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On the Origin of IPO Profits*

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Abstract

By combining investors' portfolio holdings with trading and commissions data, we analyze the determinants of IPO allocations. We distinguish among common explanations for investors' IPO profits: information revelation, quid pro quo arrangements (related to commissions), and post-IPO trading behaviors. We find that information proxies explain the majority of the variation in IPO profits, while commissions and post-IPO trading behaviors explain relatively little. Commissions and post-IPO trading matter at the extensive, but not intensive, margins, while information matters at both. Different explanations matter for allocations and IPO profits to Investment Managers, Hedge Funds, and Banks, Pension Funds and Insurers.

JEL Classifications: G23, G24, G32

Keywords: IPOs, Allocations, Institutional Investors, Underwriters, Money Left on the Table

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1 Introduction

It is well established that initial public offerings (IPOs) experience significant first-day price increases, with initial returns averaging upwards of 15% (Loughran et al., 1994; Loughran and Ritter, 2002; Ritter and Welch, 2002; Ljungqvist, 2007). These large initial returns translate into billions of dollars of profits, or money left on the table, for institutional investors. Several theories propose alternative explanations for why investors receive these IPO profits. IPO profits can be viewed as compensation for institutional investors' value-adding activities, such as information revealed during the bookbuilding process or desirable post-IPO trading behaviors. Alternatively, IPO profits can be viewed as rents extracted from firms and shared between institutional investors and underwriters on a quid pro quo basis. For regulators observing the declining use of public equity markets, understanding the economic importance of these explanations and the origins of IPO profits is of utmost importance.

The existing literature shows that each of these explanations impact IPO allocations and the resulting IPO profits. A number of cases surrounding the tech bubble of the late 1990s and early 2000s demonstrated the existence of quid pro quo arrangements between investors and underwriters (the "laddering" practice is discussed by Griffin et al. (2007) and "spinning" by Liu and Ritter (2010)). More recently, several studies link investors' trading commissions to more favorable allocations from underwriters (Reuter (2006), Goldstein et al. (2011), Jenkinson et al. (2018)). Some of the same studies, and several others (Jenkinson and Jones (2004), Cornelli and Goldreich (2001), Aggarwal et al. (2002)), find evidence that information plays a significant role in allocations. Still other studies show that investor behaviors such as price support (Fjesme, 2016), and long-term holding (Chemmanur et al., 2010) affect the allocation process. It is clear that many mechanisms affect IPO allocations and profits, but which of these mechanisms are most important? Do some mechanisms matter more for different groups of investors?

To answer these questions, we assemble comprehensive data on 24,326 inferred allocations in 1,612 U.S. IPOs between 1999 and 2010. By combining 13F institutional holdings data with ANcerno trading and commissions data that identifies investors and underwriters, we are able to simultaneously analyze multiple mechanisms that drive IPO allocations. In particular, we use investor size and industry specialization to proxy for the information mechanism, commissions paid to underwriters to proxy for quid pro quo, past price support, flipping, and holding duration as measures of investors' post-IPO behaviors, and we control for investors' activity levels using trading volume. Moreover, ANcerno data enables us to identify the institutional investors who participate in IPOs and classify them as Hedge Funds, Investment Managers, or Banks, Pension Funds and Insurers (Banks/Pensions/Insurers).

At the extensive margin of whether investors receive an allocation, we find evidence consistent with each mechanism. At the intensive margins of how large or valuable allocations are, only factors related to the information mechanism are consistently economically and statistically significant. Thus, while quid pro quo arrangements and post-IPO behaviors are associated with more allocations, investor size and industry specialization are also associated with more allocations and are the dominant factors associated with larger and more profitable allocations. A variance decomposition supports our main result – we estimate that between 64.9% and 70.4% of relative variation in IPO profits is related to investors' sizes and industry specializations. We also find that different mechanisms matter to different groups of investors. While investor size is a major determinant of allocations for all investors, industry specialization is only related to allocations for Investment Managers and Hedge Funds, consistent with the view that Investment Managers and Hedge Funds are more sophisticated investors than Banks/Pensions/Insurers. Furthermore, we find that industry specializations is more important for IPO profits when firms are harder to value. Finally, we show that underwriters' brokerage revenues are not related to contemporaneous or past money left on the table, inconsistent with the quid pro quo mechanism. Taken together, our results suggest that, between 1999 and 2010 in the United States, the information mechanism was the most important determinant of IPO allocations and profits.

Our analysis uses a sample that is large and broad: it includes 24,326 inferred allocations made to 319 investors by 91 underwriters in 1,612 IPOs. Our sample is unique in that it links 13F institutional holdings data to ANcerno trading and commissions data using the names of investors and brokers that were provided by ANcerno for a brief period in 2010. By using names to link investors' portfolio holdings to trading data, we infer IPO allocations at a larger scale than prior studies. For comparison, Chemmanur et al. (2010) infers allocations using similar but anonymized data to study 4,620 allocations to 48 investors across 888 IPOs. Beyond increasing the size of our sample, investor and broker names allow us to combine traditionally disparate data. Chemmanur et al. (2010) links portfolio holdings to trades but not to commissions; Goldstein et al. (2011) links trades to commissions but not to portfolio holdings; we link portfolio holdings to both trades and commissions.

Our rich data, multiple dependent variables, and two sets of fixed effects allow us to assess the importance of the different mechanisms driving IPO allocations. First, by having data on investors' portfolios and trading activities, we can control for the mechanical effects of investors' portfolio sizes and trading activities on commissions paid to underwriters. Second, by studying the existence of allocations, their sizes, and the resulting profits, we can assess which mechanisms affect all aspects of allocations. IPO allocation theories mostly focus on profits, either as a means to compensate for investors' information or behaviors, or as an enticement in quid pro quo arrangements to earn other business. The theories suggest that whichever mechanisms drive IPO allocations and profits should impact allocations' extensive margin and intensive margins. Third, we use IPO and investor-underwriter fixed effects to separate the cross-sectional (within IPOs) and time-series (across IPOs) effects of the mechanisms. As discussed in Jenkinson et al. (2018), investor-underwriter fixed effects control for the average quality of the relationships between investors and underwriters, which likely relate to information flows and commissions payments.[1] Using investor-underwriter fixed effects allows us to determine how changes in investors' characteristics, behaviors, or commissions payments affect allocations, within each investor-underwriter pair. In contrast, using IPO fixed effects allows us to analyze how the levels of investors' characteristics, behaviors, or commissions payments are related to allocations. While understanding how levels affect IPO allocations is important, using only IPO fixed effects has a known omitted variables bias as we can not control for investor-underwriter relationships.

Our first set of results confirms several existing findings and demonstrates the importance of

[1] Hwang et al. (2018) finds that mutual funds who are connected to underwriters via education generate excess returns in months when these underwriters issue IPOs suggesting that connected funds benefit from more profitable allocations. Investor-underwriter fixed effects at least partially control for these potential relationships.

investor characteristics for explaining allocations. For comparability with the existing literature, we first regress an indicator for whether an investor receives an allocation on commissions and post-IPO behavior measures while excluding broad investor characteristics. As in prior studies, we find that commissions paid to underwriters, price support, and long-term holding are all associated with more allocations. We then add investor size, trading volume, and industry specialization to the regressions – all three are associated with more allocations. Introducing the broad investor characteristics improves the explanatory power of the regression: adjusted R^2 increases 32% from 0.111 to 0.147. While most coefficient estimates are stable when including investor characteristics, the coefficient estimate for commissions drops by 60%. This demonstrates the importance of controlling for investor size and trading volume when studying commissions.

Our second set of results shows that investor size and industry specialization are the primary drivers of IPO allocations. Across three dependent variables (allocation indicator, allocation percent, and money left on the table) and two sets of fixed effects (IPO and investor-underwriter), only investor size and industry specialization are consistently economically and statistically significant. Commissions and price support are consistently significant with IPO fixed effects, but not with investor-underwriter fixed effects. Thus, while investors with higher levels of commissions and price support enjoy better IPO allocations, investors do not appear to be rewarded by underwriters when they increase either commissions or price support. As we cannot rule out that higher levels of commissions and price support are simply reflective of better investor-underwriter relationships, we cannot conclude that the quid pro quo mechanism or post-IPO behaviors are significant drivers of allocations. Rather, only investor size and industry specialization are robust to our multiple regression specifications, suggesting that, within our sample, the information mechanism is the most important driver of IPO allocations.

We conduct a variance decomposition to quantify the relative importance of the different mechanisms for IPO profits. To do so, we repeat our money left on the table regressions, removing each variable, one at a time, to measure its contribution to the overall R^2 of the regression. We then compare the relative additions to total explanatory power across variables. Across specifications without fixed effects, with IPO fixed effects, and with investor-underwriter fixed effects, we find that industry specialization accounts for between 29.8% and 45.5% of the relative explanatory power, investor size accounts for between 19.4% and 39.5%, and trading volume accounts for between 6.0% and 19.5%.[2] Thus, consistent with our regression analyses, broad investor characteristics are more important for explaining IPO allocations and profits compared with commissions or post-IPO behaviors.

We conduct several additional tests that confirm our main results. First, we classify investors as either Hedge Funds, Investment Managers, or Banks/Pensions/Insurers. Summary statistics show that Investment Managers and Hedge Funds tend to receive IPO allocations of firms whose industries are over-weighted in their portfolios (i.e., high industry specialization), while Banks/Pensions/Insurers tend to under-weight the industries of their IPO allocations. Summary statistics also show that Banks/Pensions/Insurers pay the most commissions, followed by Hedge Funds and then Investment Managers. Thus, we expect the information mechanism to be more important for Investment Managers and Hedge Funds, and we expect the quid pro quo mechanism to be more important for Banks/Pensions/Insurers. Repeating our regressions on each group separately shows that industry specialization relates positively to IPO profits for Hedge Funds and Investment Managers, but not for Banks/Pensions/Insurers. This finding is consistent with the idea that more sophisticated, and likely informed, Hedge Funds and Investment Managers are compensated for their information through IPO profits. The by-group regressions also show that commissions are not more strongly related to allocations or IPO profits for Banks/Pensions/Insurers. In fact, the coefficient point estimates are smallest for Banks/Pensions/Insurers. Thus, while quid pro quo arrangements would suggest a strong relation between commissions and allocations to Banks/Pensions/Insurers, our results are not consistent with that explanation.

Our second additional test centers around firm uncertainty. If the information mechanism is a determinant of allocations, it should more strongly determine allocations and IPO profits in harder-to-value firms' IPOs. We split firms based on whether they have positive or non-positive pre-IPO earnings, and find that industry specialization is more strongly related to IPO profits for harder-to-value firms (those with non-positive pre-IPO earnings).

[2]Commissions measures account for between 0.0% and 8.6% of relative explanatory power, while post-IPO behavior measures account for between 0.4% and 14.0%

Our third test considers underwriters annual brokerage revenues. As discussed in Chang et al. (2017), if quid pro quo arrangements drive allocations, then we would expect to see more brokerage revenues for underwriters who leave more money on the table in their IPOs (either in the current or subsequent period). We find no relation between current or past money left on the table and the total commissions underwriters earn from ANcerno investors. Thus, in our sample, it does not appear that quid pro quo arrangements benefited investors or underwriters. Taking all of our evidence together, we conclude that the information mechanism was the most important determinant of IPO allocations and profits between 1999 and 2010 in the United States.

We make several contributions to the IPO literature. First, our main contribution is presenting new evidence regarding the relative importance of different mechanisms associated with IPO profits. Using a similar methodology to Jenkinson et al. (2018) (albeit using different outcome and control variables due to the different types of data), our evidence supports an information-based mechanism but does not support mechanisms based on quid pro quo or investor-behaviors. While higher levels of commissions or price support are associated with better allocations, increased commissions or price support do not lead to better allocations when controlling for investor-underwriter relationships. Thus, we cannot conclude that quid pro quo plays a significant role in allocations in our sample. This conclusion contrasts with Jenkinson et al. (2018) which finds that quid pro quo plays a larger role than information in allocations. While different time periods and different data types may explain the opposite conclusions, as Jenkinson et al. (2018) point out, their sample contains significant variation in underwriting fees, allowing for firms to recoup potential losses from quid pro quo arrangements.

Second, we separately analyze IPO allocations at the extensive and intensive margins. While information proxies, underwriter-support activities, and quid pro quo arrangements are all associated with receiving allocations (as in Reuter (2006), Fjesme (2016), and Goldstein et al. (2011)), only the information proxies are significantly associated with the size and profitability of allocations.[3] Thus, while commissions and price support do impact whether an investor receives an allocation, those allocations tend to be smaller and less profitable (due to lower initial returns

[3]Similarly Chiang et al. (2010) finds that in in Taiwanese IPO auctions the informational advantage helps institutional investors to earn higher returns than retail investors.

in those IPOs).[4] Our analyses also demonstrate that different mechanisms matter for different groups of investors. Information drives allocations to Investment Managers and Hedge Funds, while Banks/Pensions/Insurers receive allocations based mainly on their size.

Our analysis confirms that many factors influence IPO allocations. While many anecdotes demonstrate that underwriters and institutional investors have profited at the expense of issuing firms, we find that quid pro quo arrangements are related to IPO allocations but not to investors' IPO profits. Bookbuilding methods introduce the potential for quid pro quo and rent extraction from issuing firms, however, our results suggest that regulators should acknowledge the significant role information plays in determining IPO allocations and investors' IPO profits.

2 Data and Summary Statistics

We study IPO allocations using data on IPO offerings, underwriters and institutional investors' trades and portfolio holdings. We use the Thomson Securities Data Corporation (SDC) Platinum Global New Issues database for data on 1,612 IPOs of U.S. firms' common stocks completed between 1999 and 2010. As is common in the literature, we exclude unit offerings, real estate investment trusts, rights issues, closed-end funds and trusts, and IPOs with an offer price less than five dollars. To be included in the sample, we require that a firm be in the Center for Research in Security Prices (CRSP) database and that at least one institution reports holding shares in the first quarter after the IPO. We supplement SDC data with founding dates, monthly underpricing and issuance activity, and underwriter rankings from Jay Ritter's website.[5] We use stock price data from the Center for Research in Securities Prices (CRSP) and use Consumer Price Index (CPI) data from the Bureau of Labor Statistics to adjust dollar values to year 2005 dollars.

Our data on institutional investors' trades comes from ANcerno (Abel Noser), an industry-leading provider of Transaction Cost Analysis for investment managers, consultants and brokers.[6]

[4] It is important to note that even smaller, less profitable allocations are economically valuable. In our sample, almost 95% of allocations are profitable, and the median allocation is worth about $150,000 of profit. Thus, while commissions and price support do not lead to better allocations, they may still improve investors' profits by making any allocation possible.

[5] The data are available at https://site.warrington.ufl.edu/ritter/ipo-data/.

[6] For more details on ANcerno data see Hu et al. (2018). According to their estimation, ANcerno data covers around 15% of all institutional trading volume from 1999 to 2011.

We use the most complete version of ANcerno trading data which contains detailed information about institutional trades and broker commissions per trade from 1999 to 2011. Importantly, our data originates from a short period of time starting in 2010 when ANcerno provided identification files for both clients (investment management companies) and executing brokers.[7] Given the data issues discussed in Hu et al. (2018), we perform a multi-step cleaning and matching procedure to match 98.9% of ANcerno transactions to CRSP PERMNOs.

Our data on institutional investors' portfolio holdings come from Thomson Reuters Institutional 13F (s34) Holdings. We correct for known errors in the database following Sias et al. (2016). Data are winsorized at the 1% and 99% levels to reduce the influence of outliers. Institutional investors are classified as Hedge Funds based on the hedge fund classifications introduced in Agarwal et al. (2013a) and Agarwal et al. (2013b). Institutions who are not classified as Hedge Funds are classified as either Investment Managers or Banks/Pensions/Insurers based on the legal type classifications provided by Brian Bushee.[8]

To get a complete view of investors and underwriters in the IPO process, we link our datasets together. To map ANcerno trading data to the 13F holdings, we first compute investors' quarterly IPO position changes implied by both the ANcerno trading data and the 13F holdings data. We then calculate correlations in position changes and the matching measures implemented by Chemmanur et al. (2010) for all pairwise combinations of investors without conditioning on names. Because names change over time and not all trades are reported to ANcerno, we base our final mappings on name similarity and matching measures, supplementing with web searches as needed. Each mapping is validated by at least two co-authors, resulting in 319 mapped institutions.

To measure investors' commission payments to underwriters (and other post-IPO behaviors), we manually match lead IPO underwriters to ANcerno brokers by name.[9] While most of the brokers were matched to the list of underwriters unambiguously, cases involving name changes or mergers among brokers were matched manually. Our sample includes 91 lead IPO underwriters matched to

[7] The sample period is restricted by the availability of identification files crucial for our analysis. After the 3rd quarter of 2011, all client/manager identifiers were removed by the data provider, and in 2017 ANcerno stopped providing data for academic research.

[8] See https://accounting-faculty.wharton.upenn.edu/bushee/.

[9] Broker identification files were updated quarterly by ANcerno.

brokers.

2.1 Inferring IPO Allocations and Flipping

We identify IPO allocations using the combined trading and holdings data. First, we calculate the net after-market trading position of each institution in each IPO stock starting from the first day of trading until the last date of the quarter. Second, we subtract the net trading position from the position in the end-of-quarter holdings report, giving the inferred allocation. We assume zero shares were allocated to an institution whenever trading and holdings data are populated for a given institution in the same quarter as the IPO but no trades or position are reported for the IPO in question.[10] We use the inferred allocations to generate our main dependent variables: (i) an indicator for whether an investor received an allocation, *Allocation Indicator*, (ii) the size of the inferred allocation as a percentage of the shares offered, *Allocation Percent*, and (iii) the value of the inferred allocation to the investor, *Money Left*. *Money Left* is calculated by multiplying the inferred allocation in shares by the offer price and the initial return on the first day of trading.

There are strengths and weaknesses associated with studying IPO profits using inferred allocations. The first strength is a large sample size. Studies that use actual order books to analyze allocations, such as Cornelli and Goldreich (2001) and Jenkinson and Jones (2004), are often limited to a single underwriter and relatively few offerings. Jenkinson et al. (2018) is an exception, in that they utilize order book data on 221 IPOs across 19 underwriters. In contrast, we analyze 1,612 IPOs across 91 underwriters. The second strength of using inferred allocations is the ability to link those allocations to investors' portfolio holdings. While Jenkinson et al. (2018) study a large sample of IPOs from many underwriters, their study is limited by an inability to link investors across underwriters. Our sample allows for an investor-focused perspective on allocations and IPO profits. There are two main weaknesses of inferred allocations. The first is the noise inherent in the calculation, which relies on both noisy trading data and noisy holdings data.[11] The second is the lack of detailed order book data, which is useful for testing information-based theories of

[10] The inferences from our analyses are robust to more restrictive definitions of non-allocations. In the appendix, Tables A4, A5 and A6 repeat our main tests using samples including fewer zero allocations.

[11] Institutional investors report most (but not all) of their trading activity to ANcerno, and investors are only required to report positions of at least 10,000 shares in their 13F filings.

underpricing.

To separate flipping (i.e., sales of IPO allocations) from standard post-IPO trading, we follow the last-in-first-out algorithm implemented by Chemmanur et al. (2010).[12] Consider a simple example of an institution that sells 100 shares of an IPO on day 1, buys 200 shares of the same IPO on day 2, and then sells 300 shares on day 3. The allocation sales will be equal to 100 shares on day 1, 0 on day 2, and 100 shares on day 3 ($|200 - 300|$). The cumulative allocation sales by the end of day 3 is 200 shares. As the order of daily trading positions matters, we compute cumulative daily positions and allocation sales for each trading day recursively. We define flipping as allocation sales that occur in the first 30 days after the IPO.

2.2 Summary Statistics

Table 1 summarizes our sample IPOs and inferred allocations. Our 1,612 IPOs have total proceeds of $330 billion. Our inferred allocations are made to 319 investors with a total value of $97 billion, or 29% of the total proceeds. Panel A displays summary statistics by year from 1999 to 2010, showing the hot IPO markets of 1999–2000 and 2004–2007. Importantly, the proportion of total proceeds made up by our inferred allocations are relatively stable over time. Panel B display summary statistics by underwriter, showing that the underwriting business is concentrated. The top 16 (out of 91) underwriters account for 84% of the offerings, and the top 3 underwriters alone account for 35% of the offerings, The proportion of total proceeds made up by our inferred allocations are relatively stable across underwriters.

Table 2 displays investor summary statistics. Following Chemmanur et al. (2010), we divide the 319 investors into quartiles by the number of inferred IPO allocations in our sample: institutions with very high, high, low, and very low allocations. The investors in the top quartile receive 270 allocations on average (median of 199) and participate in 20.8% (median of 13.4%) of IPO issues. The average (median) size of their allocations amounts to 1.7% (1.4%) of the issued shares, which represents $3.4 ($2.4) million invested per allocation and $1.0 million ($0.7 million) of money left of the table. The number of allocations and allocation frequency are very skewed across quartiles.

[12]The algorithm is consistent with the Depository Trust Company's (DTC) IPO Tracking System

The second highest quartile of investors receive significantly less allocations; on average 37 (31) allocations per institution. The lowest quartile investors mostly receive 1 allocation throughout the entire sample. Interestingly, investors in the bottom two quartiles tend to receive larger allocations than investors in the two top quartiles. However, despite the larger allocations they receive less money left on the table, indicating that investors in these quartiles receive less lucrative allocations. As these investors rarely receive allocations, we drop investors with below median allocations (14) from our main analysis. In the appendix we repeat our main analysis including these low allocation investors and our inferences are unchanged (see Tables A7 and A8).

Even among investors with above median allocations, there is substantial heterogeneity in investors' sizes and IPO profits. Figure 1 plots investors' average assets under management (AUM) and their profits from participating in IPOs (realized Money Left). One might expect the largest investors to make the highest profits, but this is not necessarily the case. There are relatively small funds that make a lot of money in IPOs, e.g., the second-ranked investor. At the same time, some very large funds gain little from participating in IPOs. Figure 2 shows a similar pattern for the number of IPO allocations. Once again, some investors participate in many IPOs but do not realize high profits in them, while others manage to earn significant profits by participating in a smaller number of IPOs.

Table 3 reports summary statistics for the main variables used in the analysis. The summary statistics are based on allocations to investors in the top two quartiles of inferred allocations. We discuss these variables in detail in Section 4 and definitions are in Table A1 of the appendix.

3 Empirical Approach

Shares in IPOs can be allocated in many different ways. However, in our sample, and around the world (Sherman, 2005), bookbuilding dominates. In a typical IPO, underwriters "build the book" by contacting potential investors and eliciting their opinions and willingness to buy shares. Once investors submit bids, underwriters use their discretion to allocate shares to investors. Through this bookbuilding process, underwriters can direct allocations to valued investors. How underwriters use their discretion, who those valued investors are, and why those investors are valued, are of debate.

Bookbuilding-based theories of IPO allocations and underpricing can roughly be divided into two groups: those in which underwriters maximize the firm's proceeds and those in which underwriters maximize their own profits. Classic bookbuilding models ignore potential agency conflicts, and underwriters maximize proceeds by using allocation quantities and offer prices (and the associated underpricing) to elicit private information from investors (Benveniste and Spindt, 1989; Benveniste and Wilhelm, 1990) and to compensate investors' information production costs (Sherman and Titman, 2002).[13] Alternatively, underwriters may maximize their own profits by directing underpriced allocations to the investors who are most likely to return a portion of their gains through other lines of business, e.g., brokerage commissions (see Ljungqvist (2007) for a review of several quid pro quo theories). Note that, if/when underwriters use quid pro quo mechanisms to maximize profits, it must be the case that they expect a higher return from the quid pro quo than their typical 7% fee (Chen and Ritter, 2000).[14] In addition, funds affiliated with underwriters are more likely to get hot IPO allocations (Ritter and Zhang (2007)) (but they also provide unprofitable price support (Pratobevera (2019))). It also need not be the case that maximizing underwriter profits via a quid pro quo decreases firm welfare. As Jenkinson et al. (2018) points out, using quid pro quo arrangements can also be associated with lower fees, such that firms may pay lower explicit costs while paying higher implicit costs.

Regardless of the underwriter's objective function, underwriters' discretion over allocations allows them to distribute (expected) IPO profits to investors. IPO profits combine several underwriter decisions with the initial (first day) return of the IPO. First, the underwriter decides who to invite to the roadshow, effectively limiting the population of investors who have a reasonable chance of receiving an allocation (Sherman (2000), Sherman and Titman (2002), Yung (2005)).[15] Thus, just receiving an allocation is an indication of part of the allocation process. Second, based on whatever mechanisms are at play, the underwriter must decide how much of each investors' bids to fill, i.e.,

[13] James and Valenzuela (2020) develops an alternative theory where underwriters need to underprice in order to bring informed investors to unattractive IPOs.

[14] Kang and Lowery (2014) estimates that much of the money left on the table in IPOs accrues to underwriters, suggesting that the returns to quid pro quo likely exceed 7%.

[15] Under quid pro quo theories, investors need not attend a roadshow to receive an allocation. However, the underwriter would likely limit the potential pool of investors based on who is likely to provide desirable kickbacks.

the size of each allocation. Information theories suggest the size of the allocation will be tied to the information revealed, while quid pro quo theories suggest larger allocations will go to those with more discretionary dollars to direct to the investment bank through other channels. Most empirical studies of IPO allocations focus on the size of allocations (often relative to the total offering size). Third, the underwriter influences the initial return of the IPO by setting the offer price. The resulting IPO profits provide the basis for compensating information production/revelation, for compensating other value-adding activities, or for the kickbacks the underwriter can expect to earn. While neither investors nor underwriters know IPO profits ex ante, both likely have more information than can be simply gleaned from publicly observable variables. Thus, using IPO profits as an outcome variable does incorporate some noise, but IPO profits reflect the true economic value of allocations.

Our main dependent variable is Money Left on the Table (*Money Left*) because IPO profits, and not allocations per se, are the means for compensating investors through any of the allocation mechanisms. IPO profits encompass not only whether an investor receives allocations and how big those allocations are, but also whether those IPOs tend to be more or less underpriced. For example, investors who are either well-informed or well-favored likely receive more and larger allocations in more underpriced IPOs. Conversely, uninformed investors may only receive allocations in fairly or overpriced IPOs, and may even receive larger allocations in such IPOs. Thus, we focus on *Money Left* as our main dependent variable. We also use an indicator for whether investors receive an allocation (*Allocation Indicator*) and the size of the allocation (*Allocation Percent*) as dependent variables. Including *Allocation Indicator* and *Allocation Percent* provides comparability with the existing literature and allows for a more nuanced perspective on which mechanisms drive which parts of underwriters' allocation decisions.

A key identification challenge in relating *Money Left* and the other dependent variables to allocation mechanisms is that all of the mechanisms depend on investor-underwriter relationships. When an investor and underwriter (and the investment banks' other business units) have a strong relationship, it is likely that employees regularly communicate about analyst reports and recommendations, upcoming deal flow (including invitations to IPO roadshows, a la Sherman and Titman

(2002)), and other investment opportunities. Moreover, an existing relationship is likely a prerequisite for brokerage business, and stronger relationships are likely associated with more brokerage business. So if an investor with a strong relationship receives underpriced allocations, it could be due to high levels of commissions, post-IPO behaviors like price support, or stronger information flows' being incorporated into offer prices. Thus, we must control for these relationships between investors and underwriters to identify the mechanisms driving allocations.

To control for investor-underwriter relationships, we use investor-underwriter pair fixed effects. As Jenkinson et al. (2018) argue, investor-underwriter pair fixed effects control for the average relationship quality over the sample period, and thereby focus the analysis on how the dependent variables relate to the variation within each investor-underwriter pair. For example, suppose an investor pays high commissions to an underwriter and receives high money left on the table. That could be evidence of a quid pro quo arrangement, or the high commissions and high profits could simply reflect a strong relationship. If quid pro quo is driving the association, then we would expect to see relatively higher commissions from that investor to that underwriter associated with more profitable allocations. By controlling for the average level of commissions, the investor-underwriter fixed effects focus on that within pair variation, and quid pro quo will only be supported if underwriters tend to give the same investors better allocations after receiving relatively higher commissions. As a caveat, note that we cannot distinguish the IPO mechanisms (including quid pro quo) from strengthening or weakening relationships that may also be associated with changes in other measures (e.g., commissions). However, by including dynamic measures of investor characteristics, like size and trading volume (discussed below), the potential bias from omitting measures of strengthening or weakening relationships is likely mitigated.[16]

While our cleanest identification is from using investor-underwriter fixed effects, we also use IPO fixed effects in each of our analyses. IPO fixed effects allow us to examine how the levels of the independent variables are related to the allocations measures. For example, high commissions may be related to more profitable allocations in the cross-section (comparing across investors within IPOs). While this information is helpful in identifying which relations are evident in the

[16]Ideally, researchers could measure dynamic relationships using communication logs (phone transcripts or emails) between investors or underwriters. Unfortunately, access to such data is unlikely.

cross-section versus the time-series (within investor-underwriter pairs across IPOs and time), it is important to remember that we cannot control for investor-underwriter relationships with IPO fixed effects, so such specifications will suffer from a known omitted variables bias.

Overall, our identification strategy focuses on analyzing IPO profits using investor-underwriter fixed effects. We also analyze an allocation indicator and allocation size, and use IPO fixed effects, to understand how the different mechanisms influence allocations. Understanding how mechanisms relate to allocations also relies on good proxies for each mechanism. We follow the existing literature in developing each of our proxies.

Beginning with quid pro quo, we create two measures of brokerage commissions following Goldstein et al. (2011). The first measure, *Client Size*, reflects the more stable, longer-term commissions paid from an investor to an underwriter. It is calculated by dividing an investor's total commissions paid to an underwriter by the total commissions earned by that underwriter over the prior 9 months. Similar to the measures used in Reuter (2006) and Jenkinson et al. (2018), *Client Size* measures the relative importance of an investor's commissions to an underwriter over a long period of time.[17] These prior studies have all found strong relations between investors' allocations and long-term commissions. The second measure, *Abnormal Commissions*, reflects short-term, allocation-chasing behavior by investors. It is calculated by dividing the commissions paid by an investor in the 10 days prior to the IPO by the investor's "normal" level of commissions. Goldstein et al. (2011) finds that transient investors, those with less stable commissions to any particular underwriters, are rewarded with allocations when they direct abnormally high commissions to underwriters prior to IPOs.

Turning to investors' post-IPO behaviors, we focus on price support, flipping (selling allocations within the first month), and long-term holding. These behaviors are all of particular interest to underwriters who often attempt to keep post-IPO prices from falling in the first month of trading.[18]

[17] We follow the existing literature in using a backwards-looking measure of commissions. This implicitly assumes that underwriters form their expectations of kickback values based on past commissions. However, investors may respond to good IPO allocations with increased commissions, so the timing and formation of expectations may be reversed. Accordingly, we construct *Future Client Size* using the 9 months following an IPO. Table A9 shows that our results are unchanged using either the backwards or forwards looking commissions measures.

[18] Underwriters' incentives to support prices can be driven by agency conflicts (Hao, 2007) or can be in the interest of the issuing firms (Chen and Wilhelm Jr., 2008),(Ellis et al., 2000), LEWELLEN (2006).

Thus, underwriters may prefer to allocate shares to investors who do not sell shares immediately, hold shares for a long time, or even engage in price support by buying shares in the post-IPO market.[19] To measure price support, we follow Fjesme (2016) and calculate *Past Price Support* as the percentage of past offerings by an underwriter in which the investor purchased shares in the first month of trading.[20] Importantly, we only include IPOs that occurred at least one month in the past and that were issued by the same underwriter, ensuring that *Past Price Support* could have been known by the underwriter at the time of the IPO. Using a similar delay to ensure measurability, we calculate *Past Flipping* as the average percentage of allocated shares sold by the investor in the first month after that underwriter's IPOs. Lastly, we follow Chemmanur et al. (2010) to measure investor's holding times. *Past Hold Time* is calculated as the average holding time of allocated shares assuming LIFO accounting and using only IPOs by an underwriter that occurred at least a year earlier.[21] Cornelli and Goldreich (2001), Chemmanur et al. (2010), Jenkinson and Jones (2004), and Jenkinson and Jones (2009) all find evidence that underwriters favor long-term investors with allocations.

Finally, we use several proxies to measure the information investors may have about IPO firms. To measure IPO-specific information, we follow Reuter (2006) and proxy for an investor's industry expertise using *Industry Specialization*. *Industry Specialization* is the relative weight of an IPO firm's industry in an investor's portfolio.[22] We implicitly assume that an investor with a portfolio concentrated in a particular industry has an expertise in this industry and may have superior information about an IPO firm in this industry relative to other investors. We also use an investor's size, measured using the logarithm of assets under management (*Log Investor AUM*), to proxy for their overall skill (and ability to produce valuable information) in the spirit of Berk and Green

[19]While flipping is often viewed as in direct conflict with maintaining an IPO's price, some degree of flipping is required to create an active secondary market. Thus, it is unclear ex-ante whether investors as a whole, and specific investors in particular, should be punished for flipping (or rewarded for long-term holding).

[20]Our measures of price support, flipping and long-term holding are all adjusted by subtracting the average value for the underwriter over the period of interest.

[21]As in Chemmanur et al. (2010), shares that are held at the end of the first year are assumed to be held for 24 months.

[22]The relative weight is calculated as the percentage of an investor's 13F holdings in the IPO firm's industry minus the percentage of all investors' 13F holdings in the IPO firm's industry. Industries are based on the 48 industries defined in Fama and French (1997) adjusted for software firms, bank holdings companies, pharmaceuticals and Internet firms as in Edelen and Kadlec (2005). Internet firms are identified using Jay Ritter's list of Internet IPOs available at https://site.warrington.ufl.edu/ritter/ipo-data/.

(2004). Thus, *Log Investor AUM* reflects an investor's more general information while *Industry Specialization* reflects IPO-firm-specific information. Investors' overall activity level may also be related to their skill, so our last proxy for potential information is *Trading Volume*, which is an investor's relative trading volume reported to ANcerno in the nine months prior to the IPO.[23] While actively trading investors are likely to be better informed than passive investors, investors can also be more active in order generate commissions and attract IPO allocations (Nimalendran et al., 2007). Thus, *Trading Volume* can be interpreted in several ways, so we use *Industry Specialization* and *Log Investor AUM* as our main proxies for information and consider *Trading Volume* as an important control variable.

Using our proxies for each allocation mechanism, we analyze how those mechanisms are related to IPO profits and other allocation outcomes using an ordinary least squares regression framework.[24] Formally, we estimate,

$$\begin{aligned} Y_{i,j} &= \alpha + \beta InvestorUnderwriterVars_{i,uw(j),t(j)} + \lambda InvestorVars_{i,t(j)} + \\ &\quad \Gamma X_j + FixedEffects + \epsilon_{i,j}, \end{aligned} \tag{1}$$

in which i indexes IPOs, j indexes investors, $uw(j)$ indicates the underwriter of IPO j, $t(j)$ indicates the time of IPO j, $Y_{i,j}$ is either *Allocation Indicator Allocation Percent*, or *Money Left*, $InvestorUnderwriterVars$ includes measures specific to an investor-underwriter pair (*Client Size*, *Abnormal Commissions*, *Past Price Support*, *Past Flipping*, and *Past Hold Time*), $InvestorVars$ includes *Trading Volume*, *Log Investor AUM*, and *Industry Specialization*, ΓX_j includes IPO characteristics (*Offer Price Revision*, indicators for whether the final offer price is above (*High Demand*) or below (*Low Demand*) the filing price range, *Log Firm Age*, indicators for whether firms are VC-backed (*VC-Backed*) or in technology industries (*Tech Firm*), *Log Proceeds*, and *Underwriter Rank*), $FixedEffects$ are either IPO-based or investor-underwriter pairs (or excluded), and standard errors are calculated by clustering at both the quarter and investor-underwriter pair levels. In

[23] Relative trading volume is measured by dividing the total shares traded by the investor by the total shares traded by all ANcerno investors.

[24] As our sample includes many zero allocations, we repeat our analyses using the inverse hyperbolic-since transformation of Bellemare and Wichman (2020). Appendix Table A10 shows that our main results are robust to this alternative specification.

all regressions, the independent variables are standardized by subtracting their means and dividing by their standard deviations.[25]

4 Determinants of IPO Allocations and Profits

4.1 Which Investors Receive Allocations?

Table 4 shows the results of estimating equation (1) using *Allocation Indicator* as the dependent variable $Y_{i,j}$. As all of the independent variables are standardized by subtracting their means and dividing by their standard deviations, the coefficient estimates can be interpreted as increases in probabilities of receiving an allocation for a one-standard deviation increase in the independent variables.[26] The first column of Table 4 provides our baseline results without any fixed effects and excluding broad investor characteristics. The results show that *Past Price Support* and *Client Size* are most strongly related to whether investors receive allocations. A one-standard deviation increase in *Client Size* is associated with a 7.59% increase (t-statistic of 17.44) in the probability of receiving an allocation, while *Past Price Support* is associated with a 2.77% increase (t-statistic of 5.53). *Past Hold Time* and, perhaps surprisingly, *Past Flipping* are also positively associated with receiving an allocation, increasing the allocation probabilities by 0.69% (t-statistic of 2.28), and 1.69% (t-statistic of 5.14). While flipping is often viewed negatively, some degree of flipping is essential to secondary market trading and is expected by underwriters. A theory developed in Fishe (2002) shows that flipping may benefit underwriters by allowing them to make money in the aftermarket. The coefficient on *Abnormal Commissions* is not significantly related to allocation probabilities.

Several control variables are significantly related to whether investors receive allocations. Consistent with larger offerings making allocations to more investors, a one-standard deviation increase in *Log Proceeds* is associated with a 4.08% (t-statistic of 12.67) increase in probability of an investor getting an IPO allocation. Investors are also more likely to receive allocations in *High Demand* IPOs (3.01%, t-statistic of 8.49) in which the final offer price is above the initial offer price range.

[25] The independent variables are standardized using only the observations included in each regression.

[26] The unconditional probability of receiving an allocation is 13.7%.

Similarly, a one-standard deviation increase in the offer price revision is associated with a 2.69% (t-statistic of 4.52) increase in the probability of an allocation. Finally, *Low Demand* IPOs are associated with lower allocations probabilities (−0.92%, t-statistic of −2.39), and *VC Backed* IPOs are associated with higher allocation probabilities (1.21%, t-statistic of 4.68).

The results reported in Columns 2 through 4 of Table 4 include broad investor characteristics and various fixed effects: Column 2 uses no fixed effects, Column 3 includes IPO fixed effects, and Column 4 includes investor-underwriter fixed effects that capture stable relationships between investors and underwriters. All three broad investor characteristics are positively related to IPO allocations and the estimated coefficients are statistically significant. Without fixed effects, a one-standard deviation increase in *Log Investor AUM* is associated with a 5.83% probability increase (t-statistic of 14.25). Similarly, a one-standard deviation increase in *Trading Volume* is associated with a 3.12% probability increase (t-statistic of 5.73), and a one-standard deviation increase in *Industry Specialization* with a 1.97% probability increase (t-statistic of 7.99). These estimates suggest that skill and information help investors to receive IPO allocation, possibly because they are favorably treated by underwriters. Interestingly, when we introduce broad investor characteristics, the estimated coefficient for *Client Size* is cut by nearly 60%. This demonstrates the importance of controlling for investors' characteristics when testing allocation mechanisms.

Adding IPO fixed effects in Column 3 increases the R^2 of the regression (from 0.147 to 0.186), but has little effect on the coefficient estimates. Adding investor-underwriter fixed effects, however, results in significant reductions in the coefficient estimates for *Client Size*, *Past Price Support*, and *Past Flipping*.[27] With investor-underwriter fixed effects, *Log Investor AUM* has the largest estimated coefficient (5.00, t-statistic of 8.39), followed by *Trading Volume* (3.31, t-statistic of 5.71), *Past Price Support* (1.68, t-statistic of 6.93), *Industry Specialization* (1.51, t-statistic of 8.79) and *Client Size* (1.37, t-statistic of 2.92). Comparing across specifications shows that including broad investor characteristics and investor-underwriter fixed effects are important for assessing the importance of different mechanisms. These results suggest several mechanisms drive IPO allocations, and also suggest that information may be a more robust mechanism than quid pro quo or post-IPO

[27]The coefficient estimates remain statistically significant.

behaviors.

4.2 How Big Are the Allocations Investors Receive?

Table 5 shows the results of estimating equation (1) using *Allocation Percent* as the dependent variable $Y_{i,j}$. The sample includes all observations with positive allocations. The coefficient estimates can be interpreted as increases in allocation size (as a percentage of the shares offered) for a one-standard deviation increase in the independent variables.[28] The first column of Table 5 provides our baseline results without any fixed effects and excluding broad investor characteristics. Column 2 adds broad investors characteristics, Column 3 adds IPO fixed effects and Column 4 adds investor-underwriter fixed effects.

Commissions appear important for allocations in the baseline specification in Column 1: a one standard deviation increase in *Client Size* is related to 0.13% increase in *Allocation Percent* (t-statistic of 3.99). However, once we include broad investor characteristics, the corresponding coefficients are no longer significant. The coefficient on *Abnormal Commissions* is positive but small in Columns 1-3: a one standard deviation increase in excess commissions is related to 0.03-0.04% increase in *Allocation Percent*. *Abnormal Commissions* loses significance once we introduce investor-underwriter fixed effects in Column 4.

While past flipping does not negatively relate to the probability of an allocation in Table 4, it is negatively related to the allocation size in some specifications. In Columns 1-3, a one standard deviation increase in *Past Flipping* is related to a 0.24%-0.37% decrease in *Allocation Percent*, this is consistent with Aggarwal (2000) which finds that underwriters tend to penalize flipping. Surprisingly, *Past Hold Time* is also negatively associated with the allocation size in all specifications, in contrast to the findings in Cornelli and Goldreich (2001), Chemmanur et al. (2010), Jenkinson and Jones (2004), and Jenkinson and Jones (2009).[29] The effect of *Past Price Support* on the size of the allocation is positive in regressions without investor-underwriter fixed effect reported Columns 1-3, which is consistent with findings in Fjesme (2016) and Fjesme (2019)

[28]The mean (median) allocation size is 1.8% (0.5%) of the shares offered.

[29]We reconcile our results with Chemmanur et al. (2010) in Table A11 in the appendix. *Past Hold Time* is positively related to allocation size if *Past Flipping* is excluded from the regression and if *Past Hold Time* is measured over the entire sample (instead of being measurable at the time of the IPO).

that use similar specifications. Yet, when we include investor-underwriter fixed effects (Column 4) the effect becomes negative, suggesting that once we control for stable relationship between an investor and an underwriter, engaging in price support does not help the investor to receive larger allocations.

Columns 2-4 of Table 5 show how broad investor characteristics *Trading Volume*, *Log Investor AUM*, and *Industry Specialization* are related to *Allocation Percent*. Consistent with the information theories of IPO allocations, the size of the investor and the industry specialization have the most explanatory power for the allocation size and remain significant across all specifications. In Column 4 a one-standard deviation increase in *Log Investor AUM* is associated with a 0.82% increase in the size of the allocation (t-statistic of 6.21), while *Industry Specialization* is associated with a 0.21% increase (t-statistic of 4.51). Interestingly, *Trading Volume*, is not related to the size of allocations.

Overall, our results suggest that somewhat different factors explain the size of allocations from the factors that explain whether an investor gets an allocation. Industry specialization and investor's size seem to be robust in their effects and positively affect both allocation measures, therefore, the information-based explanation is relevant for both measures. At the same time, high commissions paid to underwriters seem to help investors to get an allocation, but do not influence its size, suggesting that the overall importance of this channel for explaining IPO allocations is limited. Finally, long-term holding appears to help investors get an allocation, but conditional on getting an allocation, they longer holding is negatively associated with its size.

4.3 The Origins of IPO Profits

While many papers have focused on factors that affect IPO allocations, few have tried to look at individual investors' profits measured as money left on the table. Clearly, similar factors that affect IPO allocations can also explain investors' profits: past commissions, past holding behavior, and investors' expertise can help them to get profitable IPO allocations. Table 6 shows the results of estimating equation (1) using *Money Left* as the dependent variable $Y_{i,j}$. The coefficient estimates can be interpreted as increases in IPO profits (in millions of dollars) for a one-standard deviation increase in the independent variables.[30] The first column of Table 6 provides our baseline results without any fixed effects and excluding broad investor characteristics. Column 2 adds broad investors characteristics, Column 3 adds IPO fixed effects and Column 4 adds investor-underwriter fixed effects.

Starting with commissions, Columns 1-3 show that past commissions positively relate to IPO profits: a one standard deviation increase in *Client Size* is associated with $60,000-140,000 of additional IPO profits (the coefficient estimates are all statistically significant at the 1% level). Yet, once we include investor-underwriter fixed effects in Column 4, the coefficient is zero and is not statistically significant, suggesting that variation in *Client Size* within investor-underwriter pairs has no relation with investors' realized profits in IPOs. In other words, the same investors are important clients for underwriters through the sample period, and investor-underwriter fixed effects capture that. Thus, we find no evidence that IPO profits increase when commissions payments to underwriters increase, suggesting quid pro quo may not be an important mechanism for IPO allocations and profits.

In regressions without investor-underwriter fixed effects, measures of investors' post-IPO behaviors are related to their profits. Columns 1-3 of Table 6 show that a one standard deviation increase in *Past Flipping* is associated with $40,000-60,000 less profits (coefficients are between -0.04 and -0.0 and t-statistics are between -3.11 and -3.46), and one standard deviation increase in *Past Hold Time*, is associated with $20,000-30,000 less profits (coefficients are between -0.02 and -0.04 and t-statistics are between -2.49 and - 2.60), while *Past Price Support* is associated with $30,000-40,000 extra profits (coefficient is between 0.03 and 0.04 and t-statistics are between 2.36 and 3.07). The results are intuitive for *Past Price Support* and *Past Flipping*: underwriters favor investors that engage in price support and penalize those that flip (i.e., sell) shares soon after the IPO. The negative relation between *Past Hold Time* and IPO profits is less intuitive. It might be explained by the fact that many long-term investors are passive and purchase many IPOs without trying to pick the best deals, and as a result they tend to get somewhat less profits than other IPO investors. These results become insignificant except for *Past Hold Time* once we introduce investor-

[30] Average IPO profits are $156,000 per potential IPO allocation.

underwriter fixed effects in Column 4. This suggests that a stable relationship between investor and underwriter captured by the fixed effect can explain much of investors' post IPO behaviors. Interestingly, in this case *Past Hold Time* is negatively associated with profits (the coefficient is -0.05 and t-statistic is -2.30).

In Columns 2-4 of Table 6 our measures of investor's skill and information, proxied by *Trading Volume*, *Log Investor AUM* and *Industry Specialization* are positively associated with IPO profits. Even when we control for investor-underwriter fixed effects, a one standard deviation increase in *Log Investor AUM* is associated with $120,000 increase in profits (the coefficient is 0.12 and t-statistic is 4.34), a one standard deviation increase in *Trading Volume* is associated with $120,000 increase in profits (the coefficient is 0.12 and t-statistic is 2.27), and a one standard deviation increase in *Industry Specialization* is associated with $60,000 increase in profits (the coefficient is 0.06 and t-statistic is 5.16).

Overall, our results suggest that the importance of commissions-based motives for IPO profits is limited, especially when controlling for investor-underwriter relationships. Similarly, arguments suggesting that long-term investors or investors that engage in price support will be favored by underwriters find mixed support. While past price support does help an investor to receive an allocation, it has negative effect on the allocation size, and no effect on profits. Overall, our results suggest that information based theories find strong and robust support in all three sets of regressions because measures associated with investor's skill and information are positively associated with investors' allocations and profits in most specifications.

4.4 Variance Decomposition

Our regression analysis highlights the mechanisms that have statistically significant effects on investors' IPO allocations and profits. In this section, we analyze what fractions of the variation in investors' profits are explained by different mechanisms, i.e. what mechanisms explain most of the differences in IPO profits among investors.

We decompose the variance by analyzing the marginal explanatory power of each of our main independent variables while including investor-underwriter fixed effects and controls. To do so, we start by recording the total R^2 from estimating equation (1) using *Money Left* as the dependent variable $Y_{i,j}$ with all of our main independent variables included. We then re-estimate equation (1) excluding each main independent variable and record the resulting total R^2 values. Formally, if V is the collection of all explanatory variables and $v \in V$ is a particular variable, the incremental R^2 is calculated as

$$\Delta R_v^2 = R_V^2 - R_{V/v}^2. \tag{2}$$

We compute the contribution of each explanatory variable v' to an increase in R^2 as

$$PercentExplainedVariance(v') = \frac{\Delta R_{v'}^2}{\sum_{v \in V} \Delta R_v^2}. \tag{3}$$

Table 7 presents the results. Focusing on Panel A using our full sample, the results using investor-underwriter fixed effects show that 84.4% of the explained variance comes from investor characteristics: *Trading Volume* (19.5%), *Log Investor AUM* (19.4%) and *Industry Specialization* (45.5%). In contrast, *Client Size*, *Abnormal Commissions*, *Past Price Support* and *Past Flipping* each account for less than 1% of the explained variance. *Past Hold Time* accounts for 14.0% of the explained variance, with shorter holding times associated with more money left on the table. These results reinforce the conclusion that investor characteristics are the primary drivers of investors' profits in IPOs. However, commissions, past price support and past flipping account for more of the explained variance when using no fixed effects or IPO fixed effects. Thus, it does appear that the levels of commissions and post-IPO behaviors do relate to IPO allocations (although less significantly then investor characteristics). Unfortunately, we cannot separate those level effects from relationships between investors and underwriters, so our results suggest that commissions and post-IPO behaviors that may be desirable to underwriters play a lesser role in explaining IPO profits.

5 Additional Tests

We conduct three additional tests to analyze the robustness of the information mechanism and to clarify the roles of the mechanisms in the allocation process.

5.1 Investor Heterogeneity

Prior studies document that different mechanisms help investors receive shares in IPOs in different environments. Thus, we hypothesize that different mechanisms can matter for different investors. To test this hypothesis we classify investors as either Hedge Funds, Investment Mangers, or Banks/Pensions/Insurers.

Table 8 reports summary statistics for Hedge Funds, Investment Mangers, and Banks/Pensions/Insurers. There are several interesting differences across investor types. First, Banks/Pensions/Insurers are more than an order of magnitude bigger than Investment Managers, who are nearly an order of magnitude bigger than Hedge Funds. Consistent with their large size, Banks/Pensions/Insurers on average get allocations more often (205 allocations) than Investment Managers (150), and Hedge Funds (131). They also pay larger commissions with an average *Client Size* of 0.792, versus 0.506 for Investment Managers and 0.655 for Hedge Funds (note that Hedge Funds on average generate more commissions than Investment Managers despite their smaller size). These summary statistics suggest that Banks/Pensions/Insurers are more desirable investors from a quid pro quo perspective as underwriters can potentially capture more kickbacks from the investors who pay the largest commissions.

Second, Table 8 shows that investors behave differently in the post-IPO market. For instance, Investment Managers more actively engage in price support (average value of *Past Price Support* is 0.158), than Hedge Funds (0.126), or Banks/Pensions/Insurers (0.091). At the same time, Banks/Pensions/Insurers hold IPOs for a longer time period (average value of *Past Hold Time* is 0.204) compared to Investment Managers (0.090) and Hedge Funds (-0.087). Hedge Funds tend to flip nearly two-thirds of their allocations (59.5%), while Investment Managers and Banks/Pensions/Insurers tend to flip only about one-third of their allocations (36.1% and 31.1%). Thus, there is considerable scope for these behaviors to be rewarded or punished differentially among investors.

Third, the three groups of inventors differ substantially on *Industry Specialization.* Investment Managers tend to be highly specialized in the industries related to their IPO allocations (average *Industry Specialization* of 1.426), Hedge Funds are somewhat less specialized (0.685), and

Banks/Pensions/Insurers are actually not specialized at all (-0.225). It is possible that Banks/Pensions/Insurers' large sizes and diversified natures prevent them from focusing on specific industries.[31] Given that Investment Managers and Hedge Funds do tend to specialize in industries related to their allocations, we expect *Industry Specialization* to matter more for their allocations and IPO profits.

Motivated by the differences among the three groups of investors, we repeat our analyses by regressing *Allocation Indicator*, *Allocation Percent*, and *Money Left* on the same set of explanatory variables as in the main analysis, i.e. we estimate equation (1) for each sub-sample of investors. To control for relationships between investors and underwriters we include investor-underwriter fixed effects. Table 9 reports the regression results.

Table 9 shows that, while investor groups differ along a number of dimensions, only the relations between information and allocations vary among investors. Whether investors receive allocations and how profitable those allocations are strongly related to *Industry Specialization* only for Hedge Funds and Investment Managers. The standardized coefficient estimates for Hedge Funds and Investment Managers are 3-4 times larger than those for Banks/Pensions/Insurers. In contrast, the relations for commissions and post-IPO behaviors do not vary among investors. While Banks/Pensions/Insurers pay the most commissions, the estimated coefficients for *Client Size* are the smallest across regressions, which is the opposite of what one would expect from quid pro quo arrangements. For post-IPO behaviors, differences in coefficient estimates are insignificant, particularly when analyzing the profitability of allocations. Thus, the only appreciable difference among investors in what drives allocations is that information is a key determinant for Investment Managers and Hedge Funds, but not for Banks/Pensions/Insurers.

Focusing on our *Money Left* regressions highlights the key drivers of IPO profits for each group. For Banks/Pensions/Insurers, only investor size (*Log Investor AUM*) is a significant determinant of IPO profits. In contrast, both size and specialization are significant determinants for Hedge Funds and Investment Managers. Interestingly, size appears relatively more important for Hedge Funds, while investor activity (*Trading Volume*) is only positively related to IPO profits for Investment

[31] As Banks/Pensions/Insurers are the largest investors on average, they likely have resources to hire experts and become informed about each industry. Thus, our measure may be ill-suited to measuring information for larger investors.

Managers.

The results in Table 9 are supported by the variance decompositions by investor types in Panels B, C and D of Table 7. For Hedge Funds and Investment Managers, the most important component in the variance decomposition is *Industry Specialization* (explaining 38.5% and 44.2% of the variation), while *Industry Specialization* only explains 6.6% of variation for Banks/Pensions/Insurers. These results suggest that information motives play much larger roles in allocations to Hedge Funds and Investment Managers. The variance decompositions also show that size plays a larger role in allocations for Banks/Pensions/Insurers, particularly without investor-underwriter fixed effects. This suggests that relationships may be particularly related to investor size for Banks/Pensions/Insurers. For Investment Managers, relationships may be more related to commissions via *Client Size*. Without investor-underwriter fixed effects, nearly a quarter of the explained variation comes from *Client Size* suggesting that commissions may be more strongly related to relationships for Investment Managers.

Overall, our analyses by investor type support our main results. Information motives are most important for investors who are thought to be more informed and specialized in their portfolios. In contrast, investors who have more capacity to provide kickbacks to underwriters do not show stronger relations between allocations and commissions. Post-IPO behaviors are not more strongly related to allocations for any group of investors.

5.2 Firm Heterogeneity

As many mechanisms determine allocations, it is likely that some mechanisms matter more than others under certain circumstances. For example, information is likely more important when issuing firms' valuations are more uncertain. As our prior results suggest that information is the primary driver of allocations, we predict that *Industry Specialization* is more strongly related to allocations in IPOs with more uncertain valuations. Firms with zero or negative earnings are often thought of as harder-to-value and more uncertain, as their values are comprised mainly of growth options. Thus, we split our sample into IPO firms with positive pre-IPO earnings and those with zero or negative (non-positive) pre-IPO earnings.[32] We predict that allocations in IPOs of firms with non-positive earnings will be more strongly related to our measure of firm specific information, *Industry Specialization*. To test our prediction, we repeat our main analyses across the earnings sub-samples, focusing on regressions with investor-underwriter fixed effects.

Table 10 reports the regression results. Comparing between the positive and non-positive earnings samples, there are relatively few significant differences across the regressions. Notably, the coefficient estimates on *Industry Specialization* are very similar using either *Allocation Indicator* or *Allocation Percent* as the dependent variable. For *Money Left*, however, the coefficient estimate on *Industry Specialization* is twice as big in the non-positive earnings sample of harder-to-value firms.[33] That only the *Money Left* regressions show significant differences is consistent with most bookbuilding theories. Rather than giving more allocations or larger allocations to investors who are likely to be informed, it appears that underwriters use underpricing as the primary means for compensating investors' information revelation.[34] As there are no consistent patterns between positive earnings and non-positive earnings firms for measures of commissions or investors' behaviors, these results reinforce the relative importance of information to allocations in our sample.

5.3 Underwriters' Brokerage Revenues

Our main analysis shows that investors' commissions paid to underwriters are related to whether investors receive allocations, but also that commissions paid are not related to allocations' profitability. Thus, it is unclear how important commissions are to the allocations process. Theories of quid pro quo arrangements assume that underwriters receive a significant portion of the money left on the table back through brokerage commissions or other lines of business, suggesting a positive relation between underwriters commissions and the total money left on the table from the IPOs they underwrite. Consistent with this hypothesis, Chang et al. (2017) finds that a 10% increase

[32]Benveniste et al. (2003) uses the present value of growth options as a measure of valuation uncertainty. As 60% of our sample firms have non-positive earnings, and 100% of their values would be attributed to growth options, we simply split our sample based on earnings.

[33]Estimating the regression coefficients simultaneously using dummy variables shows that the coefficient estimate on *Industry Specialization* is significantly larger in the non-positive sample (at the 10% level, t-statistic is 1.95).

[34]Consistent with this finding Chiang et al. (2019) documents that lead underwriters themselves benefit from their own informational advantage in post-IPO trading, especially if underwriters specialize in the IPO firm industry and if there is a significant information asymmetry about the IPO firm.

in Taiwanese underwriters' money left on the table from their IPOs leads to a 0.54% increase in underwriters' brokerage revenues.

To test this hypothesis in our sample, we follow Chang et al. (2017) and regress underwriters' annual ANcerno brokerage revenues (in the current and next year) on underwriters' annual money left on the table.[35] As several large underwriters dominate our sample, we include underwriter fixed effects and conduct sub-sample analyses including either the top 16 or top 5 most active underwriters.[36] Using fixed effects focuses our analysis on how within-underwriter changes in commissions are related to changes in money left on the table. We also control for the overall level of market trading using the total ANcerno trading volume in each year.

Table 11 reports the regression results. Our results do not show evidence of a positive relation between underwriters' commissions and the total money left on the table from the IPOs they underwrite.[37] Across six specifications (three using contemporaneous money left on the table and three using the prior year's money left on the table), no coefficient estimate is significantly positive and one estimate is significantly negative at the 5% level. Focusing on the top 16 or top five underwriters in our sample, the coefficient estimates are nearly zero with no t-statistic in excess of 1 (in absolute value). Thus, in our sample, we do not find evidence that underwriters' brokerage commissions increase when they leave more money left on the table for investors. This finding reinforces our earlier results that suggest information is relatively more important than commissions for determining IPO allocations and IPO profits.

6 Conclusion

We combine institutional holdings data with ANcerno trading and commissions data to simultaneously test competing explanations for why institutional investors get allocations and profits in IPOs: 1) paying high commissions to underwriters (i.e, quid pro quo), 2) having large size or specializing in the IPO firm's industry (i.e., being informed), 3) or engaging in post-IPO price support

[35]In a departure from Chang et al. (2017), we do not use the log of money left on the table nor commission as several underwriter-year observations report negative money left on the table. Taking logs and excluding negative observations yields qualitatively similar results to those reported.

[36]See Table 1 for the underwriters included in each group.

[37]Repeating the analysis at the quarterly frequency yields similar conclusions.

and holding shares for the long-term. We find that all explanations help investors to receive an allocation in an IPO, yet the size of the allocation and it's profitability are only related to the information mechanism via investors' sizes and industry specializations. We further show that the majority of the variation in investors' IPO profits is explained by the information mechanism. We find that the information mechanism is more pronounced for Investment Managers and Hedge Funds, and is more important in hard-to-value firms' IPOs. Finally, we show that underwriters' profits are not related to the money left on the table in their IPOs, inconsistent with a quid pro quo mechanism. We conclude that, within our sample, the information mechanism is most important to determining IPO allocations and the associated IPO profits.

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Figure 1: The figure shows individual investors' assets under management (grey bars and right axis) and total money left on the table (blue line and left axis). The 100 largest investors, based on their total money left on the table, are ordered based on their total money left on the table across all sample IPOs.

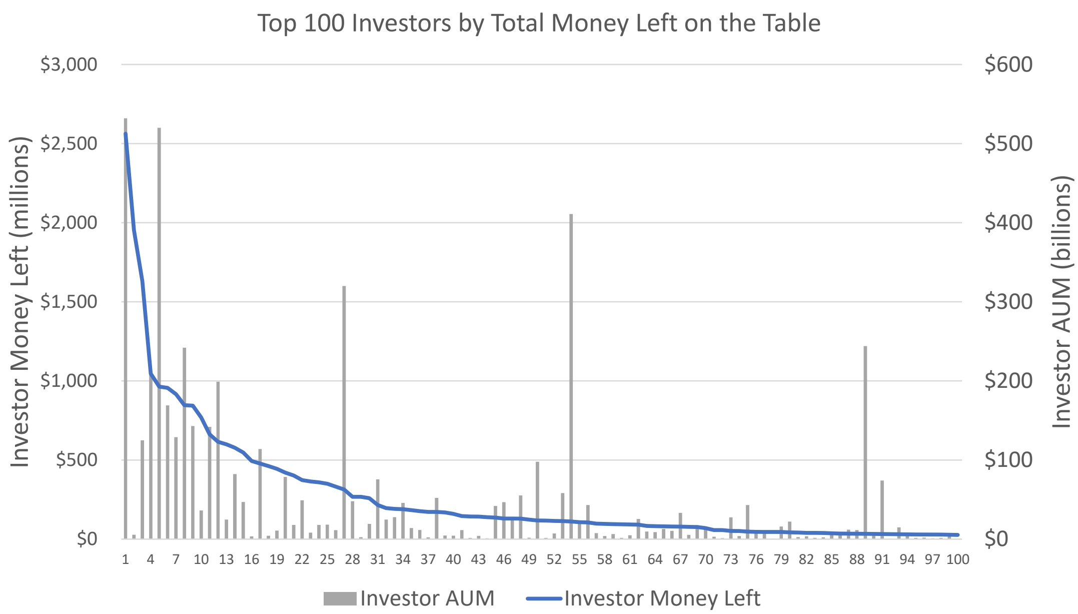

Figure 2: The figure shows individual investors' number of allocations (grey bars and right axis) and total money left on the table (blue line and left axis). The 100 largest investors, based on their total money left on the table, are ordered based on their total money left on the table across all sample IPOs.

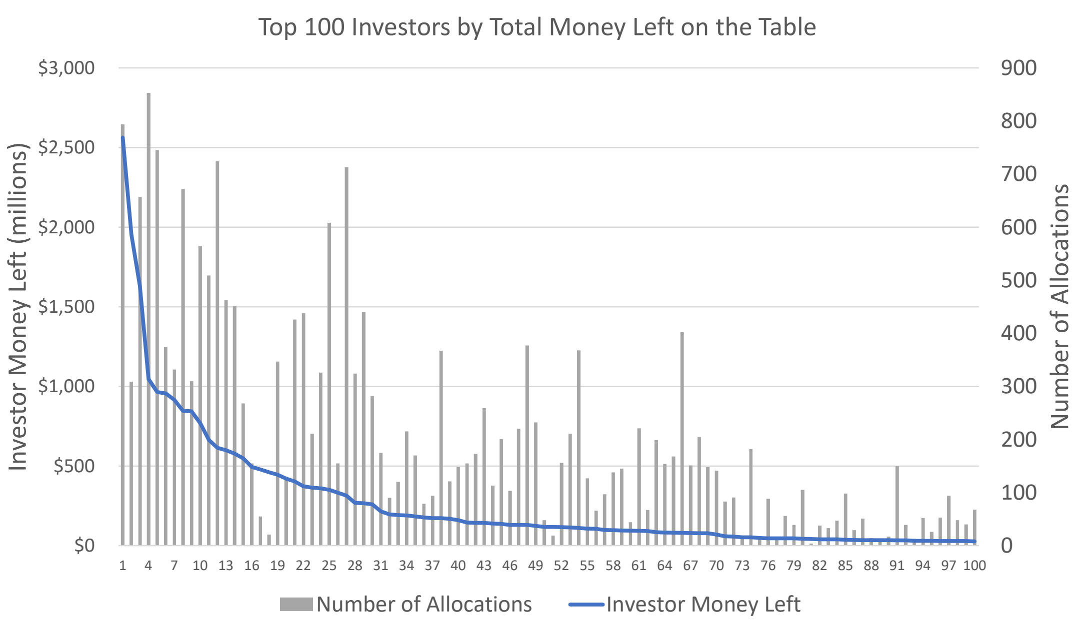

Table 1: Sample Summary. Panel A displays sample statistics by year and Panel B displays sample statistics by underwriter. Each panel lists the number of IPOs in our sample, the number of inferred allocations, the number of managers who receive an allocation, the total proceeds of all IPOs, the total dollar value of all inferred allocations, and the percent of the proceeds represented by our inferred allocations. Allocations are inferred by combining the 13F institutional holdings data with ANcerno trading data.

Panel A: Summary Statistics by Year

Year	Number of IPOs	Inferred Allocations per IPO	Number of Investors	Total Proceeds	Inferred Allocation Dollars	Inferred Allocation Percent
1999	413	16.7	169	$69,746	$17,963	25.8%
2000	306	15.7	158	$46,377	$13,717	29.6%
2001	69	19.3	142	$31,648	$10,402	32.9%
2002	54	21.3	137	$18,512	$7,129	38.5%
2003	53	20.5	114	$9,320	$3,383	36.3%
2004	157	13.9	157	$29,699	$10,625	35.8%
2005	127	13.7	133	$24,629	$6,078	24.7%
2006	152	13.8	137	$29,820	$7,633	25.6%
2007	142	14.9	142	$30,447	$9,981	32.8%
2008	17	13.2	84	$4,043	$1,140	28.2%
2009	30	14.4	83	$8,856	$3,028	34.2%
2010	92	10.2	112	$27,331	$6,147	22.5%
Total	1612	15.5	319	$330,429	$97,225	29.4%

Panel B: Summary Statistics by Underwriter

Year	Number of IPOs	Inferred Allocations per IPO	Number of Investors	Total Proceeds	Inferred Allocation Dollars	Inferred Allocation Percent
Goldman Sachs & Co	198	20.1	227	$70,389	$22,976	32.6%
Credit Suisse First Boston	195	19.6	213	$49,837	$15,536	31.2%
Morgan Stanley Dean Witter	171	22.1	240	$77,655	$20,845	26.8%
Merrill Lynch	110	14.6	190	$20,777	$6,346	30.5%
Lehman Brothers	92	13.8	157	$14,364	$3,661	25.5%
Salomon Smith Barney	88	14.6	176	$21,544	$5,997	27.8%
JP Morgan	78	14.5	161	$14,015	$5,231	37.3%
Fleet Boston Corp	68	17.8	100	$5,030	$1,286	25.6%
Deutsche Bank Securities Corp	65	13.7	128	$6,432	$1,581	24.6%
Chase H&Q	55	10.7	98	$3,701	$825	22.3%
Donaldson Lufkin & Jenrette	51	14.6	97	$6,840	$1,737	25.4%
UBS Warburg	46	10.1	113	$5,535	$1,114	20.1%
Bear Stearns & Co Inc	46	18.0	142	$6,198	$2,365	38.2%
Banc of America Securities LLC	42	15.7	129	$6,133	$2,016	32.9%
Piper Jaffray Cos	32	12.0	102	$2,405	$821	34.1%
SG Cowen Securities Corp	30	8.0	87	$1,762	$413	23.4%
75 Other Underwriters	245	8.6	186	$17,813	$4,473	25.1%
Total	1612	15.5	319	$330,429	$97,225	29.4%

Table 2: Investor Summary Statistics. Investors are divided into categories based on the number of inferred allocations in our sample. The very high number of allocations group has 79 investors and each other group has 80 investors. Averages are calculated by first averaging within investor (across IPOs) and then averaging across investors (within category). Variable definitions are provided in the appendix.

	Very High # of Allocations		High # of Allocations		Low # of Allocations		Very Low # of Allocations	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Number of Allocations	270	199	37	31	7	7	1	1
Allocation Frequency (%)	20.8	13.4	4.0	3.7	0.8	0.8	0.2	0.1
Allocation Size (%)	1.7	1.4	1.8	1.2	1.4	0.7	1.0	0.1
Allocation Value ($millions)	3.395	2.422	3.645	2.442	8.345	1.740	4.749	0.567
Money Left ($millions)	1.028	0.742	1.079	0.451	0.714	0.281	0.332	0.025
Client Size (%)	0.933	0.226	0.241	0.041	0.136	0.010	0.049	0.001
Abnormal Commissions (%)	-0.150	-0.049	-0.060	0.000	0.032	-0.004	0.084	0.000
Past Price Support	0.156	0.125	0.124	0.093	0.063	0.000	0.000	0.000
Past Flipping	-0.016	-0.050	-0.037	-0.063	-0.033	-0.043	-0.002	0.000
Past Hold Time	0.042	0.041	0.082	0.021	0.046	0.000	0.006	0.000
Trading Volume (%)	0.814	0.153	0.193	0.028	0.072	0.012	0.051	0.014
Log Investor AUM	23.6	23.4	22.2	22.1	21.8	21.6	21.5	21.6
Industry Specialization (%)	0.756	0.371	1.242	0.609	0.826	0.355	0.422	0.105
Average Holding (months)	11.2	11.6	13.1	11.9	14.9	16.4	13.8	18.7
Average Flipping (%)	46.0	43.4	36.6	35.6	30.0	19.2	29.5	0.0
Average Price Support (%)	20.0	16.7	24.5	21.9	25.9	16.7	0.0	0.0

Table 3: Sample Summary Statistics (above median). The tables displays means, standard deviations, and distributional values for the dependent and independent variables used in our regression analyses. Positive allocations are inferred by combining the 13F institutional holdings data with ANcerno trading data. Zero allocations are inferred when both 13F institutional holdings data and ANcerno trading data are available and no positive allocation exists. Variable definitions are provided in the appendix.

Variable	Observations	Mean	Std. Dev.	Min	10th Pctl.	Median	90th Pctl.	Max
Allocation Indicator	177,443	0.137	0.344	0.000	0.000	0.000	1.000	1.000
Client Size (%)	177,443	0.543	1.847	0.000	0.000	0.011	0.946	11.085
Abnormal Commissions (%)	177,443	-0.116	5.316	-22.152	-1.533	0.000	0.693	24.444
Past Price Support	177,443	0.095	0.205	0.000	0.000	0.000	0.333	1.000
Past Flipping	177,443	-0.031	0.285	-0.776	-0.449	0.000	0.405	0.876
Past Hold Time	177,443	0.050	0.480	-1.597	-0.600	0.000	0.882	1.556
Trading Volume (%)	177,443	0.513	1.557	0.000	0.003	0.035	0.870	8.526
Log Investor AUM	177,443	22.952	1.747	18.617	20.833	22.872	25.411	26.829
Industry Specialization (%)	177,443	0.174	3.703	-11.558	-4.007	-0.235	5.033	10.717
Offer Price Revision	177,443	0.019	0.145	-0.353	-0.175	0.000	0.190	0.438
Low Demand	177,443	0.270	0.444	0.000	0.000	0.000	1.000	1.000
High Demand	177,443	0.171	0.376	0.000	0.000	0.000	1.000	1.000
Underwriter Rank	177,443	8.246	1.235	3.001	7.001	9.001	9.001	9.001
Log Firm Age	177,443	2.345	0.976	0.000	1.386	2.197	3.761	4.779
Tech Firm	177,443	0.505	0.500	0.000	0.000	1.000	1.000	1.000
VC Backed	177,443	0.522	0.500	0.000	0.000	1.000	1.000	1.000
Log Proceeds	177,443	4.685	0.879	2.958	3.743	4.534	5.880	7.711
Allocation Percent (%)	24,329	1.829	3.196	0.000	0.013	0.540	5.082	19.594
Money Left ($million)	24,329	1.142	4.464	-11.106	0.000	0.150	2.419	163.650

Table 4: Explaining Whether an Investor Receives an Allocation

The table displays the results of the regressions of 177,426 IPO allocation outcomes to institutional investors in the US IPOs between 1999 and 2010 on several investor and relationship characteristics. The dependent variable *Allocation Indicator* is equal to 1 if an investor received an allocation in an IPO and 0 otherwise. Columns (1)-(3) include variables related to investors' relationships with underwriters including commission payments and post-IPO behaviors. Columns (4)-(6) include additional investor-specific characteristics. All independent variables are standardized by subtracting their means and dividing by their standard deviations. We provide a detailed description of all variables in Table A1. Standard errors clustered at the investor-underwriter level, *t*-statistics are below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% respectively.

	Allocation Indicator			
	(1)	(2)	(3)	(4)
Client Size	7.59***	3.04***	2.96***	1.37***
	(17.45)	(7.09)	(6.94)	(2.92)
Abnormal Commissions	-0.06	-0.08	-0.10	-0.14
	(-0.38)	(-0.63)	(-0.77)	(-1.33)
Past Price Support	2.77***	2.74***	2.96***	1.68***
	(5.53)	(6.88)	(7.28)	(6.93)
Past Flipping	1.69***	2.39***	2.47***	0.70***
	(5.14)	(6.45)	(6.38)	(2.91)
Past Hold Time	0.68**	0.63**	0.60*	1.08***
	(2.28)	(2.13)	(1.89)	(4.13)
Trading Volume		3.12***	3.13***	3.31***
		(5.73)	(5.81)	(5.71)
Log Investor AUM		5.83***	5.93***	5.00***
		(14.25)	(14.31)	(8.39)
Industry Specialization		1.97***	1.87***	1.51***
		(7.99)	(7.26)	(8.79)
Offer Price Revision	2.69***	2.57***		2.58***
	(4.51)	(4.28)		(4.02)
High Demand	3.01***	2.99***		3.09***
	(8.48)	(8.39)		(8.71)
Low Demand	-0.92**	-0.99**		-1.00**
	(-2.39)	(-2.57)		(-2.41)
Underwriter Rank	0.21	0.29		0.33
	(0.87)	(1.27)		(0.36)
Log Firm Age	0.62**	0.60**		0.57**
	(2.41)	(2.35)		(2.28)
Tech Firm	0.01	-0.09		-0.04
	(0.03)	(-0.33)		(-0.15)
VC Backed	1.20***	1.18***		1.23***
	(4.68)	(4.62)		(4.42)
Log Proceeds	4.08***	4.18***		4.13***
	(12.67)	(12.94)		(11.57)
Constant	13.71***	13.71***	13.71***	13.93***
	(34.02)	(35.81)	(61.83)	(49.55)
Fixed Effects	None	None	IPO	InvUW
Adjusted R^2	0.111	0.147	0.186	0.226
Observations	177,443	177,443	177,443	172,830

Table 5: Explaining the Size of an Allocation

The table displays the results of the regressions of 24'326 non-zero IPO allocations to institutional investors in the US IPOs between 1999 and 2010 on several investor and relationship characteristics. The dependent variable *Allocation Percent* is the end-of-quarter shares held reported in the 13F institutional holdings data minus net shares bought from the IPO data to the quarter end from the ANcerno data divided by the shares offered in the IPO. Columns (1)-(3) include variables related to investors' relationships with underwriters including commission payments and post-IPO behaviors. Columns (4)-(6) include additional investor-specific characteristics. All independent variables are standardized by subtracting their means and dividing by their standard deviations. We provide a detailed description of all variables in Table A1. Standard errors clustered at the investor-underwriter level, t-statistics are below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% respectively.

	Allocation Percent			
	(1)	(2)	(3)	(4)
Client Size	0.13***	0.04	0.03	-0.07
	(3.99)	(0.92)	(0.84)	(-1.38)
Abnormal Commissions	0.04***	0.04***	0.03**	0.02
	(2.72)	(2.80)	(2.38)	(1.34)
Past Price Support	0.17***	0.16***	0.17***	-0.18***
	(3.78)	(3.63)	(3.74)	(-4.21)
Past Flipping	-0.37***	-0.28***	-0.24***	0.08*
	(-11.77)	(-9.31)	(-7.35)	(1.85)
Past Hold Time	-0.12***	-0.11***	-0.10**	-0.17***
	(-3.42)	(-3.17)	(-2.58)	(-4.52)
Trading Volume		0.07	0.09*	-0.02
		(1.34)	(1.79)	(-0.19)
Log Investor AUM		0.22***	0.18***	0.82***
		(3.75)	(3.34)	(6.21)
Industry Specialization		0.39***	0.41***	0.21***
		(6.78)	(6.89)	(4.51)
Offer Price Revision	-0.60***	-0.60***		-0.48***
	(-5.59)	(-5.80)		(-5.07)
High Demand	0.01	0.01		-0.01
	(0.35)	(0.35)		(-0.24)
Low Demand	0.31***	0.30***		0.31***
	(3.81)	(3.80)		(3.96)
Underwriter Rank	-0.20***	-0.22***		0.03
	(-3.15)	(-3.55)		(0.24)
Log Firm Age	0.07*	0.08**		0.09**
	(2.00)	(2.10)		(2.67)
Tech Firm	0.06	0.04		0.04
	(1.51)	(1.01)		(1.36)
VC Backed	-0.02	-0.02		-0.05
	(-0.40)	(-0.55)		(-1.29)
Log Proceeds	-0.44***	-0.42***		-0.39***
	(-10.53)	(-9.80)		(-9.65)
Constant	2.27***	2.09***	1.54***	1.76***
	(31.38)	(31.78)	(48.20)	(14.82)
Fixed Effects	None	None	IPO	InvUW
Adjusted R^2	0.088	0.102	0.185	0.241
Observations	24,329	24,329	24,217	23,043

Table 6: Explaining Money Left on the Table

The table displays the results of the regressions of money left on the table per investor-IPO between 1999 and 2010 on several investor and relationship characteristics (the sample includes zero allocations). The dependent variable *Money Left* is the *Allocation Size* × *Offering price* × *Initial return*. Columns (1)-(3) include variables related to investors' relationships with underwriters including commission payments and post-IPO behaviors. Columns (4)-(6) include additional investor-specific characteristics. All independent variables are standardized by subtracting their means and dividing by their standard deviations. We provide a detailed description of all variables in Table A1. Standard errors clustered at the investor-underwriter level, t-statistics are below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% respectively.

	Money Left			
	(1)	(2)	(3)	(4)
Client Size	0.14***	0.06***	0.06***	-0.00
	(4.34)	(3.26)	(3.29)	(-0.06)
Abnormal Commissions	0.00	0.00	0.00	-0.01
	(0.11)	(0.07)	(0.17)	(-0.44)
Past Price Support	0.04**	0.03**	0.04***	-0.01
	(2.36)	(2.44)	(3.07)	(-0.93)
Past Flipping	-0.06***	-0.05***	-0.04***	-0.01
	(-3.46)	(-3.29)	(-3.11)	(-1.06)
Past Hold Time	-0.03**	-0.03**	-0.02**	-0.05**
	(-2.49)	(-2.60)	(-2.53)	(-2.30)
Trading Volume		0.06***	0.06***	0.12**
		(2.97)	(3.17)	(2.27)
Log Investor AUM		0.10***	0.10***	0.12***
		(4.85)	(4.97)	(4.34)
Industry Specialization		0.08***	0.08***	0.06***
		(4.91)	(4.81)	(5.16)
Offer Price Revision	-0.01	-0.02		-0.03
	(-0.47)	(-0.57)		(-0.74)
High Demand	0.12***	0.12***		0.12***
	(3.89)	(3.90)		(3.99)
Low Demand	-0.03	-0.03		-0.03
	(-1.54)	(-1.59)		(-1.58)
Underwriter Rank	-0.03***	-0.02***		0.02
	(-3.07)	(-3.00)		(0.72)
Log Firm Age	-0.03**	-0.03***		-0.03***
	(-2.60)	(-2.80)		(-2.77)
Tech Firm	0.03**	0.02**		0.02*
	(2.44)	(2.10)		(1.97)
VC Backed	0.05***	0.05***		0.05***
	(3.96)	(3.99)		(3.91)
Log Proceeds	0.16***	0.17***		0.18***
	(4.81)	(4.85)		(5.34)
Constant	0.16***	0.16***	0.16***	0.16***
	(7.72)	(7.99)	(23.11)	(9.72)
Fixed Effects	None	None	IPO	InvUW
Adjusted R^2	0.023	0.029	0.071	0.024
Observations	177,443	177,443	177,443	172,830

Table 7: Money Left Variance Decomposition. This table shows the percentage of variance explained by commissions variables (*Client Size* and *Abnormal Commissions*), post-IPO variables (*Past Price Support*, *Past Hold Time* and *Past Flipping*), and investor variables (*Log Investor AUM*, *Industry Specialization* and *Trading Volume*). To calculate the percentages, we first regress money left on all explanatory variables (plus control variables) and regressions with each variable omitted. We then calculate the incremental R^2 contributed by each variable, and then divide by the sum of the incremental R^2s for all variables. Panel A analyzes our full sample. Panels B, C and D analyze sub-samples of Banks, Pensions and Insurers, Hedge Funds, and Investment Managers.

		Money Left Explained By:							
	Obs.	Client Size	Abnormal Commissions	Past Price Support	Past Flipping	Past Hold Time	Trading Volume	Log Inv AUM	Industry Specialization
Panel A: Full Sample									
No Fixed Effects	177,443	8.6%	0.0%	5.1%	6.6%	3.0%	6.0%	39.4%	31.3%
IPO Fixed Effects	177,443	8.5%	0.0%	9.5%	4.6%	1.5%	6.5%	39.5%	29.8%
Inv-UW Fixed Effects	177,443	0.0%	0.5%	0.4%	0.6%	14.0%	19.5%	19.4%	45.5%
Panel B: Banks, Pensions and Insurer									
No Fixed Effects	25,889	0.0%	0.5%	2.6%	9.4%	12.0%	8.8%	63.7%	2.9%
IPO Fixed Effects	25,889	0.0%	0.4%	0.2%	5.0%	1.7%	13.4%	72.4%	7.0%
Inv-UW Fixed Effects	25,889	4.9%	2.2%	3.1%	1.2%	49.1%	2.4%	30.6%	6.6%
Panel C: Hedge Funds									
Hedge Funds	38,535	0.8%	0.0%	18.7%	7.4%	1.5%	3.5%	16.5%	51.7%
Hedge Funds	38,535	1.1%	0.0%	23.0%	8.9%	4.2%	4.1%	8.9%	49.8%
Hedge Funds	38,535	0.1%	0.2%	5.5%	0.0%	15.9%	1.6%	38.2%	38.5%
Panel D: Investment Managers									
Investment Managers	113,019	24.2%	0.0%	1.4%	4.3%	1.3%	3.9%	42.9%	22.0%
Investment Managers	113,019	23.2%	0.0%	3.8%	2.4%	0.3%	4.0%	46.8%	19.4%
Investment Managers	113,019	0.2%	1.8%	0.1%	0.6%	7.4%	35.0%	10.8%	44.2%

Table 8: Investor Summary Statistics by Type. Investors are divided into categories of either hedge funds, investment managers or banks / pensions / insurers. Averages are calculated by first averaging within manager (across IPOs) and then averaging across managers (within category). Variable definitions are provided in the appendix.

	Hedge Funds		Investment Managers		Banks/Pensions/Insurers	
	Mean	Median	Mean	Median	Mean	Median
Number of Allocations	131	71	150	89	205	120
Allocation Frequency (%)	13.6	7.4	12.7	6.9	19.3	10.1
Allocation Size (%)	1.3	1.1	2.1	1.8	1.2	1.0
Allocation Value ($millions)	2.614	1.974	4.113	2.963	2.625	1.654
Money Left ($millions)	0.655	0.519	1.302	0.692	0.711	0.424
Client Size (%)	0.655	0.087	0.506	0.078	0.792	0.066
Abnormal Commissions (%)	0.001	0.005	-0.106	-0.020	-0.279	-0.004
Past Price Support	0.126	0.092	0.158	0.123	0.091	0.070
Past Flipping	0.107	0.119	-0.058	-0.075	-0.128	-0.116
Past Time Hold	-0.087	-0.060	0.090	0.092	0.204	0.244
Trading Volume (%)	0.491	0.056	0.476	0.061	0.627	0.167
Log Investor AUM	22.1	22.1	22.8	22.7	24.2	24.1
Industry Specialization (%)	0.685	0.202	1.426	0.930	-0.225	-0.216
Average Holding (months)	8.2	7.5	13.3	12.7	14.0	13.6
Average Flipping (%)	59.5	63.2	36.1	38.7	31.1	33.4
Average Price Support (%)	18.4	15.1	25.4	21.9	15.9	16.3

Table 9: Money Left Analysis By Type of Investor

The table displays regressions of IPO money left on control variables and manager and relationship characteristics. All variables are defined in Table A1. Standard errors clustered at the institutional investor-underwriter level, *t*-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Allocation Indicator			Allocation Percent			Money Left		
	(1) BnkPnsIns	(2) InvMgr	(3) HF	(4) BnkPnsIns	(5) InvMgr	(6) HF	(7) BnkPnsIns	(8) InvMgr	(9) HF
Client Size	1.10	1.11**	1.98**	-0.19*	-0.01	-0.14	-0.04	0.01	0.01
	(1.09)	(2.03)	(2.19)	(-1.94)	(-0.08)	(-0.81)	(-1.42)	(0.35)	(0.44)
Abnormal Commissions	0.29	-0.36**	0.03	0.05*	0.01	0.00	0.01	-0.01	-0.00
	(1.02)	(-2.42)	(0.12)	(1.75)	(0.47)	(0.07)	(0.70)	(-0.64)	(-0.46)
Past Price Support	1.43**	2.01***	1.50***	-0.11**	-0.17***	-0.31***	-0.02	0.00	-0.04
	(2.63)	(7.36)	(4.21)	(-2.32)	(-3.40)	(-3.35)	(-1.40)	(0.51)	(-1.44)
Past Flipping	-0.11	0.99***	0.79	0.16**	0.06	0.02	-0.01	-0.01	-0.00
	(-0.14)	(3.48)	(1.13)	(2.05)	(1.10)	(0.19)	(-0.50)	(-1.06)	(-0.11)
Past Hold Time	0.96	0.66**	1.70**	-0.02	-0.14***	-0.24*	-0.08	-0.04*	-0.08*
	(1.14)	(2.41)	(2.43)	(-0.41)	(-3.64)	(-2.00)	(-1.48)	(-2.00)	(-1.71)
Trading Volume	-1.61	4.65***	2.30	0.35**	-0.16	0.35	-0.03	0.17**	-0.08*
	(-0.81)	(7.29)	(0.91)	(2.12)	(-1.30)	(1.09)	(-0.52)	(2.35)	(-1.76)
Log Investor AUM	8.75***	2.29***	4.20***	0.29**	0.78***	1.36***	0.09***	0.10***	0.23**
	(8.64)	(3.75)	(3.24)	(2.41)	(4.22)	(4.46)	(3.39)	(3.04)	(2.43)
Industry Specialization	0.55**	1.39***	2.28***	0.21**	0.20***	0.20***	0.02	0.07***	0.08**
	(2.11)	(7.79)	(7.21)	(2.54)	(3.21)	(3.77)	(1.02)	(5.41)	(2.45)
Offer Price Revision	1.21	2.62***	3.29***	-0.28**	-0.49***	-0.55***	-0.05	-0.03	-0.01
	(1.18)	(4.31)	(3.94)	(-2.35)	(-4.10)	(-4.54)	(-0.88)	(-0.77)	(-0.46)
High Demand	4.00***	2.81***	3.52***	-0.02	-0.02	0.03	0.14***	0.13***	0.09***
	(6.88)	(8.32)	(7.28)	(-0.32)	(-0.43)	(0.73)	(3.00)	(4.14)	(3.01)
Low Demand	-1.67**	-0.77*	-1.20**	0.06	0.38***	0.61***	-0.05	-0.03	-0.02*
	(-2.62)	(-1.99)	(-2.29)	(0.72)	(3.98)	(4.57)	(-1.63)	(-1.41)	(-1.93)
Underwriter Rank	1.62	-0.13	0.71	-0.15	0.16	0.01	0.02	0.00	0.04
	(0.74)	(-0.14)	(0.60)	(-0.70)	(0.70)	(0.04)	(0.56)	(0.13)	(1.50)
Log Firm Age	1.57***	0.45*	0.38	-0.02	0.14***	0.01	-0.02	-0.03***	-0.03*
	(3.79)	(1.99)	(1.08)	(-0.33)	(3.23)	(0.29)	(-1.33)	(-2.97)	(-1.69)
Tech Firm	0.05	-0.05	-0.06	-0.01	0.08*	0.02	0.01	0.03*	0.02
	(0.14)	(-0.23)	(-0.20)	(-0.11)	(1.73)	(0.54)	(1.12)	(1.86)	(1.56)
VC Backed	1.88***	1.05***	1.35***	-0.08*	-0.03	-0.08*	0.05**	0.06***	0.04**
	(3.86)	(4.03)	(3.88)	(-1.73)	(-0.63)	(-1.69)	(2.58)	(4.17)	(2.44)
Log Proceeds	6.66***	3.73***	3.88***	-0.28***	-0.43***	-0.40***	0.18***	0.20***	0.12***
	(11.79)	(11.33)	(7.41)	(-6.45)	(-7.90)	(-6.92)	(4.16)	(5.25)	(4.28)
Constant	19.68***	12.91***	13.78***	1.52***	2.06***	1.39***	0.17***	0.17***	0.13***
	(45.10)	(52.47)	(39.58)	(12.64)	(12.01)	(7.26)	(8.81)	(11.54)	(8.20)
Fixed Effects	InvUW	InvUW	InvUW	InvUW	InvUW	InvUW	InvUW	InvUW	InvUW
Adjusted R^2	0.249	0.222	0.213	0.146	0.232	0.332	0.031	0.023	0.033
Observations	23,774	110,132	37,486	4,528	13,576	4,935	23,774	110,132	37,486

Table 10: Analysis By Firm Earnings

The table displays regressions of IPO money left on control variables and manager and relationship characteristics using Investor-Underwriter fixed effects. Firms are split by whether they have positive or non-positive pre-IPO earnings per share. All variables are defined in Table A1. Standard errors clustered at the institutional investor-underwriter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Allocation Indicator		Allocation Percent		Money Left	
	(1) PosEarn	(2) NonPos	(3) PosEarn	(4) NonPos	(5) PosEarn	(6) NonPos
Client Size	1.16**	1.35**	-0.10	-0.08	-0.00	0.00
	(2.33)	(2.32)	(-1.30)	(-1.29)	(-0.28)	(0.10)
Abnormal Commissions	-0.17	-0.09	0.01	0.01	-0.03	0.01
	(-0.90)	(-0.71)	(0.67)	(0.69)	(-1.15)	(0.51)
Past Price Support	1.88***	1.44***	-0.22***	-0.11	0.01	-0.02*
	(5.68)	(5.28)	(-4.35)	(-1.58)	(0.68)	(-1.86)
Past Flipping	0.26	0.64**	0.08	0.10	-0.04	-0.00
	(0.77)	(2.21)	(1.33)	(1.61)	(-1.40)	(-0.14)
Past Hold Time	0.25	1.16***	-0.14**	-0.14***	-0.07**	-0.04**
	(0.70)	(3.85)	(-2.53)	(-3.23)	(-2.05)	(-2.44)
Trading Volume	3.16***	3.01***	-0.06	-0.02	0.10	0.13***
	(4.73)	(3.90)	(-0.45)	(-0.15)	(1.26)	(2.82)
Log Investor AUM	5.14***	4.43***	0.85***	0.85***	0.10***	0.13***
	(7.28)	(6.84)	(4.94)	(4.88)	(3.92)	(4.06)
Industry Specialization	1.45***	1.50***	0.19***	0.18***	0.04***	0.08***
	(7.71)	(7.49)	(4.60)	(2.84)	(2.87)	(5.74)
Offer Price Revision	3.80***	2.29***	-0.55***	-0.43***	-0.04	-0.03
	(4.71)	(3.91)	(-5.03)	(-4.72)	(-0.74)	(-0.88)
High Demand	2.96***	2.94***	-0.01	0.02	0.12*	0.12***
	(4.29)	(9.18)	(-0.14)	(0.74)	(1.94)	(5.64)
Low Demand	-0.42	-1.03**	0.16*	0.39***	-0.04	-0.03*
	(-1.01)	(-2.24)	(1.84)	(4.27)	(-1.14)	(-1.69)
Underwriter Rank	1.52	-0.10	-0.32	0.17	0.05	-0.01
	(0.90)	(-0.10)	(-1.06)	(1.11)	(1.15)	(-0.31)
Log Firm Age	0.33	0.31	0.03	0.12***	-0.02	-0.04*
	(0.69)	(0.94)	(0.54)	(3.75)	(-1.68)	(-2.01)
Tech Firm	0.01	0.04	0.07	0.01	0.05**	0.01
	(0.01)	(0.14)	(1.24)	(0.26)	(2.44)	(0.68)
VC Backed	1.52***	1.16***	-0.09	-0.02	0.04*	0.06***
	(3.19)	(4.98)	(-1.64)	(-0.71)	(1.76)	(3.88)
Log Proceeds	4.56***	3.79***	-0.37***	-0.39***	0.24***	0.15***
	(7.81)	(10.37)	(-6.48)	(-8.12)	(4.51)	(4.00)
Constant	15.26***	13.37***	1.87***	1.65***	0.15***	0.17***
	(44.86)	(47.71)	(12.99)	(10.92)	(6.45)	(12.36)
Fixed Effects	InvUW	InvUW	InvUW	InvUW	InvUW	InvUW
Adjusted R^2	0.210	0.244	0.216	0.260	-0.014	0.034
Observations	61,929	108,028	8,570	13,748	61,929	108,028

Table 11: Underwriter Brokerage Revenues

The table displays regressions of underwriters' annual ANcerno commissions on either the current year's or prior year's total money left on the table (to investors in the ANcerno data). Total ANcerno trading volume is measured in shares and is reported in thousands. All variables are defined in Table A1. The intercepts of each regression are suppressed for readability. Standard errors are adjusted for heteroskedasticity, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Annual Underwriter Commissions					
	(1)	(2)	(3)	(4)	(5)	(6)
Annual Money Left	-0.017***	-0.008	0.001			
	(-3.050)	(-1.479)	(0.145)			
Lagged Annual Money Left				-0.006	-0.003	0.004
				(-1.137)	(-0.621)	(0.676)
Total ANcerno Volume (000s)	0.497***	0.812***	1.182***	0.828***	0.978***	1.433***
	(7.586)	(7.528)	(4.368)	(6.698)	(6.617)	(4.340)
Underwriters	All	Top 16	Top 5	All	Top 16	Top 5
Adjusted R^2	0.758	0.707	0.617	0.733	0.686	0.604
Observations	263	149	57	162	126	52

A Appendix: Variable Definitions and Additional Results

This appendix defines the variables used in the paper and motivates and describes our robustness tests.

- Table A1 defines each of the variables used in our analysis.
- Table A2 and Table A3 address the concern that our results are driven by the dot-com bubble of the late 1990s and early 2000s. The main results are generally consistent with our main regression results. Relations are often stronger during the bubble period, although that is not always the case.
- Table A4, Table A5 and Table A6 address the concern that we may be including too many zero allocations in our data. Our main regressions includes zero allocations for investors who report 13F holdings and ANcerno trades within a quarter. In Table A4, we require that investors also receive at least one positive allocation in the same quarter. In Table A5, we require that investors report 13F holdings and ANcerno trades within a quarter and receive at least one positive allocation from the same underwriter (anytime in the sample). In Table A6, we require that investors report 13F holdings and ANcerno trades within a quarter, receive at least one positive allocation in the same quarter, and receive at least one positive allocation from the same underwriter (anytime in the sample, not only in the quarter of interest). Across the tables, the results are qualitatively consistent with our main regression results.
- Table A7 and Table A8 include investors who receive less than the median level of allocations (i.e. 13 or fewer allocations). Table A7 presents the consolidated results of our main analyses when including only the low allocation investors, and Table A8 presents the consolidated results of our main analyses when including all investors in the sample (i.e. investors who receive both above and below median number of allocations). While many of the relations identified in our main analyses are present for the below-median allocations investors, the relations are generally weaker and are often not significant.
- Table A9 addresses the concern that investors may adjust future commissions in response to allocations rather than underwriters' conditioning allocations based on past commissions. *Future Client Size* is constructed in a similar fashion as *Client Size*, except the 9 months after the IPO are used rather than the 9 months before the IPO.
- Table A10 addresses the concern that excessive zeros or non-linearities in the allocations data may be altering our results. Rather than using a log transformation requiring adding one to each zero, we use the inverse hyperbolic sine transformation following Bellemare and Wichman (2020). The results are generally consistent with our main regression results.
- Table A11 reconciles our results with respect to holding period with those of Chemmanur et al. (2010). The first two columns present our main regression results, using measures of past holding and flipping that are measurable at the time of the IPOs. In these regressions, past holding time is negatively related to the size of allocations. In the third and fourth columns, we use measures of holding periods and flipping based on our full sample. In these regressions, holding period is either negatively related to allocation size, or is not significantly different from zero. In the fifth and sixth columns, we use measures of holding period based on

our full sample, and exclude the controls for flipping. Once we use the full sample measure of holding period, and exclude controls for flipping, we see a significant positive relation between holding period and allocation size. Furthermore, as in Chemmanur et al. (2010), the relation is stronger for holding period in cold IPOs versus hot IPOs.

Table A1: Variable Definitions

This table contains the definitions and descriptions of the variables used in the paper.

Variable	Definition
Abnormal Commissions	The excess daily brokerage revenue paid by an investor to an underwriter in the 10 days before an IPO, following Goldstein et al. (2011). Excess daily brokerage revenue is calculated by subtracting average daily brokerage revenue from -60 to -21 days prior to an IPO from the average daily brokerage revenue from -10 to -1 days prior to an IPO. The excess daily brokerage revenues are normalized by the underwriter's average daily brokerage revenue from all investors from from -60 to -21 days prior to an IPO.
Allocation Indicator	An indicator variable equal to one if *Allocation Size* is greater than zero.
Allocation Size	The end-of-quarter shares held reported in the 13F institutional holdings data minus net shares bought from the IPO data to the quarter end from the ANcerno data.
Allocation Percent	*Allocation Size* divided by the shares offered in the IPO.
Annual Underwriter Commissions	Total commissions reported across all trades in the ANcerno data for a given year and underwriter. Commissions from investors who do not receive allocations are included in total commissions.
Annual Money Left	Total *Money Left* for all investors with allocations in our data for a given year and underwriter. Note that *Annual Money Left* does not include allocations to investors who are not in our data and thus *Annual Money Left* does not reflect the total money left on the table in each offering.
Average Flipping	An investor's percentage of their allocation sold in the first month after an IPO, averaged over all of the investors allocations.
Average Holding	An investor's average holding time across all of their allocations. Average holding time is calculated as the weighted average time each share allocated is held, and shares held at the end of the first year are assumed to be held 2 years, as in Chemmanur et al. (2010).
Average Price Support	The percentage of the past allocations to an investor in which the investor purchased shares in the first 30 days after the IPO.
Client Size	The total brokerage revenue paid by an investor to an underwriter divided by the total brokerage revenues received by that underwriter from all investors, measured from -270 to -21 days before an IPO, following Goldstein et al. (2011).
High Demand	An indicator variable equal to one if the offer price is higher than the maximum of the first offer price range, as in Chemmanur et al. (2010).
Industry Specialization	The percentage of an investor's 13F holdings in the IPO firm's industry minus the percentage of all investor's 13F holdings in the IPO firm's industry, similar to $FracSameSIC$ used in Reuter (2006).
Log Firm Age	Natural logarithm of firms age based on founding dates taken from Jay Ritter's website.
Log Investor AUM	Natural logarithm of the total 13F assets reported in the quarter.
Log Proceeds	Natural logarithm of the total IPO proceeds adjusted to year 2005 dollars.
LowDemand	An indicator variable equal to one if the offer price is lower than the minimum of the first offer price range, as in Chemmanur et al. (2010).
Money Left	$AllocationSize \times OfferPrice \times InitialReturn$. *OfferPrice* is the final offering price and *Initial Return* is the return from the IPO offer price to the price at the end of the first day of trading.

Table A1: continued from previous page

Variable	Definition
Offer Price Revision	Percentage change from the midpoint of the first offer price range to the final offering price. The positive relationship between underpricing and offer price revisions was first documented by Hanley (1993).
Past Flipping	An investor's percentage of their allocation sold in the first month in past IPOs by the underwriter minus the percentage of allocations sold in the first month in past IPOs by all investors for that underwriter. Past IPOs must have occurred at least 30 days prior to the sample IPO's date.
Past Hold Time	An investor's average holding time of allocations in past IPOs from the underwriter minus the average hold time of allocations in past IPOs by all investors for that underwriter. Past IPOs must have occurred at least 365 days prior to the sample IPO's date to ensure holding times are measurable as of that date. Average holding time is calculated as the weighted average time each share allocated is held, and shares held at the end of the first year are assumed to be held 2 years, as in Chemmanur et al. (2010).
Past Price Support	The percentage of the past allocations from an underwriter to an investor in which the investor purchased shares in the first 30 days after the IPO, following Fjesme (2016).
Tech Firm	Indicator variable equal to one if the firm's SIC code is in a technology sector as defined by Cliff and Denis (2004).
Total ANcerno Volume	The sum of all shares traded across all trades in the ANcerno data for a given year.
Trading Volume	Natural logarithm of the total shares traded in ANcerno across all securities, measured quarterly.
Underwriter Rank	Carter–Manaster rank originated in Carter and Manaster (1990), and further updated in Carter et al. (1998) and Loughran and Ritter (2004). The data are taken from Jay Ritter's website.
VC Backed	Indicator variable equal to one if the firm is backed by a venture capital firm.

Table A2: Main Regression Results: Bubble Period (1999-2000)

The table displays regressions of allocation indicators, percent allocated and money left on the table on control variables and manager and relationship characteristics, using no fixed effects, investor fixed effects, and investor-underwriter fixed effects. The sample includes IPO occurring between 1999 and 2000 and includes zero allocations for investors who report 13F holdings and ANcerno trades within a quarter. Standard errors are clustered at the investor-underwriter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Allocation Indicator			Allocation Percent			Money Left		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Client Size	3.78***	3.75***	0.32	-0.04	-0.05	-0.10	0.09	0.09*	-0.03
	(5.76)	(5.89)	(0.32)	(-0.89)	(-1.23)	(-1.76)	(2.30)	(2.38)	(-0.70)
Abnormal Commissions	-0.22	-0.20	-0.06	0.03	0.03	0.01	-0.00	0.00	-0.02
	(-0.99)	(-0.83)	(-0.29)	(2.09)	(1.76)	(0.97)	(-0.04)	(0.17)	(-0.60)
Past Price Support	3.77***	3.80***	1.60**	0.15*	0.16*	-0.20*	0.08*	0.08*	-0.03
	(6.35)	(6.33)	(4.01)	(2.54)	(2.59)	(-3.41)	(3.16)	(3.07)	(-1.29)
Past Flipping	2.75**	2.80**	0.86*	-0.30***	-0.26***	0.20**	-0.05*	-0.05*	0.03
	(5.24)	(5.28)	(2.61)	(-8.98)	(-7.08)	(3.58)	(-2.95)	(-2.92)	(1.76)
Past Hold Time	-0.32	-0.30	0.21	-0.02	-0.01	-0.04	-0.02	-0.01	-0.03
	(-0.78)	(-0.70)	(0.50)	(-0.86)	(-0.71)	(-1.62)	(-1.24)	(-1.48)	(-1.61)
Trading Volume	3.84**	3.86**	-1.23	0.14*	0.17**	0.10	0.11**	0.11**	0.13
	(4.44)	(4.52)	(-0.67)	(3.35)	(3.51)	(1.13)	(4.02)	(4.22)	(1.04)
Log Investor AUM	5.84***	5.87***	0.51	0.16*	0.13	0.84	0.14**	0.14**	0.15*
	(8.08)	(8.10)	(0.46)	(2.99)	(2.32)	(2.13)	(3.90)	(3.92)	(3.06)
Industry Specialization	2.53***	2.47***	1.39***	0.42**	0.46**	0.14	0.13***	0.13***	0.10***
	(5.85)	(5.67)	(5.63)	(4.27)	(4.37)	(1.96)	(6.96)	(6.77)	(6.76)
Offer Price Revision	1.80		1.57	-0.36**		-0.28*	-0.07		-0.08
	(2.17)		(1.75)	(-3.53)		(-3.37)	(-1.04)		(-1.20)
High Demand	3.06***		3.11***	-0.00		0.01	0.18**		0.19**
	(7.67)		(7.81)	(-0.09)		(0.39)	(3.90)		(4.08)
Low Demand	-0.75		-0.86	0.45**		0.43**	-0.04		-0.04
	(-1.55)		(-1.49)	(5.08)		(3.98)	(-1.17)		(-1.17)
Underwriter Rank	0.55		0.96	-0.13		0.00	-0.04		0.01
	(1.85)		(0.79)	(-1.81)		(0.03)	(-1.65)		(0.19)
Log Firm Age	0.07		0.21	0.15**		0.13**	-0.02		-0.02
	(0.25)		(0.61)	(3.74)		(3.72)	(-1.28)		(-1.13)
Tech Firm	0.14		0.15	-0.06*		-0.04	0.01		0.01
	(0.36)		(0.42)	(-2.40)		(-1.63)	(0.38)		(0.45)
VC Backed	0.44		0.40	-0.02		-0.02	0.04*		0.04*
	(1.67)		(1.71)	(-0.30)		(-0.38)	(2.74)		(2.50)
Log Proceeds	4.02***		3.64***	-0.31***		-0.30***	0.25**		0.23**
	(7.20)		(6.28)	(-6.13)		(-6.60)	(4.35)		(4.39)
Constant	14.47***	14.47***	14.96***	1.82***	1.42***	1.44***	0.25***	0.25***	0.26***
	(27.35)	(46.41)	(37.42)	(18.46)	(32.20)	(6.49)	(9.48)	(19.05)	(11.21)
Fixed Effects	None	IPO	InvUW	None	IPO	InvUW	None	IPO	InvUW
Adjusted R^2	0.172	0.201	0.295	0.094	0.155	0.271	0.039	0.074	0.060
Observations	79,202	79,202	75,802	11,462	11,426	10,832	79,202	79,202	75,802

Table A3: Main Regression Results: Post-Bubble Period (2001-2010)

The table displays regressions of allocation indicators, percent allocated and money left on the table on control variables and manager and relationship characteristics, using no fixed effects, investor fixed effects, and investor-underwriter fixed effects. The sample includes IPO occurring between 2001 and 2010 and includes zero allocations for investors who report 13F holdings and ANcerno trades within a quarter. Standard errors are clustered at the investor-underwriter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Allocation Indicator			Allocation Percent			Money Left		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Client Size	2.35***	2.22***	0.76	0.16*	0.15*	-0.03	0.04***	0.04***	-0.02
	(6.03)	(5.79)	(1.53)	(2.55)	(2.69)	(-0.48)	(5.85)	(5.76)	(-1.31)
Abnormal Commissions	0.06	0.01	-0.12	0.04	0.03	0.01	0.00	0.00	-0.00
	(0.47)	(0.05)	(-0.88)	(1.55)	(1.20)	(0.62)	(1.05)	(0.65)	(-0.07)
Past Price Support	1.98***	2.27***	1.38***	0.16**	0.18**	-0.24***	0.01**	0.01**	0.01
	(6.26)	(6.75)	(5.35)	(3.25)	(3.43)	(-4.60)	(2.74)	(3.47)	(1.39)
Past Flipping	1.73***	1.76***	0.80*	-0.22**	-0.18**	0.06	-0.01*	-0.01*	0.01
	(4.50)	(4.63)	(2.19)	(-3.40)	(-2.94)	(0.86)	(-2.40)	(-2.38)	(1.35)
Past Hold Time	0.55	0.44	0.59	-0.12	-0.10	-0.15*	-0.01	-0.01	-0.01
	(1.34)	(1.08)	(1.59)	(-1.60)	(-1.29)	(-2.05)	(-0.75)	(-0.64)	(-1.57)
Trading Volume	2.36***	2.39***	3.80***	-0.03	-0.02	-0.39**	0.01	0.01	-0.02
	(5.31)	(5.36)	(5.95)	(-0.32)	(-0.21)	(-3.45)	(1.07)	(1.26)	(-0.43)
Log Investor AUM	5.90***	6.06***	4.00***	0.27**	0.23*	0.54**	0.06***	0.06***	0.06***
	(14.25)	(14.06)	(5.35)	(3.01)	(2.72)	(3.20)	(4.89)	(5.00)	(4.29)
Industry Specialization	1.31***	1.19***	1.22***	0.34***	0.36***	0.18***	0.02***	0.01	0.01***
	(7.74)	(6.69)	(7.67)	(9.34)	(10.31)	(4.79)	(5.98)	(1.63)	(5.02)
Offer Price Revision	3.92***		4.19***	-0.91***		-0.78***	-0.01		-0.01
	(5.81)		(6.29)	(-8.35)		(-6.93)	(-0.86)		(-1.05)
High Demand	2.58***		2.74***	0.07		0.04	0.05**		0.05**
	(5.08)		(5.23)	(1.85)		(0.86)	(3.13)		(3.26)
Low Demand	-0.13		0.05	0.05		0.04	-0.03**		-0.03**
	(-0.32)		(0.12)	(0.52)		(0.41)	(-3.00)		(-2.95)
Underwriter Rank	0.14		-0.45	-0.27**		0.39	-0.02*		-0.00
	(0.46)		(-0.39)	(-3.25)		(1.09)	(-2.47)		(-0.16)
Log Firm Age	0.94**		0.76*	0.02		0.03	-0.00		-0.00
	(3.03)		(2.58)	(0.37)		(0.71)	(-0.60)		(-0.74)
Tech Firm	-0.25		-0.17	0.12*		0.11*	0.01		0.01
	(-0.88)		(-0.56)	(2.14)		(2.38)	(0.96)		(0.95)
VC Backed	1.80***		1.91***	-0.02		-0.09	0.03*		0.04*
	(5.17)		(5.15)	(-0.30)		(-1.47)	(2.52)		(2.36)
Log Proceeds	4.27***		4.57***	-0.47***		-0.47***	0.11***		0.13***
	(11.98)		(10.94)	(-7.23)		(-7.32)	(4.38)		(4.15)
Constant	13.10***	13.10***	13.28***	2.35***	1.65***	2.29***	0.08***	0.08***	0.09***
	(27.13)	(58.52)	(36.15)	(28.68)	(44.98)	(14.95)	(9.77)	(26.79)	(11.57)
Fixed Effects	None	IPO	InvUW	None	IPO	InvUW	None	IPO	InvUW
Adjusted R^2	0.132	0.177	0.203	0.119	0.210	0.265	0.023	0.069	0.004
Observations	98,241	98,241	95,177	12,867	12,791	11,806	98,241	98,241	95,177

Table A4: Main Regression Results: Sample Requires Allocation in Same Quarter

The table displays regressions of allocation indicators, percent allocated and money left on the table on control variables and manager and relationship characteristics, using no fixed effects, investor fixed effects, and investor-underwriter fixed effects. The sample includes zero allocations for investors who report 13F holdings and ANcerno trades within a quarter and who receive at least one positive allocation in that quarter. All variables are defined in Table A1. Standard errors are clustered at the investor-underwriter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Allocation Indicator			Allocation Percent			Money Left		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Client Size	3.13***	3.00***	1.51**	0.04	0.04	-0.08	0.07**	0.07**	-0.00
	(6.55)	(6.21)	(2.79)	(0.92)	(0.84)	(-1.38)	(3.18)	(3.23)	(-0.09)
Abnormal Commissions	-0.10	-0.14	-0.17	0.04**	0.03*	0.02	0.00	0.00	-0.01
	(-0.74)	(-0.96)	(-1.45)	(2.80)	(2.38)	(1.34)	(0.04)	(0.13)	(-0.45)
Past Price Support	2.98***	3.01***	2.21***	0.16***	0.17***	-0.18***	0.04*	0.05**	-0.01
	(6.94)	(6.88)	(7.89)	(3.63)	(3.74)	(-4.21)	(2.36)	(3.08)	(-0.87)
Past Flipping	2.80***	2.76***	0.89**	-0.29***	-0.25***	0.08	-0.05**	-0.05**	-0.01
	(7.34)	(7.01)	(2.85)	(-9.31)	(-7.35)	(1.85)	(-3.43)	(-3.24)	(-0.81)
Past Hold Time	0.66	0.54	1.03**	-0.11**	-0.09*	-0.17***	-0.03*	-0.02*	-0.05*
	(1.98)	(1.57)	(3.31)	(-3.17)	(-2.58)	(-4.52)	(-2.51)	(-2.39)	(-2.09)
Trading Volume	2.82***	2.82***	2.96***	0.07	0.10	-0.02	0.05*	0.05**	0.13*
	(4.38)	(4.37)	(4.36)	(1.34)	(1.79)	(-0.19)	(2.53)	(2.74)	(2.10)
Log Investor AUM	6.19***	6.25***	4.98***	0.22***	0.18**	0.82***	0.11***	0.11***	0.15***
	(14.51)	(14.26)	(5.88)	(3.75)	(3.34)	(6.21)	(4.97)	(5.02)	(3.84)
Industry Specialization	2.10***	1.92***	1.87***	0.38***	0.41***	0.21***	0.09***	0.09***	0.08***
	(7.95)	(6.94)	(8.91)	(6.78)	(6.89)	(4.51)	(5.52)	(5.23)	(5.76)
Offer Price Revision	2.61**		2.80**	-0.60***		-0.48***	-0.03		-0.04
	(3.29)		(3.31)	(-5.80)		(-5.07)	(-0.72)		(-0.86)
High Demand	3.76***		3.92***	0.01		-0.01	0.14***		0.15***
	(8.86)		(9.17)	(0.35)		(-0.24)	(4.21)		(4.32)
Low Demand	-1.50**		-1.56**	0.30***		0.30***	-0.04		-0.05
	(-3.19)		(-3.07)	(3.80)		(3.96)	(-1.81)		(-1.81)
Underwriter Rank	0.41		0.05	-0.22***		0.03	-0.03**		0.02
	(1.40)		(0.04)	(-3.55)		(0.24)	(-2.95)		(0.74)
Log Firm Age	1.01**		0.88**	0.08*		0.09*	-0.04**		-0.04**
	(3.31)		(2.79)	(2.10)		(2.67)	(-2.86)		(-2.84)
Tech Firm	-0.24		-0.17	0.04		0.04	0.03*		0.03
	(-0.69)		(-0.56)	(1.01)		(1.36)	(2.08)		(1.89)
VC Backed	1.37***		1.47***	-0.02		-0.05	0.06***		0.07***
	(4.05)		(3.95)	(-0.55)		(-1.29)	(4.07)		(3.98)
Log Proceeds	5.43***		5.23***	-0.41***		-0.39***	0.22***		0.22***
	(14.07)		(11.87)	(-9.80)		(-9.65)	(5.30)		(5.80)
Constant	17.36***	17.36***	17.71***	2.12***	1.60***	1.83***	0.20***	0.20***	0.20***
	(37.05)	(74.10)	(52.67)	(32.01)	(53.81)	(17.39)	(8.83)	(23.92)	(10.33)
Fixed Effects	None	IPO	InvUW	None	IPO	InvUW	None	IPO	InvUW
Adjusted R^2	0.145	0.200	0.214	0.102	0.185	0.241	0.032	0.079	0.024
Observations	140,168	140,168	135,835	24,329	24,217	23,043	140,168	140,168	135,835

Table A5: Main Regression Results: Sample Requires Allocation from Underwriter

The table displays regressions of allocation indicators, percent allocated and money left on the table on control variables and manager and relationship characteristics, using no fixed effects, investor fixed effects, and investor-underwriter fixed effects. The sample includes zero allocations for investors who report 13F holdings and ANcerno trades within a quarter and who receive at least one positive allocation from the IPO's underwriter. Standard errors are clustered at the investor-underwriter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Allocation Indicator			Allocation Percent			Money Left		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Client Size	3.00***	2.89***	1.62**	0.04	0.04	-0.08	0.07**	0.07**	-0.00
	(6.21)	(5.93)	(3.01)	(0.92)	(0.84)	(-1.38)	(3.07)	(3.05)	(-0.04)
Abnormal Commissions	-0.12	-0.14	-0.17	0.04**	0.03*	0.02	-0.00	0.00	-0.01
	(-0.88)	(-1.02)	(-1.41)	(2.80)	(2.38)	(1.34)	(-0.02)	(0.08)	(-0.45)
Past Price Support	2.42***	2.79***	1.84***	0.17***	0.18***	-0.19***	0.03*	0.05**	-0.01
	(5.71)	(6.53)	(7.07)	(3.63)	(3.74)	(-4.21)	(2.42)	(3.08)	(-0.90)
Past Flipping	2.82***	2.90***	0.80**	-0.32***	-0.27***	0.09	-0.05**	-0.04**	-0.01
	(6.25)	(6.23)	(3.02)	(-9.31)	(-7.35)	(1.85)	(-3.14)	(-2.94)	(-1.01)
Past Hold Time	0.68	0.65	1.26***	-0.12**	-0.11*	-0.19***	-0.04*	-0.02*	-0.05*
	(1.96)	(1.73)	(4.17)	(-3.17)	(-2.58)	(-4.52)	(-2.55)	(-2.45)	(-2.26)
Trading Volume	3.32***	3.22***	3.51***	0.07	0.09	-0.02	0.06**	0.06**	0.14*
	(5.33)	(5.28)	(5.47)	(1.34)	(1.79)	(-0.19)	(2.74)	(2.96)	(2.27)
Log Investor AUM	6.51***	6.66***	5.81***	0.22***	0.18**	0.83***	0.12***	0.12***	0.14***
	(13.87)	(13.96)	(8.77)	(3.75)	(3.34)	(6.21)	(4.82)	(4.89)	(4.30)
Industry Specialization	2.39***	2.26***	1.81***	0.38***	0.41***	0.21***	0.10***	0.10***	0.08***
	(7.57)	(6.80)	(8.44)	(6.78)	(6.89)	(4.51)	(4.95)	(4.81)	(5.12)
Offer Price Revision	3.71***		3.46***	-0.60***		-0.48***	-0.02		-0.03
	(4.56)		(4.40)	(-5.80)		(-5.07)	(-0.41)		(-0.59)
High Demand	3.27***		3.44***	0.01		-0.01	0.14***		0.14***
	(7.49)		(8.08)	(0.35)		(-0.24)	(3.74)		(3.85)
Low Demand	-0.94		-1.01	0.31***		0.31***	-0.03		-0.04
	(-1.89)		(-1.99)	(3.80)		(3.96)	(-1.43)		(-1.43)
Underwriter Rank	-2.24***		0.46	-0.14***		0.03	-0.01		0.02
	(-5.84)		(0.53)	(-3.55)		(0.24)	(-1.38)		(0.91)
Log Firm Age	0.72*		0.68*	0.08*		0.09*	-0.04**		-0.04**
	(2.31)		(2.29)	(2.10)		(2.67)	(-3.02)		(-2.92)
Tech Firm	-0.32		-0.14	0.04		0.04	0.03		0.03
	(-1.09)		(-0.49)	(1.01)		(1.36)	(1.86)		(1.70)
VC Backed	1.23***		1.42***	-0.02		-0.05	0.07***		0.06***
	(3.59)		(4.19)	(-0.55)		(-1.29)	(3.82)		(3.75)
Log Proceeds	4.49***		4.70***	-0.41***		-0.39***	0.20***		0.20***
	(10.43)		(11.55)	(-9.80)		(-9.65)	(4.92)		(5.38)
Constant	17.25***	17.24***	17.11***	2.02***	1.60***	1.76***	0.20***	0.20***	0.20***
	(39.02)	(64.22)	(51.80)	(32.63)	(51.99)	(17.47)	(8.22)	(23.58)	(9.93)
Fixed Effects	None	IPO	InvUW	None	IPO	InvUW	None	IPO	InvUW
Adjusted R^2	0.140	0.197	0.220	0.102	0.185	0.241	0.031	0.072	0.043
Observations	141,015	140,996	140,769	24,329	24,217	23,043	141,015	140,996	140,769

Table A6: Main Regression Results: Sample Requires Allocation in Same Quarter and Allocation from Underwriter

The table displays regressions of allocation indicators, percent allocated and money left on the table on control variables and manager and relationship characteristics, using no fixed effects, investor fixed effects, and investor-underwriter fixed effects. The sample includes zero allocations for investors who report 13F holdings and ANcerno trades within a quarter, who receive at least one positive allocation in that quarter, and who receive at least one positive allocation from the IPO's underwriter. Standard errors are clustered at the investor-underwriter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Allocation Indicator			Allocation Percent			Money Left		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Client Size	3.03***	2.86***	1.73**	0.05	0.04	-0.08	0.07**	0.07**	-0.00
	(5.71)	(5.26)	(2.85)	(0.92)	(0.84)	(-1.38)	(3.00)	(3.00)	(-0.08)
Abnormal Commissions	-0.14	-0.18	-0.19	0.04**	0.03*	0.02	-0.00	0.00	-0.01
	(-0.96)	(-1.16)	(-1.51)	(2.80)	(2.38)	(1.34)	(-0.04)	(0.06)	(-0.46)
Past Price Support	2.56***	2.77***	2.36***	0.17***	0.18***	-0.19***	0.04*	0.06**	-0.01
	(5.50)	(6.04)	(7.99)	(3.63)	(3.74)	(-4.21)	(2.35)	(3.11)	(-0.87)
Past Flipping	3.18***	3.15***	0.97**	-0.32***	-0.27***	0.09	-0.05**	-0.04**	-0.01
	(7.15)	(6.89)	(2.88)	(-9.31)	(-7.35)	(1.85)	(-3.25)	(-3.04)	(-0.78)
Past Hold Time	0.69	0.56	1.17**	-0.12**	-0.10*	-0.18***	-0.03*	-0.02*	-0.06*
	(1.81)	(1.43)	(3.36)	(-3.17)	(-2.58)	(-4.52)	(-2.42)	(-2.28)	(-2.05)
Trading Volume	3.01***	2.87***	3.07***	0.08	0.10	-0.02	0.05*	0.06*	0.14*
	(4.25)	(4.08)	(4.16)	(1.34)	(1.79)	(-0.19)	(2.33)	(2.56)	(2.10)
Log Investor AUM	6.66***	6.80***	5.56***	0.22***	0.18**	0.82***	0.14***	0.14***	0.16***
	(14.11)	(14.10)	(6.10)	(3.75)	(3.34)	(6.21)	(4.91)	(4.93)	(3.81)
Industry Specialization	2.51***	2.30***	2.15***	0.38***	0.41***	0.21***	0.12***	0.12***	0.09***
	(7.68)	(6.59)	(8.63)	(6.78)	(6.89)	(4.51)	(5.51)	(5.20)	(5.69)
Offer Price Revision	3.65***		3.55***	-0.60***		-0.48***	-0.03		-0.04
	(3.59)		(3.66)	(-5.80)		(-5.07)	(-0.57)		(-0.72)
High Demand	4.03***		4.25***	0.01		-0.01	0.16***		0.17***
	(8.20)		(8.89)	(0.35)		(-0.24)	(4.03)		(4.17)
Low Demand	-1.49*		-1.58*	0.30***		0.31***	-0.04		-0.05
	(-2.53)		(-2.65)	(3.80)		(3.96)	(-1.64)		(-1.66)
Underwriter Rank	-2.27***		0.13	-0.15***		0.03	-0.01		0.02
	(-5.12)		(0.12)	(-3.55)		(0.24)	(-1.45)		(0.81)
Log Firm Age	1.14**		0.99**	0.08*		0.09*	-0.05**		-0.05**
	(3.15)		(2.79)	(2.10)		(2.67)	(-3.10)		(-2.98)
Tech Firm	-0.49		-0.26	0.04		0.04	0.03		0.03
	(-1.33)		(-0.73)	(1.01)		(1.36)	(1.92)		(1.74)
VC Backed	1.43**		1.66***	-0.02		-0.05	0.08***		0.08***
	(3.42)		(3.88)	(-0.55)		(-1.29)	(3.98)		(3.85)
Log Proceeds	5.68***		5.73***	-0.41***		-0.39***	0.25***		0.25***
	(11.79)		(11.92)	(-9.80)		(-9.65)	(5.36)		(5.82)
Constant	20.95***	20.94***	20.77***	2.05***	1.64***	1.82***	0.24***	0.24***	0.24***
	(39.63)	(76.85)	(53.76)	(32.53)	(55.45)	(20.32)	(9.09)	(24.34)	(10.57)
Fixed Effects	None	IPO	InvUW	None	IPO	InvUW	None	IPO	InvUW
Adjusted R^2	0.135	0.207	0.207	0.102	0.185	0.241	0.034	0.080	0.043
Observations	116,102	116,083	115,831	24,329	24,217	23,043	116,102	116,083	115,831

Table A7: Main Regression Results: Low Allocation Investors

The table displays regressions of allocation indicators, percent allocated and money left on the table on control variables and manager and relationship characteristics, using no fixed effects, investor fixed effects, and investor-underwriter fixed effects. The sample includes ony investors who receive 13 or fewer allocations and includes zero allocations for investors who report 13F holdings and ANcerno trades within a quarter. Standard errors are clustered at the investor-underwriter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Allocation Indicator			Allocation Percent			Money Left		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Client Size	0.24**	0.24**	0.08	0.02	0.04*	-0.44	0.00	0.00	0.00
	(3.12)	(3.14)	(1.86)	(0.39)	(2.07)	(-1.21)	(1.86)	(1.69)	(0.47)
Abnormal Commissions	0.03	0.03	0.01	0.09	0.13	0.25*	0.00	0.00	0.00
	(0.82)	(0.89)	(0.22)	(1.48)	(1.06)	(2.07)	(0.63)	(0.71)	(1.08)
Past Price Support	0.33***	0.33***	0.19	0.03	0.04	-0.03	0.00*	0.00*	0.00
	(4.22)	(4.39)	(1.88)	(1.03)	(0.89)	(-0.43)	(2.55)	(2.54)	(1.31)
Past Flipping	0.05	0.07	0.47***	0.02	-0.03	0.15	-0.00	0.00	0.01*
	(0.77)	(1.11)	(3.55)	(0.24)	(-0.25)	(0.97)	(-0.10)	(0.02)	(2.54)
Past Hold Time	-0.04	-0.01	-0.02	0.25	0.11	0.08	-0.00	0.00	-0.00
	(-0.64)	(-0.18)	(-0.20)	(1.97)	(1.03)	(0.60)	(-0.20)	(0.00)	(-0.74)
Trading Volume	0.01	0.02	-0.01	-0.21***	-0.13	0.03	-0.00	-0.00	-0.00
	(0.23)	(0.36)	(-0.25)	(-3.54)	(-1.16)	(0.11)	(-0.91)	(-0.96)	(-1.16)
Log Investor AUM	-0.03	-0.01	-0.05	0.45***	0.31*	1.95	0.00*	0.00*	0.01*
	(-0.85)	(-0.29)	(-0.48)	(3.64)	(2.40)	(1.83)	(2.24)	(2.04)	(2.65)
Industry Specialization	0.17***	0.17***	0.17***	0.30***	0.15	-0.13	0.00**	0.00*	0.00
	(5.29)	(5.08)	(4.30)	(4.40)	(1.51)	(-0.57)	(2.82)	(2.48)	(1.80)
Offer Price Revision	-0.16**		-0.17**	-0.43*		-0.50	-0.00		-0.00
	(-2.92)		(-2.73)	(-2.36)		(-1.82)	(-1.43)		(-1.41)
High Demand	0.17**		0.16**	0.02		0.25	0.00*		0.00*
	(3.19)		(3.01)	(0.22)		(1.21)	(2.02)		(2.10)
Low Demand	-0.13**		-0.13**	0.07		0.23	-0.00		-0.00
	(-2.79)		(-2.76)	(0.32)		(0.66)	(-1.76)		(-1.74)
Underwriter Rank	-0.15***		0.12	-0.47		0.66	-0.00		0.00
	(-4.97)		(1.34)	(-1.82)		(0.46)	(-1.65)		(1.13)
Log Firm Age	0.16***		0.17***	0.08		-0.13	0.00		0.00
	(3.99)		(3.88)	(0.88)		(-0.73)	(1.10)		(1.11)
Tech Firm	0.01		0.01	-0.17*		0.01	0.00		0.00
	(0.59)		(0.25)	(-2.14)		(0.04)	(1.40)		(1.12)
VC Backed	0.10**		0.13**	-0.04		0.06	0.00		0.00
	(2.82)		(3.09)	(-0.35)		(0.30)	(1.83)		(1.88)
Log Proceeds	0.66***		0.71***	-0.46***		-0.39	0.01*		0.01*
	(8.17)		(8.08)	(-3.85)		(-1.54)	(2.39)		(2.36)
Constant	0.51***	0.51***	0.51***	1.76***	0.75***	1.49	0.00***	0.00***	0.00***
	(12.11)	(42.00)	(19.32)	(10.66)	(14.29)	(1.77)	(3.59)	(15.52)	(5.32)
Fixed Effects	None	IPO	InvUW	None	IPO	InvUW	None	IPO	InvUW
Adjusted R^2	0.013	0.029	0.030	0.165	0.138	0.181	0.002	0.008	-0.017
Observations	128,571	128,571	124,830	657	373	305	128,571	128,571	124,830

Table A8: Main Regression Results: All Investors

The table displays regressions of allocation indicators, percent allocated and money left on the table on control variables and manager and relationship characteristics, using no fixed effects, investor fixed effects, and investor-underwriter fixed effects. The sample includes ony investors who receive 13 or fewer allocations and includes zero allocations for investors who report 13F holdings and ANcerno trades within a quarter. Standard errors are clustered at the investor-underwriter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Allocation Indicator			Allocation Percent			Money Left		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Client Size	2.65***	2.61***	1.04**	0.03	0.03	-0.05	0.05**	0.05**	-0.00
	(7.72)	(7.63)	(2.89)	(0.94)	(0.86)	(-1.38)	(3.41)	(3.40)	(-0.05)
Abnormal Commissions	-0.06	-0.06	-0.10	0.03**	0.02*	0.01	0.00	0.00	-0.00
	(-0.55)	(-0.57)	(-1.21)	(2.82)	(2.43)	(1.38)	(0.10)	(0.18)	(-0.41)
Past Price Support	2.96***	3.11***	1.28***	0.13***	0.14***	-0.14***	0.03**	0.04**	-0.01
	(9.24)	(9.61)	(6.45)	(3.83)	(3.93)	(-4.21)	(3.17)	(3.50)	(-0.93)
Past Flipping	1.72***	1.80***	0.63**	-0.23***	-0.20***	0.07	-0.04**	-0.03**	-0.01
	(6.84)	(6.93)	(3.52)	(-9.35)	(-7.41)	(1.93)	(-3.04)	(-2.95)	(-1.11)
Past Hold Time	0.47*	0.53*	0.70***	-0.09**	-0.08*	-0.14***	-0.02*	-0.02*	-0.04*
	(2.41)	(2.50)	(3.94)	(-3.02)	(-2.49)	(-4.43)	(-2.46)	(-2.36)	(-2.31)
Trading Volume	3.03***	3.03***	2.58***	0.05	0.06	-0.02	0.05**	0.05**	0.10*
	(7.25)	(7.32)	(5.72)	(1.26)	(1.72)	(-0.21)	(3.36)	(3.47)	(2.26)
Log Investor AUM	4.67***	4.76***	3.02***	0.22***	0.19***	0.83***	0.07***	0.07***	0.08***
	(14.58)	(14.78)	(7.03)	(4.16)	(3.79)	(6.32)	(5.11)	(5.18)	(4.42)
Industry Specialization	1.51***	1.49***	0.99***	0.39***	0.41***	0.21***	0.05***	0.05***	0.04***
	(8.08)	(7.77)	(8.69)	(7.05)	(7.07)	(4.50)	(4.56)	(4.67)	(4.64)
Offer Price Revision	1.57***		1.47***	-0.60***		-0.48***	-0.01		-0.02
	(4.42)		(3.84)	(-5.92)		(-5.10)	(-0.48)		(-0.73)
High Demand	1.79***		1.87***	0.01		-0.01	0.07***		0.07***
	(8.18)		(8.67)	(0.37)		(-0.24)	(3.82)		(3.94)
Low Demand	-0.62*		-0.62*	0.29***		0.31***	-0.02		-0.02
	(-2.55)		(-2.45)	(3.72)		(3.93)	(-1.58)		(-1.57)
Underwriter Rank	0.05		0.25	-0.23***		0.03	-0.02**		0.01
	(0.37)		(0.43)	(-3.67)		(0.24)	(-3.10)		(0.79)
Log Firm Age	0.33*		0.38*	0.08*		0.08*	-0.02**		-0.02**
	(2.03)		(2.47)	(2.23)		(2.58)	(-2.78)		(-2.73)
Tech Firm	0.04		0.02	0.03		0.04	0.02*		0.02*
	(0.26)		(0.11)	(0.93)		(1.39)	(2.49)		(2.14)
VC Backed	0.77***		0.79***	-0.02		-0.05	0.03***		0.03***
	(4.95)		(4.78)	(-0.55)		(-1.33)	(3.99)		(3.93)
Log Proceeds	2.64***		2.69***	-0.42***		-0.39***	0.10***		0.11***
	(12.58)		(11.68)	(-10.22)		(-9.79)	(4.71)		(5.17)
Constant	8.16***	8.16***	8.31***	1.94***	1.39***	1.54***	0.09***	0.09***	0.09***
	(29.23)	(54.55)	(46.61)	(30.07)	(35.97)	(10.51)	(7.25)	(22.30)	(9.26)
Fixed Effects	None	IPO	InvUW	None	IPO	InvUW	None	IPO	InvUW
Adjusted R^2	0.151	0.175	0.248	0.104	0.186	0.240	0.024	0.050	0.019
Observations	306,014	306,014	297,660	24,986	24,875	23,348	306,014	306,014	297,660

Table A9: Main Regression Results: Future Commissions

The table displays regressions of allocation indicators, percent allocated and money left on the table on control variables and manager and relationship characteristics, using no fixed effects, investor fixed effects, and investor-underwriter fixed effects. In these regressions, *Future Client Size* replaces *Client Size*. *Future Client Size* is calculated similarly to *Client Size* using the following 9 months rather than the preceding 9 months. The sample includes zero allocations for investors who report 13F holdings and ANcerno trades within a quarter. Standard errors are clustered at the investor-underwriter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Allocation Indicator			Allocation Percent			Money Left		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Future Client Size	3.26***	3.15***	1.62***	0.04	0.03	-0.04	0.05***	0.05***	0.01
	(9.22)	(9.02)	(4.28)	(0.83)	(0.73)	(-0.80)	(3.11)	(3.09)	(0.22)
Abnormal Commissions	-0.02	-0.04	-0.12	0.04***	0.03**	0.01	0.00	0.00	-0.01
	(-0.17)	(-0.35)	(-1.10)	(2.82)	(2.38)	(1.29)	(0.12)	(0.21)	(-0.43)
Past Price Support	2.74***	2.96***	1.68***	0.16***	0.17***	-0.18***	0.03**	0.04***	-0.01
	(6.87)	(7.27)	(6.97)	(3.61)	(3.71)	(-4.23)	(2.44)	(3.06)	(-0.92)
Past Flipping	2.39***	2.46***	0.72***	-0.28***	-0.24***	0.08*	-0.05***	-0.04***	-0.01
	(6.54)	(6.46)	(2.99)	(-9.41)	(-7.40)	(1.82)	(-3.25)	(-3.05)	(-1.06)
Past Hold Time	0.62**	0.60*	1.07***	-0.11***	-0.10**	-0.17***	-0.03**	-0.02**	-0.05**
	(2.11)	(1.88)	(4.09)	(-3.16)	(-2.57)	(-4.52)	(-2.59)	(-2.54)	(-2.30)
Trading Volume	3.16***	3.19***	3.50***	0.07	0.09**	-0.06	0.07**	0.07***	0.12*
	(6.85)	(6.95)	(5.94)	(1.62)	(2.15)	(-0.59)	(2.58)	(2.79)	(1.92)
Log Investor AUM	5.72***	5.83***	4.97***	0.22***	0.18***	0.82***	0.09***	0.09***	0.12***
	(14.20)	(14.22)	(8.29)	(3.76)	(3.35)	(6.24)	(4.80)	(4.92)	(4.32)
Industry Specialization	2.00***	1.91***	1.52***	0.39***	0.42***	0.21***	0.08***	0.08***	0.06***
	(7.87)	(7.19)	(8.77)	(6.76)	(6.87)	(4.49)	(4.93)	(4.83)	(5.17)
Offer Price Revision	2.54***		2.58***	-0.60***		-0.48***	-0.02		-0.03
	(4.18)		(4.01)	(-5.80)		(-5.09)	(-0.58)		(-0.74)
High Demand	3.01***		3.09***	0.01		-0.01	0.12***		0.12***
	(8.48)		(8.74)	(0.37)		(-0.27)	(3.91)		(3.99)
Low Demand	-1.00**		-1.00**	0.30***		0.31***	-0.03		-0.03
	(-2.57)		(-2.42)	(3.80)		(3.97)	(-1.60)		(-1.58)
Underwriter Rank	0.30		0.27	-0.22***		0.04	-0.02***		0.02
	(1.30)		(0.28)	(-3.56)		(0.29)	(-2.93)		(0.70)
Log Firm Age	0.60**		0.57**	0.08**		0.09**	-0.03***		-0.03***
	(2.35)		(2.29)	(2.11)		(2.66)	(-2.80)		(-2.77)
Tech Firm	-0.09		-0.04	0.04		0.04	0.02**		0.02*
	(-0.35)		(-0.16)	(1.01)		(1.37)	(2.09)		(1.97)
VC Backed	1.17***		1.22***	-0.02		-0.05	0.05***		0.05***
	(4.56)		(4.41)	(-0.56)		(-1.29)	(3.98)		(3.91)
Log Proceeds	4.17***		4.13***	-0.42***		-0.39***	0.17***		0.18***
	(12.90)		(11.59)	(-9.79)		(-9.67)	(4.85)		(5.34)
Constant	13.71***	13.71***	13.93***	2.09***	1.54***	1.76***	0.16***	0.16***	0.16***
	(36.29)	(62.14)	(50.08)	(32.00)	(47.36)	(14.73)	(8.04)	(22.96)	(9.72)
Fixed Effects	None	IPO	InvUW	None	IPO	InvUW	None	IPO	InvUW
Adjusted R^2	0.148	0.187	0.226	0.102	0.185	0.241	0.029	0.071	0.024
Observations	177,443	177,443	172,830	24,329	24,217	23,043	177,443	177,443	172,830

Table A10: Main Regression Results: Inverse Hyperbolic Sine Transformation

The table displays regressions of inverse hyperbolic sine transformations of allocation indicators, percent allocated and money left on the table on control variables and manager and relationship characteristics, using no fixed effects, investor fixed effects, and investor-underwriter fixed effects. The sample includes zero allocations for investors who report 13F holdings and ANcerno trades within a quarter. Standard errors are clustered at the investor-underwriter level, t-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	IHS(Allocation Indicator)			IHS(Allocation Percent)			IHS(Money Left)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Client Size	0.03***	0.03***	0.01**	0.00	0.00	-0.00	0.36***	0.35***	0.11
	(7.09)	(6.94)	(2.92)	(0.92)	(0.84)	(-1.38)	(6.61)	(6.59)	(1.77)
Abnormal Commissions	-0.00	-0.00	-0.00	0.00**	0.00*	0.00	0.01	0.01	0.01
	(-0.63)	(-0.77)	(-1.33)	(2.80)	(2.38)	(1.34)	(0.61)	(0.44)	(0.29)
Past Price Support	0.02***	0.03***	0.01***	0.00***	0.00***	-0.00***	0.31***	0.35***	0.17***
	(6.88)	(7.28)	(6.93)	(3.63)	(3.74)	(-4.22)	(6.30)	(6.61)	(5.80)
Past Flipping	0.02***	0.02***	0.01**	-0.00***	-0.00***	0.00	0.22***	0.23***	0.06*
	(6.45)	(6.38)	(2.91)	(-9.32)	(-7.35)	(1.86)	(5.52)	(5.43)	(2.39)
Past Hold Time	0.01*	0.01	0.01***	-0.00**	-0.00*	-0.00***	0.04	0.04	0.09**
	(2.13)	(1.89)	(4.13)	(-3.17)	(-2.58)	(-4.52)	(1.39)	(1.33)	(2.84)
Trading Volume	0.03***	0.03***	0.03***	0.00	0.00	-0.00	0.39***	0.40***	0.48***
	(5.73)	(5.81)	(5.71)	(1.35)	(1.80)	(-0.18)	(4.82)	(5.04)	(5.18)
Log Investor AUM	0.05***	0.05***	0.04***	0.00***	0.00**	0.01***	0.61***	0.61***	0.53***
	(14.25)	(14.31)	(8.39)	(3.76)	(3.34)	(6.22)	(10.94)	(11.03)	(8.18)
Industry Specialization	0.02***	0.02***	0.01***	0.00***	0.00***	0.00***	0.25***	0.24***	0.18***
	(7.99)	(7.26)	(8.79)	(6.79)	(6.90)	(4.51)	(8.05)	(7.00)	(8.97)
Offer Price Revision	0.02***		0.02***	-0.01***		-0.00***	0.36***		0.36**
	(4.28)		(4.02)	(-5.81)		(-5.07)	(3.59)		(3.40)
High Demand	0.03***		0.03***	0.00		-0.00	0.50***		0.52***
	(8.39)		(8.71)	(0.34)		(-0.25)	(7.94)		(8.31)
Low Demand	-0.01*		-0.01*	0.00***		0.00***	-0.17*		-0.17*
	(-2.57)		(-2.41)	(3.80)		(3.96)	(-2.47)		(-2.38)
Underwriter Rank	0.00		0.00	-0.00***		0.00	0.03		0.09
	(1.27)		(0.36)	(-3.55)		(0.24)	(0.95)		(0.56)
Log Firm Age	0.01*		0.01*	0.00*		0.00*	0.04		0.05
	(2.35)		(2.28)	(2.10)		(2.68)	(1.06)		(1.15)
Tech Firm	-0.00		-0.00	0.00		0.00	-0.02		-0.01
	(-0.33)		(-0.15)	(1.01)		(1.36)	(-0.30)		(-0.12)
VC Backed	0.01***		0.01***	-0.00		-0.00	0.18***		0.19***
	(4.62)		(4.42)	(-0.56)		(-1.30)	(4.65)		(4.37)
Log Proceeds	0.04***		0.04***	-0.00***		-0.00***	0.43***		0.43***
	(12.94)		(11.57)	(-9.81)		(-9.65)	(6.21)		(5.61)
Constant	0.12***	0.12***	0.12***	0.02***	0.02***	0.02***	1.47***	1.47***	1.49***
	(35.81)	(61.83)	(49.55)	(31.82)	(48.30)	(14.85)	(28.47)	(60.65)	(35.24)
Fixed Effects	None	IPO	InvUW	None	IPO	InvUW	None	IPO	InvUW
Adjusted R^2	0.147	0.186	0.226	0.102	0.185	0.241	0.132	0.210	0.185
Observations	177,443	177,443	172,830	24,329	24,217	23,043	177,443	177,443	172,830

Table A11: Replicating Results in Chemmanur et al. (2010)

The table displays regressions of the percent of an offer received by an investor (*Allocation Percent*) on hold time measures and other control variables (omitted). Standard errors are clustered at the investor-underwriter level, *t*-statistics are shown below the estimates in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Allocation Percent					
	(1)	(2)	(3)	(4)	(5)	(6)
Past Flipping	-1.00***	-1.01***				
	(-9.31)	(-9.17)				
Past Hold Time	-0.23***					
	(-3.17)					
Past Hold Time Cold		-0.01**				
		(-2.13)				
Past Hold Time Hot		-0.15**				
		(-2.49)				
Avg Flipping			-2.14***	-1.94***		
			(-3.71)	(-3.94)		
Avg Hold Time			-0.02		0.06***	
			(-0.85)		(5.74)	
Avg Hold Time Cold				0.02*		0.04***
				(1.76)		(3.35)
Avg Hold Time Hot				-0.03		0.03
				(-1.53)		(1.67)
Constant	2.52***	2.44**	5.04***	4.78***	3.26***	3.19***
	(2.76)	(2.68)	(5.02)	(4.89)	(3.51)	(3.38)
Fixed Effects	None	None	None	None	None	None
Adjusted R^2	0.102	0.103	0.112	0.112	0.109	0.109
Observations	24,329	24,329	24,329	24,315	24,329	24,315