decile is plotted on the y-axis.

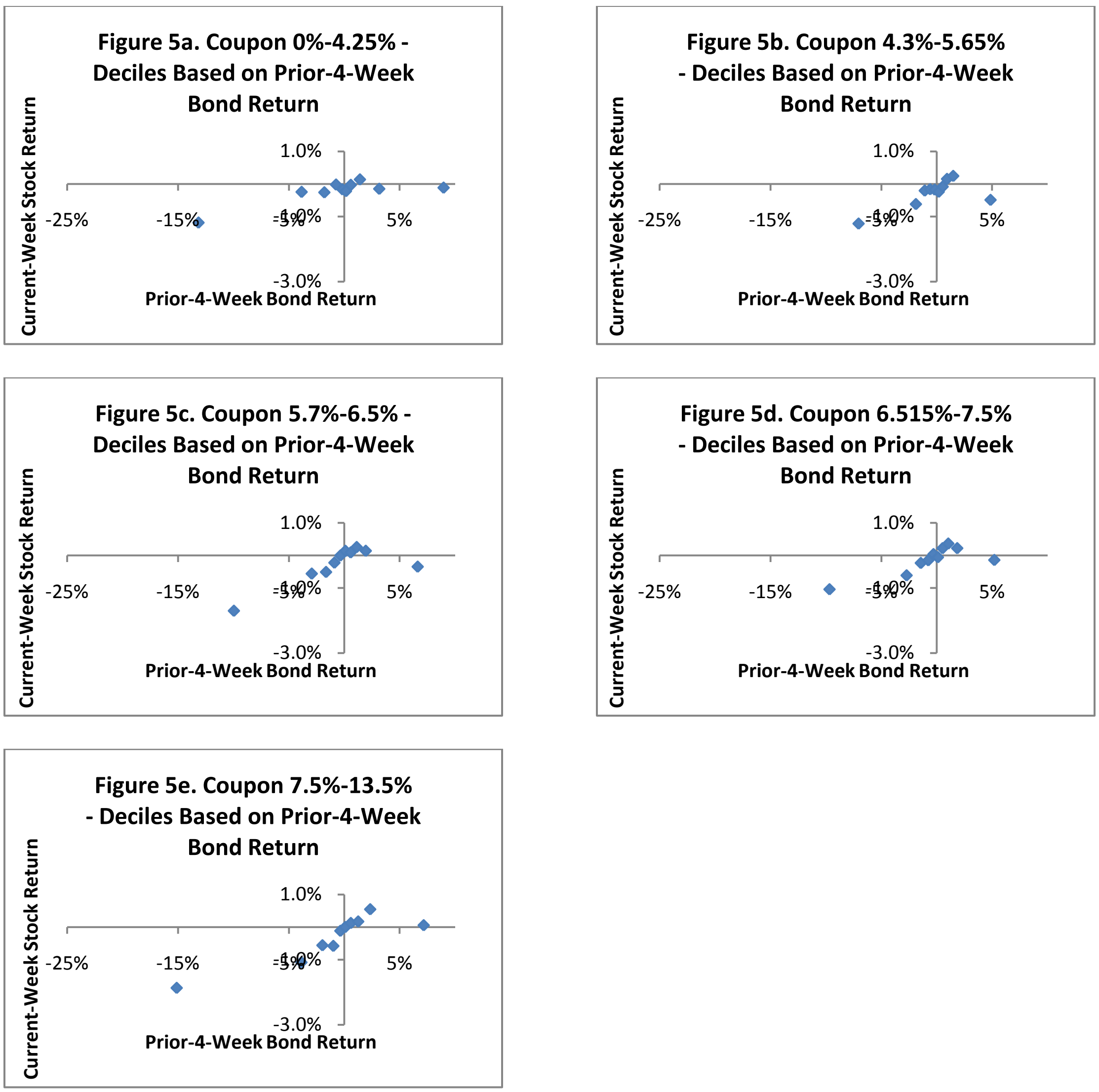


Figure 6 – Trading Strategies by Years to Maturity. The following five charts represent trading strategies identical to Figure 1, but broken out by bond years to maturity quintiles. For example, Figure 6a displays the quintile with the lowest years left before maturity. Within that subset, deciles are formed based on prior-4-week bond returns, which are plotted on the x-axis. The current weekly stock return for each decile is plotted on the y-axis.

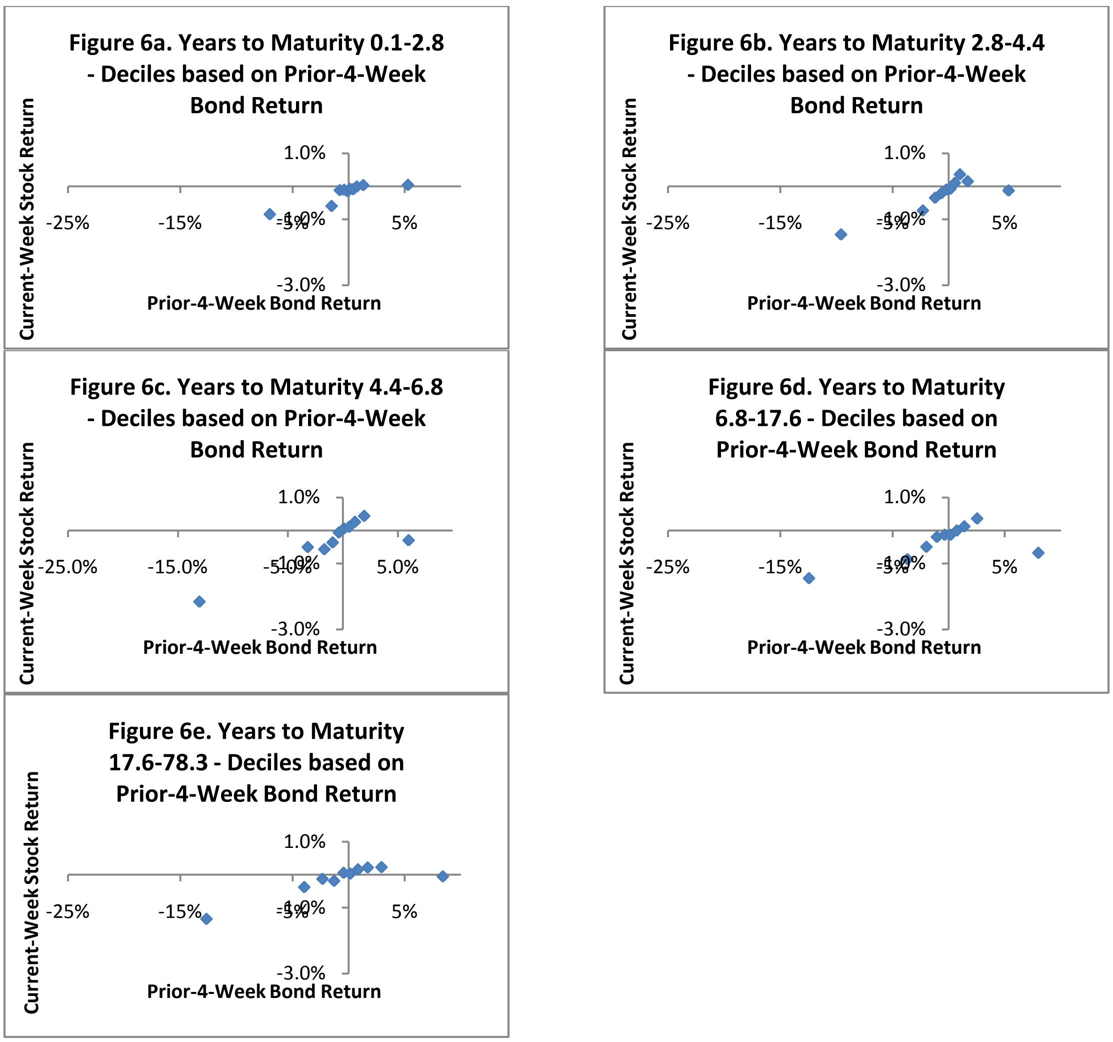


Figure 7 – Trading Strategies by Trades per Day. The following five charts represent trading strategies identical to Figure 1, but broken out by bond trades per day quintiles. For example, Figure 7a displays the quintile with the lowest bond trades per day. Within that subset, deciles are formed based on prior-4-week bond returns, which are plotted on the x-axis. The current weekly stock return for each decile is plotted on the y-axis.

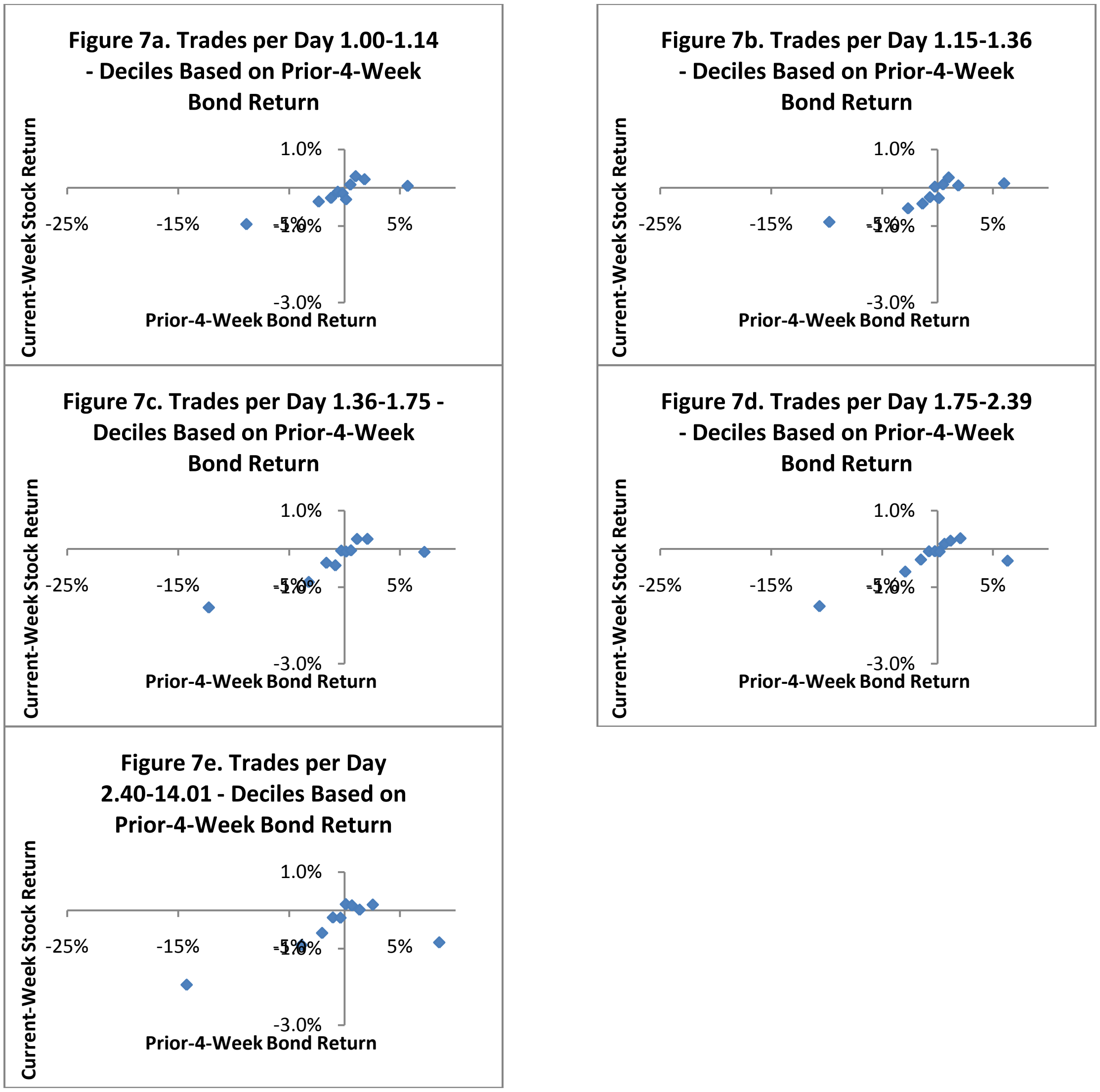


Figure 8 – Trading Strategies by Standard Deviation of Stock Returns. The following five charts represent trading strategies identical to Figure 1, but broken out by stock volatility quintiles. For example, Figure 8a displays the quintile with the lowest standard deviation of stock returns. Within that subset, deciles are formed based on prior-4-week bond returns, which are plotted on the x-axis. The current weekly stock return for each decile is plotted on the y-axis.