Time since targets' initial public offerings, learning, and acquisition pricing[*]

Jan Jindra[a] and Thomas Moeller[b]

Abstract
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JEL Classification: G24, G34

Keywords: Mergers and acquisitions, initial public offerings, learning, target listing effect.

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Abstract

Acquirer announcement returns decrease and takeover premiums increase with the length of time since targets' initial public offerings. Declining costs of learning about target firms can explain these effects. Newly public firms should be more opaque than established public firms with long track records. An acquirer with an advantage in learning about a newly public firm can negotiate a favorable takeover price because less knowledgeable potential acquirers face bidding handicaps. Over time, as more information about the target becomes publicly and easily available to all potential acquirers, the benefits to acquirers with learning advantages decline.

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1. Introduction

More information about a firm should lead to a more precise valuation. As more publicly available information accumulates after a firm's initial public offering (IPO), valuations should become both easier to carry out and more precise. We examine how this declining cost of learning affects acquisition pricing. The effects of evolving firm characteristics on acquisition pricing are poorly understood, have received limited attention in the literature, and can offer new explanations for results that are well-established in the literature, such as the target listing effect (Chang 1998).

In our sample of acquisitions that occur within ten years after the targets' IPOs, acquirer announcement returns decrease and takeover premiums increase with the time since the targets' IPOs, suggesting that acquirers concede less when they take over younger targets soon after the targets' IPOs. Simultaneously, various measures of target valuation uncertainty decline over the same time period, indicating that investors are successfully learning about these target firms' values.

We develop and test a possible explanation for how time-varying costs and benefits of learning can affect acquisition pricing based on the differential cost of learning about targets. Specifically, learning about a target that is a young firm is both costlier and more important in order to arrive at a precise valuation. An acquirer with more information about the young target firm, and a correspondingly more precise valuation of the target, has a competitive advantage compared to less-informed potential acquirers that would have to engage in costly learning. Such a competitive bidding advantage can reduce competition for the target, allowing the best-informed acquirer to take over the target at a price that is advantageous to the acquirer. However, as more information about a potential target becomes available over time, potential acquirers find it easier (and less costly) to learn about the target. Hence, the cost of learning should decline, and the acquisition price should become less advantageous to the acquirer. An implication of this learning framework is that with the passage of time since targets' IPOs, acquirer announcement returns should decline and takeover premiums should increase. Our empirical results support the predictions of the learning framework.[1]

What we collectively call "learning" in this study has two distinct, yet closely-related, dimensions: passive and active. Passive learning is the knowledge that investors gain from being (unintentionally) exposed to easily accessible information about a potential target. For example, articles about the target firm or its industry in the Wall Street Journal that lead to investors' learning by simply browsing the newspaper. Active learning refers to the process of purposefully collecting and analyzing information about a potential target to better understand its value. Examples are the in-depth analyses of targets' financial reports or extensive study of the target industry to learn about the economics of the target firm.

We cannot prove directly that our proxy, the time since a target's IPO, measures learning, but our empirical evidence is supportive of this conjecture. We find that it is not the age of the (target) firm *per se*, a measure some of the existing literature uses instead of the length of a firm's public life,[2] but primarily the time since the target's IPO that leads to our findings. This result points to publicly available information as the channel that facilitates learning. We test this conjecture by replacing the time since a target's IPO with the number of the target's quarterly filings with the U.S. Securities and Exchange Commission (SEC) since the IPO. Both the time since the target's IPO and the number of the target's SEC quarterly filings show similar relations to acquisition pricing and behave substantially as substitutes. We argue that this evidence shows a high correlation between time and learning, and also suggests a channel through which learning may occur: cumulative and readily available information about the target firm.

Because the time since a target's IPO can measure other effects than learning, we try to control for such other influences. For example, we control for industry, valuation uncertainty, target pre-acquisition performance, and analyst coverage. To be a viable alternative hypothesis, any other systematic change in

[1] There are alternative explanations that predict opposite results. For example, acquirer managers with asymmetric compensation contracts can benefit from more risk and therefore may be willing to overpay, from the acquirer's shareholders perspective, for risky targets. As targets become less risky over time, such managers would overpay less, resulting in lower target premiums and higher acquirer announcement returns.

[2] For example, Wei and Zhang (2006), Gaspar and Massa (2006), Brown and Kapadia (2007), and Cao, Simin, and Zhao (2008). For a debate over the use of firm age as a proxy of valuation uncertainty, see Cremers and Yan (2016) and Pástor and Veronesi (2016).

target features over time would require an explanation that is consistent with increasing takeover premiums and declining acquirer announcement returns.

We contribute to the literature by documenting how learning over time about target firms is related to acquisition pricing. Our analyses show that the length of targets' public lives is significantly related to acquirer and target announcement returns. The results give new insights into the well-documented target listing effect in acquisitions, the empirical finding that acquirers realize on average positive announcement returns when acquiring private targets and negative or zero announcement returns when acquiring public targets.[3] We find that similar to the target listing effect for private versus public targets, gradual learning and the resulting continual resolution of target valuation uncertainty has comparable effects in acquisitions of public targets, and primarily in those involving targets with recent IPOs. Our learning hypothesis for public targets is an addition to, not a substitute for, the established explanations of the target listing effect for private targets, for example, the illiquidity discount (Officer 2007).

There is little doubt that the time between a target's IPO and its acquisition by another firm is an endogenous variable because acquirers and targets usually choose the timing of acquisitions. We try to address this concern econometrically, but recognize that our instruments may not be perfect. Hence, in the absence of exogenous shocks affecting the timing of acquisitions and with less than perfect instruments, traditional econometric methods to address endogeneity may not fully work. This caveat demands caution when interpreting our results as causal. Still, we argue that our learning-based explanation is plausible and the supportive empirical results give our explanation credibility. Furthermore, we contend that our study provides important insights by showing strong associations between information, learning, uncertainty, and acquisition pricing. Ignoring such results only because causality cannot be indubitably established would adversely impact researchers' ability to further our understanding of various empirical findings that otherwise appear puzzling.

[3] For example, Chang (1998), Fuller, Netter, and Stegemoller (2002), Faccio, McConnell, and Stolin (2006), and Moeller, Schlingemann, and Stulz (2004).

2. Related literature and connection to target valuation uncertainty

Investors learn about valuation parameters by observing, collecting, and analyzing new information. Thus, learning should reduce valuation uncertainty. Accordingly, our use of the time since a firm's IPO as a proxy for learning is not entirely new. Pástor and Veronesi (2003) establish the time since a firm's IPO as a proxy for changing valuation uncertainty. They document that, as market participants accumulate more information and learn more about a firm following its IPO, the uncertainty about the firm's valuation parameters decreases. We confirm in our sample that other proxies for target valuation uncertainty also decline over time after a target's IPO.

Pan, Wang, and Weisbach (2015) study the effect of learning on stock price volatility following a CEO turnover. Their learning model is based on Pástor and Veronesi (2003, 2009) and proposes that uncertainty declines following a CEO turnover. Empirically, they find an increase and subsequent decline in stock price volatility around CEO turnovers.

Chatterjee, John, and Yan (2012) find that the divergence of investor opinion about a target's equity value, as well as a target's idiosyncratic volatility, are positively related to takeover premiums. Their results focus entirely on absolute differences in opinion divergence and rely on downward sloping demand curves for target shares. In contrast, the time since a target's IPO, the cost of learning, and the related changes in target valuation uncertainty are the primary dimensions in our study, providing evidence of learning. While Chatterjee et al.'s (2012) and our results may seem contradictory, they are not mutually exclusive. In our empirical analysis, we reconcile the seeming contradiction by including measures for the divergence of investor opinion.

We examine the effects of learning about a potential target since its public listing by all potential acquirers. In contrast, Aktas, de Bodt, and Roll (2013) focus on serial acquirers' learning from each acquisition and whether the acquirers make better, i.e., more value-increasing, acquisitions as their experience accumulates over time. Aktas, de Bodt, and Roll (2009) predict that a CEO's learning over time lowers the valuation risk of an acquisition and causes the CEO to be willing to pay a higher price for the target. While both our and Aktas et al.'s (2009, 2013) research study the effects of learning by acquirers in mergers and acquisitions, each type of learning is distinctly different. In other related research, Hsieh, Lyandres, and Zhdanov (2011) propose that a private firm first completes an IPO to learn about its own value before attempting a restructuring by either acquiring other firms or by getting acquired by another firm. Similar to Aktas et al. (2009, 2013), the learning in Hsieh et al. (2011) is focused on the acquirer learning about itself, or learning to become a better acquirer, instead of learning about another firm, i.e., a potential target.

Massa and Xu (2013) report that public acquirers prefer targets with more liquid stocks and that they pay higher takeover premiums for such targets. This rationale may explain some of our target premium results if the stocks of firms become more liquid over time after their IPOs. However, it does not predict any effect on acquirer announcement returns (acquirers pay more because acquirer shareholders place higher values on targets with liquid stocks). In contrast, we find a strong negative relation between the time that passed since the target's IPO and acquirer announcement returns, indicating that the effects observed in our study are distinctly different from those in Massa and Xu (2013).

3. Analytical framework

We discuss our proxy for learning and develop our main hypothesis.

3.1. Time since target's IPO as a proxy for learning

Our main proxy for learning is the time since a target's IPO. We contend it is a natural proxy for both passive and active learning. While it is a broad proxy, it is almost tautologically related to learning because firms become less opaque as more information about them becomes publicly available. More information flow inevitably results in passive learning while, at the same time, it makes active learning easier and less costly. For example, the information from financial statements that appears in financial news services over longer periods of time helps accumulate more passive learning and should allow investors to better actively learn how changing business conditions affect a firm and how well a firm's management deals with different economic circumstances.

We must rely on a proxy for learning because actual learning is inherently unobservable. Our rationale for the suitability of this proxy is that more exposure to information about a target firm, coupled with the observation that valuation uncertainty declines over time since the IPO, strongly suggests that learning took place. A parallel example are foreign languages. If a person that gets more and more exposure to a foreign language over time becomes more proficient in that language, it is natural to conclude that the person learned from the exposure over time. Furthermore, with more exposure and more proficiency, additional learning of the language likely becomes easier.

3.2. Hypothesis development

We contend that an acquirer that is interested in a particular target firm can learn about the target and obtain superior information relative to other potential acquirers. Since potential acquirers have limited resources, they are unable to learn about every firm and therefore self-select into learning about firms where they have an initial competitive advantage, in our setup in the form of lower costs of learning.[4] The initial competitive learning advantage can be due to the acquirer and target being close competitors or having close customer-supplier relationships, geographic proximity, current or former employee overlap, personal relationships among managers, or many other similar reasons. The superior information allows the acquirer to value the target more accurately which in turn limits competition from less-informed potential acquirers who avoid winner's curse problems. Less competition for the target should result in a lower takeover premium and corresponding higher acquirer payoffs.[5] These effects should be more pronounced the higher the valuation uncertainty of the target is. Over time, as more information becomes available and learning takes place, both the amount of uncertainty that can be resolved by learning and the

[4] The assumption that acquirers select targets for which they have a competitive bidding advantage is supported by Ragozzino and Reuer (2011) who find that targets that give credible valuation signals are acquired by more geographically distant acquirers than targets that do not give such signals. The signals (venture capital backing, reputation of target's lead underwriter, and IPO underpricing) reduce asymmetric information that is likely greater the farther away target and acquirer are located. Without target signals, only local acquirers compete for the target.

[5] The argument we propose in this paper is similar in spirit to the hold-up problem in relationship lending. As, for example, Sharpe (1990) and Rajan (1992) argue, relationship lending provides a bank with an information monopoly about a firm that can allow the bank to price loans to the firm at non-competitive terms. We contend that the information monopoly that a bank acquires through learning about a borrower is similar to the information monopoly that a potential acquirer obtains through learning about a target.

cost of learning should decrease. As the cost differential of learning about the target declines over time, at least latent competition for the target should increase, and the rent an acquirer can extract from learning about the more seasoned target shrinks.

Learning hypothesis: If learning affects acquisition pricing, the time since a target's IPO should affect acquirer announcement returns negatively and takeover premiums positively.

The rationale why acquirers should benefit from their superior information is similar in spirit to Grossman and Stiglitz (1980). They show that prices should only partially reflect the information of informed investors so that there is compensation for investors who incur costs to obtain information. As in our learning framework, in Grossman and Stiglitz (1980) investors self-select into becoming informed.

An example can illustrate the learning hypothesis. Let us assume that one potential acquirer has a competitive advantage in learning about a highly uncertain target's value, i.e., this acquirer can learn at a lower cost than any other potential acquirer. Suppose the target and all potential acquirers know the distribution of the target's value, but only costly learning can determine the target's exact value. In this situation, the acquirer with the competitive advantage (lowest learning cost) self-selects into learning about the target's value. If the target value plus any synergy is less than the unconditional expected value of the target, i.e., the target's market value before any acquisition news, the acquirer walks away. If the acquirer learns that the target's value plus synergy is higher than the current market value, it can set the takeover bid price below the conditional expected value of the target (conditional on being higher than the current market value) by the amount sufficient to keep the next best acquirer from making a bid. This amount is slightly lower than the learning cost of the next best acquirer. As the second best acquirer anticipates such strategic bidding, it knows that it is guaranteed a negative payoff if it bids. Hence, it rationally chooses not to enter the bidding. Therefore, the competitive advantage in learning allows the acquirer to take over the target at an advantageous price.[6]

[6] We are focusing on one aspect of the takeover process. See Eckbo (2009) for a comprehensive review of bidding strategies and takeover premiums.

As the target's valuation uncertainty declines over time and the next best acquirer's cost of learning approaches the cost of learning of the first acquirer, the first acquirer's bidding advantage shrinks. With fewer benefits from learning and more latent competition, the takeover price ends up being closer to the target's conditional value plus synergy, resulting in lower acquirer announcement returns and higher takeover premiums. Therefore, the length of a target's public listing affects acquirer announcement returns negatively and takeover premiums positively. An extended example of the effects of learning on acquisition pricing is in Appendix A.

4. Data

We start with all completed U.S. IPOs in the Thomson Reuters SDC New Issues database that took place between 1979 and 2008. Using the Thomson Reuters SDC Mergers & Acquisitions database, we identify firms that are acquired within ten years of their IPOs. We capture all acquisitions that are announced and recorded in the SDC database through December 31, 2013. Allowing each IPO firm at least five years to get acquired substantially reduces any concerns due to censored data. Furthermore, there is little IPO activity during and after the recent financial crisis. We only consider completed U.S. domestic acquisitions by public acquirers that seek to own at least 90% of the target's equity and do not own more than 10% before the acquisition announcement. We further require acquirer and target data in the Center for Research in Securities Prices (CRSP) and Compustat databases. Finally, we only use observations for which the ratio of target to acquirer market value of equity, measured at the last fiscal year-end before the acquisition announcement, exceeds 0.02.[7] These requirements reduce our sample to 810 observations.[8] Our sample accounts for approximately 30% of all similar acquisitions in the SDC

[7] Jarrell and Poulsen (1989) show that acquisitions of relatively small targets have little impact on the values of acquirers. The inclusion or exclusion of the relatively small targets does not substantially affect our results or conclusions.

[8] Our sample contains three acquisitions of targets that were previously owned by leveraged buyout firms. Excluding these three observations from our sample does not alter our conclusions.

Mergers & Acquisitions database, i.e., same selection criteria except for the proximity of the acquisition to the target's IPO date.[9]

Descriptive statistics are in Table 1 and all variables are defined in Appendix B. We contend that the market learns about a firm over time, in particular after the firm becomes public, costs of learning decline, and that such learning reduces the firm's valuation uncertainty. Therefore, our proxy for learning is *Time since IPO*, the number of calendar days from the target's IPO to the acquisition announcement scaled by the number of calendar days in a ten-year period. *Time since IPO* has a median of 0.35, indicating that a typical firm in our sample gets acquired 3.5 years after its IPO.

With respect to acquisition pricing, our focus variables are the acquirer announcement return and target premium. *Acquirer CAR* is calculated as the return in excess of the CRSP equal-weighted index for the three days centered on the acquisition announcement date. The average and median *Acquirer CAR* for our sample are statistically significant -1.9% and -1.5%, respectively. These acquirer announcement returns are similar to the -1% reported for acquisitions of public targets in Moeller et al. (2004). Although our targets only recently became public, in terms of *Acquirer CAR*, our sample deals are more similar to acquisitions of public than private targets. We calculate *Target premium* as the target return in excess of the CRSP equal-weighted index, starting ten trading days prior to the announcement date and ending on the earlier of 180 calendar days (roughly six months) after the announcement or on delisting date (Schwert 1996). The average *Target premium* in our sample is 30.1%.

Since learning should be more costly and more beneficial when valuation uncertainty is high, we proxy for valuation uncertainty with the target industry-wide measure *Target industry M/B stdev* and the target-specific variable *Target return stdev*. Similar to the prior literature, we calculate *Target industry M/B stdev* as the standard deviation of market-to-book ratios of firms in the same industry with assets between half and twice the target size (Cooney, Moeller, and Stegemoller 2009). We define industry using

[9] We have 568 acquirers that make exactly one acquisition in our sample and 101 that make more than one (a total of 242) acquisitions. The median number of acquisitions by multiple acquirers is two and the median number of days between acquisitions is 841. The presence of acquirers who make multiple acquisitions in our sample does not materially affect our results.

the four-digit standard industrial classification (SIC) code and require at least ten matching firms in each industry. If there are fewer matches, we use the first three digits of the SIC code, then the first two, and if there are still fewer than ten matches only the first digit. *Target return stdev* is the standard deviation of the daily target returns from the IPO date to two weeks before the acquisition announcement. Both measures of target valuation uncertainty show considerable cross-sectional variation.

The time between the target's IPO and its acquisition is likely influenced by its ability to raise outside capital. We control for this ability by assessing the target's (potential) seasoned equity offerings (SEOs). Arguably, it is easier and less costly to issue equity when the target's stock is highly valued, in absolute or in relative (to book equity) terms. The average *Target market value* (of equity) is \$463 million with a median of \$136 million. The average and median *Target market-to-book* ratio, calculated as (market value of equity + total assets – book value of equity) divided by total assets, are 3.3 and 1.5, respectively. While the average appears high, the median *Target market-to-book* ratio is consistent with Pástor and Veronesi (2003). Finally, we control for actual SEOs with an indicator variable. Approximately 46% of the target firms issued primary shares in a seasoned equity offering (*Target SEO*), as indicated in the SDC New Issues database.

Panel B of Table 1 shows that 70% of acquisitions are paid with at least some acquirer stock (*Stock*). The SDC Mergers & Acquisitions database classifies only 1% of our acquisitions as hostile (*Hostile*)[10] and 16.9% as tender offers (*Tender*). About 50% of the targets in our sample were backed by venture capitalists (VCs) at the time of the IPOs. Approximately 56% (8%) of the targets went public during hot (cold) IPO periods. We discuss the remaining variables as they become relevant in our analyses.

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[10] In addition to the SDC classification, Schwert (2000) uses characterizations of hostility in the Wall Street Journal and the Dow Jones News Retrieval, unnegotiated tender offers, "bear hugs," pre-takeover 13D filings, merger rumors about the target, and principal component analysis to identify hostile deals. Overall, he concludes that "most deals described as hostile in the press are not distinguishable from friendly deals in economic terms, except that hostile transactions involve publicity as part of the bargaining process." (p. 2599)

5. Results

We first analyze the effects of *Time since IPO* on target market-to-book ratio, acquirer announcement returns, target premiums, and target as well as acquisition characteristics in a univariate setting.

5.1. Univariate results

Pástor and Veronesi (2003) show that market-to-book ratios of firms decline with the length of listing and attribute such decline to the effects of learning about the valuation parameters of the firm. In Table 2, we report the average and median market-to-book ratios for subsamples based on the amount of time that elapsed since the IPO. Specifically, we split the sample intro three groups based on the relative timing of the acquisition to the IPO: (i) acquisition is announced within the first year of listing; (ii) acquisition is announced in years two or three after the IPO; (iii) acquisition is announced between years four and ten after the IPO. The median market-to-book ratio of targets acquired in the first year after the IPO is 3.7 which is higher than the market-to-book ratio of 2.3 for firms one year after the listing in Pástor and Veronesi (2003). However, for later acquisitions, the market-to-book ratios decline and their levels are consistent with those reported by Pástor and Veronesi (2003). Overall, the univariate results for our sample targets show a significant decline in the market-to-book ratios over time.

In Table 3, we confirm our univariate finding by calculating the market-to-book ratio each year after the IPO for each firm in our sample. Then, following the approach of Pan et al. (2015), we analyze the relation of *Target market-to-book* with *Time since IPO* (regressions 1 through 3). Even after controlling for calendar, industry, and firm fixed effects, the results show a declining trend in market-to-book ratios of target firms over time. For our regression indicator variables, we define industry based on 2-digit SIC codes. Results are similar with 1-digit SIC codes or the Fama-French 49-industry classification. Overall, the declining pattern in target firms' market-to-book ratios in our sample is comparable to the pattern reported for all IPO firms in Pástor and Veronesi (2003).

In Table 2, we also report univariate results for the average, median, and standard deviation of *Acquirer CAR* and *Target premium*. We expect that *Acquirer CAR* declines while *Target premium* increases over time. With respect to the precision of acquisition pricing, the standard deviations of both *Acquirer CAR* and *Target premium* should decline over time. The reason is that with greater target valuation uncertainty, it is harder for investors to evaluate an acquisition, leading to greater variability in how they respond. Essentially, the investor reaction can be varied if they react based on limited information.

First, we note that the averages and medians of *Acquirer CAR* do not follow a monotonic trend. Furthermore, the changes in *Acquirer CAR* are not significant. However, the standard deviation of *Acquirer CAR* is significantly lower for the subsample of targets acquired later, i.e., at least four years after their IPOs. Second, the average and median *Target premium* are the lowest for firms acquired within one year of the IPO. The differences in average and median *Target premium* between acquisitions taking place in the first versus the second window are statistically significant at the 0.05 level. The difference in the average *Target premium* between acquisitions taking place in the first versus the third windows is statistically significant at the 0.1 level. As is the case for *Acquirer CAR*, the changes in *Target premium* over time are not monotonic. Finally, there are no significant changes over time in the standard deviations of *Target premium*.

Overall, these univariate results provide only weak evidence of a relation between the time since the target's IPO and acquisition pricing. However, the univariate results are potentially confounded by other effects that can cause the decline in acquirer announcement returns and increase in target premiums over time to be understated. For example, the proportion of acquisitions paid with stock also decreases with the time since the target's IPO, and the use of stock instead of cash is associated with more negative acquirer announcement returns and lower target premiums (Wansley, Lane, and Yang 1983; Huang and Walkling 1987; Travlos 1987).

Other target characteristics likely affect acquisition pricing as well. We specifically examine the role of target size because firm size should be positively correlated with the amount of information about the firm that is available to the market. The median *Target market value* shows a monotonic and significant decline over time. The decline in target size should therefore work against finding support for the learning hypothesis since information availability should be positively correlated with firm size.

To assess the role of uncertainty about the target, we examine proxies for target valuation uncertainty at the time of the acquisition as well as over time since the target's IPO. In Table 2, the measures of valuation uncertainty decline significantly over time. For example, the averages of *Target industry M/B stdev* for firms acquired in the first, second, and third groups are 6.1, 2.1, and 1.9, respectively. This decline suggests that targets acquired shortly after their IPOs are from industries with higher dispersions of valuation multiples than firms acquired later on. It is also consistent with the notion that a firm's valuation uncertainty declines over time. Based on the univariate analysis, most of the decline in uncertainty occurs relatively soon, i.e., during the first three years, after the target's IPO.

In Table 3, we also analyze the year-by-year levels of *Log Annual target industry M/B stdev* and *Log Monthly target return stdev* using the approach in Pan et al. (2015).[11] The results show a declining pattern from the time of the target's IPO through acquisition (regressions 4 through 9). Here, we use calendar time, industry, and firm fixed effects to isolate the changes in valuation uncertainty of individual firms over time from changes in the composition of firms that are acquired at different time periods after their IPOs and from changes in the overall market and industry environment. The significantly negative coefficients of *Time since IPO* in the presence of firm fixed effects show that the valuation uncertainty of the individual firms declines over time.

5.2. Regression results: *Acquirer CAR*

We begin the multivariate testing of the learning hypothesis with regression analyses of *Acquirer CAR*. To reduce the impact of outliers, we use the natural logarithm of (1 + continuous variable) in the regressions, indicated by "Log" in front of the variable name. We use typical mergers and acquisitions control variables in our analysis: *Acquirer market-to-book*, *Acquirer market value*, *Relative size*, and

[11] To reduce the impact of outliers, we use natural logarithms of *Target industry M/B stdev* measured at annual intervals (*Annual target industry M/B stdev*) and *Target return stdev* measured at monthly intervals (*Monthly target return stdev*).

several indicator variables. We include *Log acquirer market-to-book* because Lang, Stulz, and Walkling (1989) show that acquirers with high Tobin's *Q* gain more than acquirers with low Tobin's *Q* and Rhodes-Kropf, Robinson, and Viswanathan (2005) find significant effects of market-to-book ratios on takeover activity. Moeller et al. (2004) find that larger acquirers earn lower announcement returns than do smaller acquirers. Faccio et al. (2006) and Asquith, Bruner, and Mullins (1983) find positive relations between acquirer announcement returns and relative size in private and public acquisitions, respectively. Indicator variables control for the method of payment (*Stock*), venture capital presence at the target's IPO (*VC*), whether the deal is characterized as *Hostile*, and whether the merger is classified as a *Tender*. We include industry and acquisition year indicator variables in all regressions as is customary (for example, Moeller et al. 2004). Finally, we use heteroskedasticity consistent standard errors clustered at the acquirer level.

In regressions 1 and 2 of Table 4, we analyze *Log Acquirer CAR*. Regression 1 uses the entire sample and regression 2 the subsample of acquisitions taking place within three years after the target's IPO. We expect the most pronounced effects of learning within the first few years after a firm's IPO. In regression 1, the coefficient on *Time since IPO* is negative and significant at the 0.05 level. The size of the coefficient implies that one additional year of target listing results in a 0.9% incremental decline in *Acquirer CAR*. In regression 2, for the subsample of early acquisitions, the effect is more negative, i.e., a 2.9% decline in *Acquirer CAR* per year, indicating that the effects of learning are stronger in the first three years after the target's IPO.

With respect to the measures of pre-acquisition performance, we observe a negative and significant effect of *Target net income/ assets* on *Acquirer CAR* and a positive and significant effect of *Target cash burn* on *Acquirer CAR*. *Target cash burn* equals one if the ratio of the target's cash flow from operating activities to cash and short-term investments, all measured at the last fiscal year-end prior to the acquisition announcement, ranks in the bottom 20% of all targets in the sample. The coefficients on *Target net income/ assets* and *Target cash burn* indicate that acquisitions of targets experiencing poor operating performance are more profitable for acquirers. The measures of pre-acquisition stock returns have insignificant coefficients. Among the other control variables, *Log relative size* has a significantly negative coefficient. If acquirers on average overpay for targets, relatively larger targets appear to magnify the effect. Acquirer market-to-book and stock payment (only for the entire sample) are negatively related to *Acquirer CAR*.[12] Overall, the regression results show that acquirer announcement returns are negatively related to *Time since IPO*, which is what our learning hypothesis predicts.[13]

5.3. Regression results: *Target premium*

We examine whether the length of the target's public listing is related to the takeover premium. If the negative effect of *Time since IPO* on *Acquirer CAR* reflects the acquirer's ability to capture a higher proportion of synergies, or to buy firms shortly after the IPO at a discount relative to firms that are listed for a longer period of time, we should observe a positive relation between *Time since IPO* and *Target premium*.

To mitigate the effects of outliers, we use the natural logarithm of (1 + *Target premium*) as the dependent variable in regressions 3 and 4 of Table 4. The regressions follow the specifications for *Log Acquirer CAR*. In regression 3, *Time since IPO* has a positive coefficient that is significant at the 0.10 level (*p*-value of 0.077). Targets acquired shortly after their IPOs are purchased at a discount compared to targets acquired at a later time. This discount is complementary to the higher *Acquirer CAR* in acquisitions of recently listed targets documented in regressions 1 and 2. This conclusion is reinforced by the results in regression 4 that uses only targets acquired within three years after their IPOs. The coefficient of *Time since IPO* in regression 4 is larger and is significant at the 0.05 level. On average, each year after the target's IPO adds 20.7% to the *Target premium* in the subsample of acquisitions that occur

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[12] In untabulated results, we also control for the runup in the target's stock price starting one month prior to the announcement date. The coefficient of target runup is insignificant and its inclusion in the regression does not affect our conclusions about the significance of the *Time since IPO* coefficient. We also replace *Stock* with *Cash only* and *Stock only* indicator variables. The coefficient of *Cash only* is significantly positive at the 0.01 level, again only for the entire sample. Hence, these alternative specifications do not affect our conclusions.

[13] Goel and Thakor (2010) predict and find the acquirer announcement returns decline over time during merger waves. Acquirer CEO envy is their explanation for this result. Our focus on the time since the target's IPO is distinctly different from the temporal position in a merger wave. While their acquirer announcement return result is similar to ours, other results differ. For example, they find that target size increases over time during merger waves while, in our sample, it is slightly smaller for targets that are acquired later after their IPOs. Similarly, Carow, Heron, and Saxton (2004) find a first-mover advantage in industry merger waves that manifests itself in higher acquirer and combined acquirer and target returns.

within three years of the target's IPO and 3.4% in the whole sample that extends up to 10 years after a target's IPO. These results further support the learning hypothesis.

With respect to the proxies for pre-acquisition performance, we find a negative and significant effect of *Log Prior market return* on *Target premium*. Among the other control variables, the hostile and the tender offer indicators have significantly positive coefficients, suggesting that acquirers pursuing hostile tender offers tend to pay richer premiums. *Log relative size* has significantly negative coefficients.[14]

Overall, supporting the learning hypothesis, the target's length of listing is negatively related to acquirer announcement returns and positively to target premiums.

6. Endogeneity considerations

Heckman (1979) shows that statistical analyses based on non-random samples can lead to erroneous conclusions. The endogeneity of the acquirer's choice to acquire a particular target and the target's choice to get acquired can affect our conclusions. For example, targets may choose between a seasoned equity offering and being acquired. Acquirers may try to acquire attractive targets before other potential bidders appear. Another potential endogeneity concern may arise if acquirers and their shareholders have a preference for relatively "safe" targets, i.e., targets with relatively low valuation uncertainty, and such "safe" targets get acquired later after listing. In this case, our results would obtain because targets that are acquired later are fundamentally different from targets that are acquired earlier, not because acquirers learn about targets over time.

We implement Heckman's (1979) estimation method to address these potential endogeneity concerns where we use the following instruments: *Log Target market-to-book* ratio, *Target SEO*, *Hot IPO market*, *Cold IPO market*, and *IPO bubble*. Ideally, these instruments should predict the amount of time between a target's IPO and its acquisition and should not affect acquirer announcement returns or takeover

[14] In untabulated results, we also control for the runup in the target's stock price starting one month prior to the announcement date. The coefficient of target runup is negative and significant at the 0.05 level. However, the inclusion of runup in the regression does not affect our conclusions about the significance of the *Time since IPO* coefficient. Also, when we replace *Stock* with *Cash only* and *Stock only* indicator variables, the coefficient of *Cash only* is significantly positive at the 0.1 level, but only for the entire sample. Hence, these alternative specifications do not affect our conclusions.

premiums. We recognize that the statistical validity of our instruments is likely insufficient to address endogeneity issues satisfactorily. Nevertheless, this estimation approach provides similar results about the relations of *Time since IPO* to acquirer announcement returns and takeover premiums (results are not tabulated).

7. Age of target and role of post-IPO public information

In our analysis, we focus on time since the IPO and show that learning about a target firm since its listing is associated with acquisition pricing. It is possible that the age of the target, i.e., the time since the firm was founded, plays a role in the cost of learning and in resolving valuation uncertainty, and also affects acquisition pricing. While there likely is some learning about private firms over time, the lack of public disclosures suggests that most learning, and decreases in the cost of learning, occur over time after a firm's IPO. Nevertheless, to assess whether the age of target firms affects our conclusions, we calculate the age (from its founding date) at the time of the IPO (*Age at IPO*).[15]

The average *Age at IPO* of the target firms in our sample is about 15 years, while the median is about 8 years. In untabulated results, we find that *Time since IPO* and *Age at IPO* are positively correlated with a correlation coefficient of 0.08 that is significant at the 0.05 level. We include *Age at IPO* in the regression models analyzing *Log Acquirer CAR* and *Log Target premium*. The regressions reported in Table 5 follow the specifications in Table 4. The results show that *Time since IPO* retains its significant coefficients: negative in models 1 and 2 analyzing *Log Acquirer CAR* and positive in models 3 and 4 analyzing *Log Target premium*. Table 5 also shows that, with one exception, *Age at IPO* is not significantly related to acquisition pricing. The one exception is model 4, the regression analysis of *Log Target premium* for the sample of targets acquired within three years of their IPOs, where the coefficient on *Age at IPO* is positive and significant at the 0.1 level. However, in this model, the coefficient on *Time since IPO* continues to be positive and significant at the 0.05 level. Hence, overall, we find that the effect of learning on acquisition pricing is unaffected by controlling for the age of the firm at its IPO date. In

[15] The founding year data is from Jay Ritter's website (http://bear.warrington.ufl.edu/ritter/ipodata.htm).

untabulated analyses, we add *Age at IPO* and *Time since IPO*, both in years, and take the natural logarithm of the sum. This measure of the combined private and public age of the firm has significantly positive coefficients in the *Log Target premium* regressions, but is insignificant in the *Log Acquirer CAR* regressions. We conclude that learning after the firm becomes public via an IPO has the strongest effects.

We next consider the channel through which investors keep learning about the firm through continuous exposure to new information about the firm as the time since a firm's IPO elapses. To more directly assess the channel of learning through public information about the firm, we use the number of the firm's quarterly filings with the SEC as a proxy for the information that is accumulating in the public domain. The quarterly filings provide important information about the operating performance and other significant aspects of the firm. *Number of 10-K/Q filings* is the number of forms 10-Q and 10-K filed between the target's IPO and the acquisition announcement in the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. Since EDGAR was phased in over a three-year period ending on May 6, 1996,[16] the sample used in this analysis does not include acquisitions prior to the data becoming available electronically. *Number of 10-K/Q filings* ranges from 0 to 44 with a mean of 12. The correlation of *Number of 10-K/Q filings* with *Time since IPO* is 0.7. This significantly positive correlation is not surprising since these filings are required every quarter. Yet, the measures are not identical. Some firms miss quarterly filings for various reasons and additional variation comes from acquisitions that are announced immediately before or after a quarterly filing date.

In Table 6, we analyze the effects of the information accumulated in the public domain on *Log Acquirer CAR* and *Log Target premium*. The regression specifications generally follow the regression models in Table 4. Since we are interested in bargaining outcomes, we also analyze the division of acquisition gains between acquirers and targets. Following Ahern (2012), we define *Acq rel gain/ combined MV* as the acquirer's minus the target's abnormal dollar gain over the three-day acquisition announcement window divided by the sum of the acquirer's and target's market values of equity.

[16] https://www.sec.gov/edgar/aboutedgar.htm

With *Log Acquirer CAR* as the dependent variable, regression 1 confirms that in this smaller subsample the coefficient on *Time since IPO* is still negative and significant at the 0.01 level. In regression 2, *Number of 10-K/Q filings* replaces *Time since IPO* and has a negative and significant coefficient as well. Finally, in regression 3, we include both measures. *Time since IPO* retains a negative coefficient that is significant at the 0.05 level while the coefficient on *Number of 10-K/Q filings* becomes insignificant. These results demonstrate that our primary learning measure *Time since IPO* is closely related to information accumulation.

With *Log Target premium* as the dependent variable, regression 4 confirms that in this smaller subsample the coefficient on *Time since IPO* is still positive and significant at the 0.1 level. In regression 5, *Number of 10-K/Q filings* replaces *Time since IPO* and has a positive, but insignificant point estimate. Finally, in regression 6, we include both measures. *Time since IPO* retains a negative coefficient with a *p*-value of 0.051, while the coefficient on *Number of 10-K/Q filings* remains insignificant. In contrast to *Log Acquirer CAR*, with *Log Target premium* we do not observe a substitution effect between *Number of 10-K/Q filings* and *Time since IPO*. A possible explanation is that our results for *Log Target premium* are generally weaker than those for *Log Acquirer CAR* in this subsample of acquisitions with EDGAR data availability.

With *Acq rel gain/ combined MV* as the dependent variable, the results strongly support that *Number of 10-K/Q filings* and *Time since IPO* are substitutes, i.e., that the time since a target's IPO and information accumulation are largely synonymous. In regression 7, the coefficient on *Time since IPO* is negative and significant at the 0.01 level, indicating that acquirers lose bargaining advantage with the length of the target's listing. In regression 8, *Number of 10-K/Q filings* replaces *Time since IPO* and also has a negative coefficient that is significant at the 0.01 level. When we include both measures in regression 9, *Time since IPO* retains a negative coefficient with a *p*-value of 0.064 while the coefficient on *Number of 10-K/Q filings* becomes insignificant. Overall, Table 6 demonstrates that the time since the target's IPO and information accumulation about the target are closely related. Of course, quarterly filings with the SEC are only one information source among many. *Time since IPO* is a broader measure and appears to be the better proxy for learning.

8. Robustness and alternative explanations

We examine the robustness of the negative relation between the time since the target's IPO and acquirer announcement returns and the positive relation between the time since the target's IPO and target premiums.

8.1. Consideration of Chatterjee et al. (2012)

Chatterjee et al. (2012) find that the divergence of investor opinion about a target's equity value, as well as a target's idiosyncratic volatility, both measures of target valuation uncertainty, are positively related to takeover premiums. They interpret their results as evidence of downward-sloping demand curves for target shares that are steeper the more investors' opinions about a target's equity value diverge. The pre-bid target share price is the market-clearing price at which the last of the outstanding shares finds an owner. An acquirer buys shares from investors with progressively higher target valuations, causing the market-clearing price to move up along the target share demand curve, until it reaches the takeover price at which the acquirer can purchase a majority of target shares. Hence, the steeper the demand curve for target shares, the larger is the change from the pre-bid target share price to the takeover price, i.e., the takeover premium. In equilibrium, acquirers only pay the high premiums when they expect large synergies.

The time since a target's IPO is our proxy for learning, specifically the declining costs of learning, which in turn decreases valuation uncertainty. With its focus on changes over time, it differs from measures that capture purely cross-sectional differences as in Chatterjee et al. (2012). The implications of cross-sectional differences can diverge from the effects of changes over time. For example, some firms might inherently have higher valuation uncertainties, maybe related to industry, ownership, product offerings, geographic markets, etc. Chatterjee et al. (2012) find that such higher absolute valuation uncertainty results in higher takeover premiums. We identify a different effect. When firms get acquired later in their public life, after investors had more time and information to learn about them, they also receive higher takeover premiums (compared to acquisitions earlier in a target's public life), even though their absolute valuation uncertainty usually declined. Because Chatterjee et al.'s (2012) argument relies on a different mechanism, the effects of valuation uncertainty proposed in our paper are not inconsistent with those proposed by Chatterjee et al. (2012).

To test whether our results are at odds with those of Chatterjee et al. (2012), we include *Log Target return stdev* as a proxy for both divergence of investor opinion and target valuation uncertainty in our regressions. In Table 7, *Log Target return stdev* has insignificant coefficients in regressions 1 and 2 analyzing *Log Acquirer CAR*. Analyzing *Log Target premium* in regressions 3 and 4, *Log Target return stdev* has positive coefficients, with the one in regression 3 that uses the entire sample being significant at the 0.05 level. This result is consistent with Chatterjee et al. (2012) who also find a significantly positive relation between target return standard deviation and target premiums. Also important, the inclusion of *Log Target return stdev* in the regression models does not affect the sign or significance of *Time since IPO*. Figure 1 represents these effects visually - regardless of the timing of the acquisition, targets with higher absolute valuation uncertainty receive higher premiums, and, as investors learn more about them and their valuation uncertainty declines over time, their takeover premiums increase further. Overall, we conclude that the two distinct effects of absolute divergence in investor opinion in Chatterjee et al. (2012) and time-varying valuation uncertainty due to learning in our study are not contradictory.

8.2. Size of target

The size of firms should be related to the available public information about them. For example, larger firms are more likely to be followed by multiple analysts while smaller firms may not be covered at all. Hence, size should be negatively related to the cost of learning. While we control for the relative size of the target and the acquirer in our regressions, we do not specifically control for the target's absolute size. In untabulated results, we include *Log Target market value* in all regressions and note that the coefficients on *Time since IPO* retain their signs and significance. We also define an indicator variable

Target market value < median that equals one if the market value is less than the in-sample median. We include this indicator variable as well as the interaction of this indicator variable and *Time since IPO* in all regressions. Again, the coefficients on *Time since IPO* retain their signs and significance. Therefore, controlling for target size does not affect our conclusions.

8.3. Alternative measures of time between IPO and acquisition

We redefine the variable measuring the time between the target's IPO and acquisition announcement and examine the robustness of our results. First, we define *Year since IPO* as equal to one through ten for acquisitions taking place in the first through the tenth year after the IPO. Second, we define *Log Time since IPO* as the natural logarithm of the number of days between the IPO and the acquisition announcement.

In untabulated results, we note that in regressions analyzing *Log Acquirer CAR*, the coefficients on *Year since IPO* and *Log Time since IPO* are negative and significant at the 0.1 and 0.05 levels, respectively. Therefore, the results for *Acquirer CAR* are not affected by the way we define time since the IPO. In regressions analyzing *Log Target premium*, the coefficients on *Year since IPO* and *Log Time since IPO* are positive and significant at the 0.05 and 0.1 levels, respectively. Overall, the results with alternative specifications of the target's length of listing support our prior conclusions about the role of learning in acquisition pricing.

8.4. *Acquirer CAR* and *Target premium*

Table 8 presents regressions using *Acquirer CAR* and *Target premium* instead of *Log Acquirer CAR* and *Log Target premium* to assess whether the log transformation influences our results. Again, in regression 1 analyzing *Acquirer CAR* with the entire sample, the coefficient of *Time since IPO* is negative and significant at the 0.05 level. Furthermore, the coefficient estimate and statistical significance are comparable to the results reported in prior tables. In regressions 3 analyzing *Target premium* with the entire sample, the coefficient on *Time since IPO* is positive and significant at the 0.05 level. In regressions 2 and 4, we only include observations where the target is acquired within three years of its IPO. Again, the results are similar to those without taking logarithms of the dependent variables. Overall, the logarithmic specification of our dependent variables does not affect our conclusions about the effects of the target's length of listing on acquirer announcement returns and takeover premiums.

8.5. Acquirer share of gains

We make the implicit assumption of zero-sum bargaining in our learning hypothesis, i.e., the acquirer benefits at the target's expense, and vice versa. We test the hypothesis by examining acquirer announcement returns and target premiums separately. A more direct test would be to analyze what share of the acquisition gains accrues to the acquirer versus to the target. Therefore, we repeat our analysis with two such measures.

Following Ahern (2012), we use *Acq rel gain/ combined MV* as defined in section 7. In addition, following Golubov, Petmezas, and Travlos (2012), *Acq abs gain/ synergy* is the acquirer's abnormal dollar gain over the three-day acquisition announcement window divided by the sum of the acquirer's and target's abnormal dollar gains over the same window if the combined gains are positive and one minus such number when the combined gains are negative. While *Acq abs gain/ synergy* appears to be the obvious choice to measure how the acquisition gains are split between acquirer and target, it also produces large outliers when the synergies are small. Even after winsorizing at the 0.01 and 0.99 levels, *Acq abs gain/ synergy* still ranges from -28 to 2. *Acq rel gain/ combined MV* does not exactly measure how gains are split because firm market values instead of acquisition gains are in the denominator, but it does not suffer from the outlier problem.

In Table 9, we use the same setup as in prior tables with these alternative dependent variables. *Time since IPO* has negative coefficients with p-values of 0.01 or lower when *Acq rel gain/ combined MV* is the dependent variable, both for the entire sample and the subsample with targets that are acquired within three years of their IPOs. When *Acq abs gain/ synergy* is the dependent variable, *Time since IPO* has also negative point estimates, but it is only significant in the regression using the entire sample. Given the large outliers, the lower significance levels in analyses of *Acq abs gain/ synergy* are not surprising.

Overall, the acquirer's share of the acquisition gains declines significantly with the time since the target's IPO, supporting our learning hypothesis.

8.6. IPO market conditions

We next examine the effects of particular IPO time periods on our results. We conduct this analysis for two reasons. First, we want to assess whether unusual IPO market conditions unduly affect our results. Second, and potentially more interesting, time period effects can provide further insights into fundamental drivers of the learning effect. For example, the type of IPO market affects the characteristics of the firms going public, e.g., their average profitability. These characteristics can be related to the cost of learning. We focus on IPO time effects here because our acquisition year indicator variables should already capture most acquisition time effects.

First, we focus on the IPO bubble period. We analyze *Acquirer CAR* in regression 1 of Table 10's Panel A. We add *IPO bubble* (October 1998 to December 2000) and interact it with *Time since IPO*. We note that the *Time since IPO* has a marginally insignificantly negative coefficient (p-value of 0.106). *IPO bubble* has an insignificantly positive coefficient. The interaction term is insignificantly negative. Based on untabulated results, the effect of *Time since IPO* during non-bubble periods is significant at the 0.05 level. Regression 3 reports results for *Target premium*. The coefficient on *Time since IPO* is positive and significant at the 0.1 level. Neither *IPO bubble*, nor the interaction term are significant.

In regressions 1 and 3 in Panel B, we repeat the analysis for the subsample of acquisitions that are announced within three years of the targets' IPOs. Here the coefficients on *Time since IPO* are statistically significant at the 0.01 and 0.05 levels for acquirer announcement returns and target premiums, respectively. Overall, the results in regressions 1 and 3 of Panels A and B indicate that our conclusions regarding the effects of the target's length of listing on acquisition pricing are not driven by unusual market conditions during the IPO bubble period.

Second, IPO activity exhibits substantial monthly variation. To assess whether such monthly variation in IPO activity unduly affects our conclusions, we group targets based on whether their IPOs occurred during hot, neutral, or cold IPO markets. We define hot and cold IPO periods based on the monthly volume of IPO issuance as in Helwege and Lian (2004).[17] We then include *Hot (Cold) IPO market* as well as the interaction of *Hot (Cold) IPO market* with *Time since IPO* in regressions 2 and 4.

Again, in Panel A, in regression 2 that analyzes acquirer announcement returns, the coefficient on *Time since IPO* continues to be negative and significant at the 0.05 level. None of the interaction terms are significant. Only *Cold IPO market* has a negative coefficient, significant at the 0.1 level. For *Target premium*, in regression 4, the coefficient on *Time since IPO* is positive and significant at the 0.05 level. The coefficients on *Time since IPO* interacted with the hot and cold IPO market indicators are negative and significant, suggesting that the effect of *Time since IPO* on *Target premium* is reduced for targets with IPOs during such periods. Since the absolute sizes of the coefficients on the interaction terms are smaller than the coefficient on *Time since IPO*, the overall effect of *Time since IPO* on *Target premium* is still positive even during the hot and cold IPO periods. In Panel B, we repeat the analysis for the subsample of acquisitions that are announced within three years of the targets' IPOs. Results are similar to those in Panel A. In summary, we conclude that the differences among hot, neutral, and cold IPO periods do not affect our conclusions.

8.7. Competition for targets

While the learning hypothesis does not predict an increase in the actual number of bidders over time (only the bidder with the lowest cost of learning always emerges), the declining differential in learning costs among acquirers can make competition more likely. Yet, this (latent or potential) competition for an individual target is difficult to measure because much of it is unobservable. Even if some events are observable, for example in press reports or filings with the SEC, collecting, quantifying, and interpreting such data is very challenging. Instead, we follow Aktas, de Bodt, and Roll (2010) and proxy for latent

[17] Specifically, we calculate three-month centered moving averages of the number of IPOs for each month in the sample using data reported in Ibbotson, Sindelar, and Ritter (1994) and updated on Jay Ritter's website (http://bear.warrington.ufl.edu/ritter/ipodata.htm). Following Helwege and Lian (2004), hot periods are defined as months for which the number of IPOs exceeds the top quartile of the moving average. Cold periods are defined as months for which the number of IPOs is less than the bottom third of the moving average.

competition with an industry liquidity index (Schlingemann, Stulz, and Walkling 2002) and an indicator for National Bureau of Economic Research (NBER) recessions. Specifically, the industry liquidity index is the value of all corporate control transactions in the same two-digit SIC industry as the target in the calendar quarter of the acquisition announcement divided by the book value of total assets of all Compustat firms in that industry. Corporate control transactions include all disclosed and completed leveraged buyouts, tender offers, spinoffs, exchange offers, minority stake purchases, acquisitions of remaining interest, privatizations, and equity carve-outs, but exclude buybacks. The NBER recession indicator is equal to one if the acquisition announcement takes place during a recession. Hence, a low industry liquidity index and NBER recessions proxy for low latent competition.

First, we find no monotonic relation between the proxies for latent competition and *Time since IPO*. Second, when we add the industry liquidity index to our main regression specification (as in Table 4, results not tabulated), its coefficient is insignificant and the coefficients on *Time since IPO* are virtually identical to the estimates in Table 4. Similarly, the point estimates of the NBER recession indicator are consistently negative in both the acquirer announcement return and target premium regressions, but they are only significant in the sample of targets that are acquired within three years after their IPOs. The negative coefficient in the premium regression is consistent with Aktas et al. (2010). Finally, the coefficients on *Time since IPO* remain negative (positive) and significant in regressions analyzing acquirer announcement returns (target premiums).

If the latent competition variables measured competition for targets perfectly, we would have expected increased latent competition to lower acquirer announcement returns, to increase target premiums, and to weaken the effect of *Time since IPO*. The insignificance of the industry liquidity index and the consistently negative effect of NBER recessions indicate that either competition does not matter or that the variables are poor proxies for the type of competition for an individual target that we are concerned about in the context of the learning framework. We contend that the latter explanation is more likely. Specifically, even if there are many corporate control transactions in an industry, it is still possible, or even likely, that for each individual target, there is one potential acquirer with superior learning abilities that leads to the reduced competition for that individual target that we describe in our learning hypothesis.

8.8. Analyst coverage

We argue that investors learn about firms over time, in particular after the firms go public. Analysts can also reduce the cost of learning by providing and analyzing information. It is possible that the time since a firm's IPO and the number of analysts that are following the firm are correlated.

We investigate the effects of analyst coverage with Institutional Brokers' Estimate System data. We define analyst coverage as the highest number of analysts that provide one-year ahead earnings per share forecasts for the target in any month during the year of the acquisition announcement. First, we find that there is no time trend in analyst coverage in our sample. This finding makes it unlikely that analyst coverage explains our results. Firms have analyst coverage right after their IPOs, likely because they have substantial investor interest, and providing analyst coverage is frequently part of the underwriters' services. More established firms tend to have analyst coverage because they are larger and have broader investor bases.

Second, we add the number of analysts, and two indicators for analyst coverage and high number of analysts (above in-sample median of four), separately to our main regressions (as in Table 4, results not tabulated). Using the entire sample, the number of analysts and the indicator for a high number of analysts are significantly negatively related to acquirer announcement returns. This finding is consistent with our learning hypothesis because better information about the target should be associated with worse deals for acquirers. Yet, the coefficient on *Time since IPO* remains significant and largely unchanged in magnitude compared to Table 4. The impact of analyst coverage seems to be largely orthogonal. Furthermore, all three analyst coverage variables are insignificant when the takeover premium is the dependent variable. Overall, analyst coverage does not affect the significance of *Time since IPO* in analyses of acquirer announcement returns and takeover premiums. Given the lack of monotonic changes in analyst coverage over time and the fact that analyst coverage is likely part of underwriting services, it may not be a good proxy for the cost of learning in our context.

8.9. Other potential concerns

Some potential targets likely pursue an IPO only to establish a valuation that facilitates their acquisition afterwards. In these cases, the fraction of secondary shares sold in the IPO should be negatively related to the likelihood of a subsequent acquisition because insiders should prefer to sell their shares at a premium in an acquisition rather than in the IPO. To assess whether this motivation for going public affects our conclusions about the effects of learning, we collect data from the Thomson Reuters SDC New Issues database on the fraction of secondary shares sold in the IPO. The average fraction of secondary shares sold, as a percentage of total shares sold, in the IPO is 14.7% and the median is 0%. We include the fraction of secondary shares sold in the IPO as a control variable in regressions analyzing *Log Acquirer CAR* and *Log Target premium*. In untabulated results, the coefficients on the fraction of secondary shares are insignificant while the coefficients on *Time since IPO* retain their signs and significance. Therefore, it is unlikely that the possible presence of firms going public to get acquired in our sample affects our conclusions about the effects of learning on acquisition pricing.

There is evidence that firms are overvalued right after their IPOs and that such overvaluation dissipates over the five years following the IPO (Loughran and Ritter 1995). If recent IPO firms are overvalued, acquirer announcement returns should be low and become more positive for targets that are acquired later after their IPOs when they are less overvalued. We find the opposite effect in our sample. There is no such clear prediction for how target overvaluation should affect target premiums. Yet, given the contradictory evidence for acquirer announcement returns, it is unlikely that IPO firm overvaluation can explain our results.

An alternative explanation for our results can be that the time since the target's IPO is not related to learning about the target, but instead that investors learn something about the acquirer when the target is a recent IPO versus an established public firm. One such explanation would be that acquiring a young, high growth firm signals that the acquirer exhausted its internal growth opportunities. Such signal should be associated with low acquirer announcement returns for very recent IPO targets which is the opposite of what we observe. There may be other similar explanations. To account for those related to growth opportunities, we add the target market-to-book ratio as an additional control variable (acquirer market-to-book is already included). Inclusion of this variable in our analysis has no effect on our main results.

We also calculate an alternative measure of the takeover premium following Chatterjee et al. (2012). First, we divide the deal value by the target's market value two weeks before the acquisition announcement. If this measure is negative or larger than two, we replace it with the initial offer price multiplied by the target's shares outstanding divided by the target's market value. If it is still outside the 0 to 2 range, we replace the initial offer price with the final offer price. If still outside the 0 to 2 range, we drop the observation. We use this dependent variable in the same regression specification as in Table 4. *Time since IPO* is significantly positive in the subsample of targets that are acquired within three years of their IPOs, but its coefficient is insignificant, with a positive point estimate, for the entire sample (results not tabulated). In sum, our results are generally robust to alternative measures of the takeover premium.

Industry overlap between acquirer and target can affect our results. In untabulated analyses, results are virtually identical when we add a variable indicating that acquirer and target are in the same industry based on 2-digit SIC codes or the Fama-French 49-industry classification.

There are some significant correlations between *Time since IPO* and our other independent variables. As a robustness test, we orthogonalize *Time since IPO* with respect to all other independent variables. The resulting residual *Time since IPO* variable remains significant.

9. Conclusions

We find that acquirer announcement returns decrease and takeover premiums increase with the length of time since the targets' initial public offerings. The cost of learning about the target by potential acquirers that declines over time can explain these results. Higher costs of learning enhance the competitive advantage that an acquirer with superior learning abilities has over other potential acquirers.

It can thereby reduce competition for the target and lead to takeover prices that are favorable to the acquirer at the expense of the target. Over time, as more information about the target becomes publicly and easily available to all potential acquirers, the benefits to acquirers with learning advantages decline. Our results relate to the empirical fact that acquirer announcement returns in acquisitions of public targets are significantly lower than in acquisitions of private targets, but extend such effects to a more gradual process of learning that persists after a firm's IPO.

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Appendix A: Effect of learning on acquisition pricing

We provide an illustrative example of how learning can affect acquisition payoffs. We have one target and two potential acquirers. The target's stand-alone value is uncertain, however, it is common knowledge that the target's value is uniformly distributed between \$50 and \$150. Absent any takeover offer, the target's market value is its expected value of \$100. It is also common knowledge that the acquisition of the target generates synergies of \$30.

The potential acquirers can learn about the value of the target at a cost. Assume that potential acquirer A can learn at a lower cost, e.g., because it operates in the same industry, has relationships with the target, or has better analysts. In this learning framework, it is always the potential bidder with the lowest learning cost who chooses to learn. We normalize firm A's cost of learning to zero and set potential bidder B's cost of learning to \$20.[18]

A's goal is to take advantage of its knowledge of the target value that is unknown to both B and the target. To preserve its informational advantage, A has to select an offer price that keeps B from engaging in costly learning. A always makes the first bid because it is beneficial for B to wait and extract information from A's offer.

We assume that the target always rejects offers with negative premiums, i.e., offers below \$100. Therefore, A does not make a takeover offer when it learns that the target value plus synergies is below \$100. For target values plus synergies above \$100, A's goal is to find the lowest offer price that keeps B from engaging in learning. If A always offered \$100, B would learn that the true target value (including synergy) is between \$100 and \$180 with an expected value of \$140. After B spends \$20 on learning, it's expected gain from learning and making an offer would be \$20. The reason is that B would get by with offering slightly more than \$100 for a target that is worth \$140 on average. Therefore, A needs an offer schedule that varies with the target's value to prevent firm B from engaging in learning.

[18] Note that with zero cost, firm A always chooses to learn. Increasing the learning cost of firm A does not affect the implications of the learning example as long as its cost is below the learning cost of firm B.

The key to the offer schedule is that the difference between expected target value and the offer price is exactly $20, i.e., A's learning cost advantage over firm B. So, if the target value plus synergy is above $140, A offers $140, and B infers that the true target value is between $140 and $180 with an expected value of $160. B rationally does not expend resources on learning because, on average, it would acquire a target worth $160 for an amount slightly exceeding $140 plus the $20 learning cost. Following the same rationale, for target values between $100 and $140, A offers $100.

With this offer schedule, B never chooses to learn, and A is the only actual bidder. A's average payoff is $20 because it acquires the target on average at a $20 discount to the expected target value plus synergies. The target's average payoff in excess of its pre-bid value of $100 is $20. That is, the target payoff is with equal probability either zero (when A offers $100) or $40 (when A offers $140).

Over time, we expect the cost of learning of all potential acquirers to decline. We reflect the lower cost of learning by setting B's cost of learning to $10 and apply the same logic to analyze the acquisition pricing. A sets its offer prices to $10 below the average target value, its learning cost advantage over B, to prevent B from engaging in learning. Therefore, A offers $160 when the true target value is between $160 and $180, $140 when the true target value is between $140 and $160, etc. On average, relative to the high uncertainty scenario, A's payoff decreases by $10, equal to the reduction in its learning cost advantage over firm B. Since A has to share more of the synergies with the target by offering higher takeover premiums, the target's average payoff increases to $30.

To summarize, higher bidders' costs of learning about the target leads to higher payoffs for bidder A, the bidder with a learning cost advantage. Conversely, higher bidders' costs of learning about the target leads to lower payoffs for the target. Therefore, as the cost of learning declines, that is in terms of our empirical proxy, as time since a target's IPO increases, the acquirer announcement return should decline and the takeover premium should increase on average.

In our example, we prohibit B from making "blind" offers, i.e., offers without prior learning of the target value. If we allowed "blind" offers, A would be forced to always offer the target's true value. The acquirer payoffs would be zero and the target would capture all acquisition gains. We believe prohibiting "blind" offers is reasonable because it is unlikely that bidders would make takeover offers without thoroughly investigating and analyzing the target, and without performing due diligence. Alternatively, we can assume that at least part of the synergies are acquirer-specific. A potential acquirer would have to invest in (costly) learning to determine its specific synergies with the target because it could not learn about them from the other bidder's offer. Not knowing its synergies with the target would make blind offers unattractive and should have largely the same effects on the example as prohibiting blind offers outright.[19]

In our parsimonious example, both the target and acquirer payoffs are always nonnegative. Adding features, for example, acquirer agency issues such as empire building involving the pursuit of acquisitions with synergies below the other potential bidder's cost of learning, can make the acquirer payoffs negative while keeping the target payoffs positive. Yet, even with such additional features, the effects on target and acquirer payoffs of the changing costs of learning should remain the same. If bidders' costs of learning about the target decline over time, acquirer announcement returns should also decline and takeover premiums should increase.

[19] We also consider an alternative bid schedule that effectively keeps B from learning and bidding. Under this alternative, continuous bid schedule, A learns about the target and offers an amount slightly above the target value plus synergy less A's learning cost advantage over B. Because A's offer price is set to guarantee that B always realizes a loss when it expends resources on learning and submits a bid above the current bid of A, it is never optimal for B to engage in learning and to make a bid. This form of bidding has the same implications as our main setup.

Appendix B: Variable descriptions

Variable	Description and data source
Acq abs gain/ synergy	If *Synergy* > 0, *Acquirer CAR* x acquirer market value of equity/ *Synergy*. If *Synergy* < 0, 1 - *Acquirer CAR* x acquirer market value of equity/ *Synergy*. *Synergy* = *Acquirer CAR* x acquirer market value of equity + *Target CAR* x target market value of equity. Acquirer and target market values are measured two weeks before the acquisition announcement. Source: CRSP.
Acq rel gain/ combined MV	(Acquirer abnormal dollar gain – target abnormal dollar gain over the three-day acquisition announcement window)/ (acquirer market values of equity + target market values of equity). Source: CRSP.
Acquirer CAR	Acquirer's return in excess of CRSP equal-weighted index over 3 days centered on acquisition announcement. Source: CRSP.
Acquirer market value	Market value of equity measured at the last fiscal year-end prior to acquisition announcement, except earliest available when unavailable at end of prior fiscal year. Source: Compustat.
Acquirer market-to-book	(*Acquirer market value* + total assets – book value of equity)/ total assets, all measured at the last fiscal year-end prior to acquisition announcement. Source: Compustat.
Age at IPO	Age of target at the time of the IPO, measured from target's founding date. Source: Thomson Reuters SDC New Issues database; founding year data from Jay Ritter's website.
Annual target industry M/B stdev	Same as *Target industry M/B stdev* but measured separately each year. Source: Compustat.
Annual target market-to-book	Same as *Target market-to-book* but measured separately each year. Source: Compustat.
Cold IPO market	Based on the monthly volume of IPO issuance as in Helwege and Lian (2004). Source: Ibbotson, Sindelar, and Ritter (1994) and updates on Jay Ritter's website.
Hostile	Deal attitude. Source: Thomson Reuters SDC Mergers & Acquisitions.
Hot IPO market	Based on the monthly volume of IPO issuance as in Helwege and Lian (2004). Source: Ibbotson, Sindelar, and Ritter (1994) and updates on Jay Ritter's website.
IPO bubble	IPO occurred between October 1998 and December 2000. Source: Thomson Reuters SDC New Issues database.

Monthly target return stdev	Same as *Target return stdev* but measured separately each month with daily returns. Source: CRSP.
Number of 10-K/Q filings	Number of forms 10-Q and 10-K filed between the target's IPO and the acquisition announcement. Source: SEC EDGAR
Prior market return	Return of CRSP equal-weighted index from the IPO date to two weeks before the acquisition announcement. Source: CRSP.
Relative size	*Target market value*/ *Acquirer market value*.
Stock	= 1 if acquisition price is paid at least partly with acquirer's stock. Source: Thomson Reuters SDC Mergers & Acquisitions.
Target cash burn	= 1 if *Target cash flow/ cash* is in the bottom 20% of all sample firms.
Target cash flow/ cash	Target's cash flow from operating activities/ cash and short-term investments, all measured at the last fiscal year-end prior to acquisition announcement. Source: Compustat.
Target industry M/B stdev	Standard deviation of market-to-book ratios of firms in the same industry with assets between half and twice the target's assets, measured at the last fiscal year-end prior to acquisition announcement. Source: Compustat.
Target market value	Market value of equity measured at the last fiscal year-end prior to acquisition announcement, except earliest available when unavailable at end of prior fiscal year. Source: Compustat.
Target market-to-book	(*Target market value* + total assets – book value of equity)/ total assets, all measured at the last fiscal year-end prior to acquisition announcement. Source: Compustat.
Target net income/ assets	Target's net income/ total assets, all measured at the last fiscal year-end prior to acquisition announcement. Source: Compustat.
Target premium	Target's return in excess of CRSP equal-weighted index from 10 trading days prior to acquisition announcement until the earlier of 180 days after announcement or delisting. Source: CRSP.
Target prior return	Target's return from the first trading day closing price to two weeks prior to the acquisition announcement. Source: CRSP.
Target return stdev	Standard deviation of daily target returns from the IPO date to two weeks before the acquisition announcement. Source: CRSP.

Target SEO	= 1 if target raised equity between its IPO and the acquisition announcement date. Source: Thomson Reuters SDC New Issues.
Tender	Use of tender offer. Source: Thomson Reuters SDC Mergers & Acquisitions.
Time since IPO	Days between target's IPO and acquisition announcement scaled by 3,650 (days in ten-year period). Source: Thomson Reuters SDC New Issues and Mergers & Acquisition databases.
VC	Presence of venture capital firm at time of IPO. Source: Thomson Reuters SDC New Issues database.

Table 1
Sample descriptive statistics
Panel A presents means, medians, standard deviations, and the 10% and 90% percentile values for continuous variables. Panel B shows the proportion of each indicator variable that equals one. Appendix B defines all variables.

Panel A: Continuous variables

	Mean	Median	St. Dev.	10%	90%
Time since IPO	0.394	0.347	0.249	0.105	0.788
Acquirer CAR	-0.019	-0.015	0.091	-0.118	0.074
Target premium	0.301	0.243	0.466	-0.149	0.782
Target market value ($ million)	463	136	1,066	19	1,086
Target market-to-book	3.260	1.533	15.359	0.977	4.876
Acquirer market value ($ million)	3,775	837	10,871	83	8,812
Acquirer market-to-book	4.203	1.805	22.011	1.025	5.504
Relative size	0.313	0.170	0.403	0.039	0.747
Target industry M/B stdev	2.345	1.417	4.951	0.456	4.132
Target return stdev	0.046	0.042	0.021	0.023	0.074
Target prior return	0.525	-0.087	2.936	-0.899	1.887
Prior market return	2.217	1.177	2.904	0.173	5.657
Target net income/ assets	-0.109	0.013	0.388	-0.446	0.116

Panel B: Indicator variables

	Proportion variable = 1
VC	0.501
Hot IPO market	0.556
Cold IPO market	0.079
Stock	0.700
Hostile	0.010
Tender	0.169
Target SEO	0.456
Target cash burn	0.195

Table 2

Target characteristics, acquirer announcement returns, and target premiums over time since IPO

We split our sample into three bins according to the number of years between the target's IPO and acquisition. Appendix B defines all variables. ***, **, * indicate that the mean, median, or standard deviation is significantly different at the 0.01, 0.05, and 0.10 level, respectively, from the corresponding mean, median, or standard deviation of acquisitions that take place in the first year after the target's IPO.

		Acquired within 1 year from IPO	Acquired in year 2 or 3 from IPO	Acquired after 3 years from IPO
	N	76	283	451
Target market-to-book	*Ave*	13.694	2.675 *	1.869 **
	Med	3.656	1.662 ***	1.361 ***
Acquirer CAR	*Ave*	-0.018	-0.020	-0.019
	Med	-0.015	-0.019	-0.013
	Stdev	0.102	0.102	0.082 ***
Target premium	*Ave*	0.191	0.324 **	0.305 *
	Med	0.195	0.253 **	0.247
	Stdev	0.426	0.453	0.478
Stock	*Ave*	0.868	0.731 ***	0.652 ***
Target market value	*Ave*	484.5	482.8	446.3
($ million)	*Med*	227.5	134.2 ***	119.8 ***
Target industry M/B stdev	*Ave*	6.112	2.112 **	1.857 **
	Med	1.958	1.381 ***	1.378 ***
Target return stdev	*Ave*	0.052	0.047 *	0.044 ***
	Med	0.048	0.043 *	0.041 ***

Table 3
Changes in target valuation and risk measures over time
We regress *Annual target market-to-book*, *Log Annual target industry M/B stdev*, and *Log Monthly target return stdev* on *Time since IPO*. Appendix B defines all variables. Target industry indicator variables are based on 2-digit SIC codes. *p*-values, based on heteroskedasticity adjusted standard errors, are in brackets. ***, **, * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

	Annual target market-to-book			Log Annual target industry M/B stdev			Log Monthly target return stdev		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	3.488***	3.109	3.853***	0.205***	-0.111**	1.414***	-3.364***	-3.708***	-4.436***
	[0.000]	[0.168]	[0.001]	[0.000]	[0.043]	[0.000]	[0.000]	[0.000]	[0.000]
Time since IPO	-2.715***	-2.395***	-2.811***	-0.730***	-0.440***	-0.232***	-0.089***	-0.047***	-0.487
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.103]
Year FE	No	Yes	Yes	No	Yes	Yes			
Month-year FE							No	Yes	Yes
Industry FE	No	Yes	No	No	Yes	No	No	Yes	No
Target FE	No	No	Yes	No	No	Yes	No	No	Yes
Adjusted R^2	0.0288	0.1535	0.3419	0.0172	0.4670	0.8160	0.0010	0.2836	0.6004
Observations	3,164	3,164	3,164	3,545	3,545	3,545	36,959	36,959	36,959

Table 4

Regression results for acquirer announcement returns and target premiums

The dependent variable is *Log Acquirer CAR* in columns 1 and 2 and *Log Target premium* in columns 3 and 4. "*Log*" in front of the variable name indicates the natural logarithm of the variable or, if appropriate, of (1 + the variable). Columns 1 and 3 use our entire sample while columns 2 and 4 only include acquisitions that occur within three years of the target's IPO. All regressions contain intercepts, target industry indicator variables based on 2-digit SIC codes, and acquisition year indicator variables. Appendix B defines all variables. *p*-values, based on heteroskedasticity adjusted standard errors clustered at the acquirer level, are in brackets. ***, **, * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

	Log Acquirer CAR		Log Target premium	
	Entire sample	Acquired within 3 years	Entire sample	Acquired within 3 years
	(1)	(2)	(3)	(4)
Time since IPO	-0.093**	-0.295*	0.332*	1.884**
	[0.041]	[0.055]	[0.077]	[0.013]
Target pre-acquisition performance				
Log Target prior return	-0.001	-0.003	-0.029	0.000
	[0.783]	[0.799]	[0.111]	[0.992]
Log Prior market return	0.016	0.057	-0.134*	-0.476**
	[0.308]	[0.247]	[0.062]	[0.035]
Target cash burn	0.032***	0.030*	-0.094	0.030
	[0.007]	[0.060]	[0.140]	[0.759]
Target net income/ assets	-0.025*	-0.040*	-0.052	-0.123
	[0.051]	[0.082]	[0.411]	[0.191]
M&A characteristics				
Log Acquirer market-to-book	-0.018**	-0.017*	-0.011	-0.020
	[0.012]	[0.088]	[0.654]	[0.618]
Log Acquirer market value	0.002	-0.002	0.020*	-0.011
	[0.510]	[0.598]	[0.082]	[0.557]
Log Relative size	-0.008**	-0.071**	-0.021	-0.412***
	[0.013]	[0.017]	[0.125]	[0.008]
Stock	-0.025***	-0.007	-0.004	-0.057
	[0.001]	[0.624]	[0.905]	[0.343]
VC	-0.012	-0.011	-0.032	-0.073
	[0.103]	[0.352]	[0.328]	[0.186]
Hostile	0.041	-0.012	0.186*	-0.030
	[0.103]	[0.676]	[0.063]	[0.873]
Tender	0.004	0.004	0.106***	0.119**
	[0.654]	[0.816]	[0.002]	[0.037]
Adjusted R^2	0.1300	0.1973	0.0924	0.1839
Observations	781	354	764	354

Table 5
Regression results controlling for target's age at the time of the IPO
The dependent variables are *Log Acquirer CAR* in regressions 1 and 2 and *Log Target premium* in regressions 3 and 4. "*Log*" in front of the variable name indicates the natural logarithm of the variable or, if appropriate, of (1 + the variable). Columns 1 and 3 use our entire sample while columns 2 and 4 only include acquisitions that occur within three years of the target's IPO. All regressions contain intercepts, target industry indicator variables based on 2-digit SIC codes, and acquisition year indicator variables. Appendix B defines all variables. *p*-values, based on heteroskedasticity adjusted standard errors clustered at the acquirer level, are in brackets. ***, **, * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

	Log Acquirer CAR		Log Target premium	
	Entire sample	Acquired within 3 years	Entire sample	Acquired within 3 years
	(1)	(2)	(3)	(4)
Time since IPO	-0.096**	-0.319**	0.416**	1.983**
	[0.033]	[0.044]	[0.027]	[0.012]
Age at IPO	-0.0001	0.0001	-0.0001	0.0021*
	[0.764]	[0.750]	[0.881]	[0.069]
Target pre-acquisition performance				
Log Target prior return	-0.001	-0.003	-0.025	0.000
	[0.879]	[0.793]	[0.185]	[1.000]
Log Prior market return	0.018	0.066	-0.160**	-0.502**
	[0.248]	[0.190]	[0.026]	[0.033]
Target cash burn	0.033***	0.030*	-0.071	0.038
	[0.006]	[0.073]	[0.274]	[0.705]
Target net income/ assets	-0.027**	-0.041*	-0.051	-0.129
	[0.039]	[0.077]	[0.428]	[0.173]
M&A characteristics				
Log Acquirer market-to-book	-0.019**	-0.018*	-0.009	-0.018
	[0.012]	[0.072]	[0.739]	[0.666]
Log Acquirer market value	0.003	-0.002	0.020*	-0.015
	[0.338]	[0.689]	[0.096]	[0.436]
Log Relative size	-0.007**	-0.074**	-0.016	-0.441***
	[0.044]	[0.022]	[0.239]	[0.007]
Stock	-0.027***	-0.005	0.001	-0.038
	[0.000]	[0.727]	[0.965]	[0.547]
VC	-0.011	-0.013	-0.042	-0.056
	[0.149]	[0.307]	[0.198]	[0.300]
Hostile	0.044*	0.002	0.187*	-0.092
	[0.077]	[0.958]	[0.071]	[0.584]
Tender	0.004	0.003	0.105***	0.131**
	[0.680]	[0.858]	[0.002]	[0.026]
Adjusted R^2	0.1340	0.2047	0.0907	0.1908
Observations	751	339	736	339

Table 6

Regression results controlling for accumulation of public information

The dependent variables are *Log Acquirer CAR* in regressions 1 through 3, *Log Target premium* in regressions 4 through 6, and *Acq rel gain/ combined MV* in regressions 7 through 9. *Number of 10-K/Q filings* is divided by 100 to scale coefficients. "*Log*" in front of the variable name indicates the natural logarithm of the variable or, if appropriate, of (1 + the variable). All regressions contain intercepts, target industry indicator variables based on 2-digit SIC codes, and acquisition year indicator variables. Appendix B defines all variables. *p*-values, based on heteroskedasticity adjusted standard errors clustered at the acquirer level, are in brackets. ***, **, * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

	Log Acquirer CAR			Log Target Premium			Acq rel gain/ combined MV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Time since IPO	-0.156***		-0.161**	0.314*		0.579*	-0.195***		-0.139*
	[0.001]		[0.038]	[0.081]		[0.051]	[0.000]		[0.064]
Number of 10-K/Q filings/ 100		-0.154***	0.007		0.181	-0.413		-0.229***	-0.086
		[0.008]	[0.938]		[0.391]	[0.232]		[0.000]	[0.323]
Target pre-acquisition performance									
Log Target prior return	-0.001	0.000	-0.001	-0.030	-0.032	-0.030	-0.010**	-0.009**	-0.010**
	[0.859]	[0.934]	[0.860]	[0.150]	[0.129]	[0.154]	[0.022]	[0.030]	[0.022]
Log Prior market return	0.040***	0.000	0.041*	-0.129*	-0.044	-0.191**	0.045***	-0.003	0.032
	[0.009]	[0.965]	[0.055]	[0.052]	[0.187]	[0.034]	[0.002]	[0.634]	[0.121]
Target cash burn	0.029**	0.028**	0.029**	-0.032	-0.032	-0.031	0.018	0.019	0.019
	[0.040]	[0.042]	[0.040]	[0.682]	[0.676]	[0.687]	[0.166]	[0.161]	[0.166]
Target net income/ assets	-0.031**	-0.029**	-0.031**	-0.026	-0.030	-0.021	-0.012	-0.009	-0.011
	[0.027]	[0.038]	[0.027]	[0.712]	[0.663]	[0.767]	[0.421]	[0.562]	[0.466]
M&A characteristics									
Log Acquirer market-to-book	-0.020**	-0.021**	-0.020**	-0.010	-0.011	-0.012	-0.006	-0.007	-0.007
	[0.021]	[0.019]	[0.021]	[0.723]	[0.718]	[0.674]	[0.356]	[0.298]	[0.324]
Log Acquirer market value	0.003	0.004	0.003	0.024*	0.023*	0.026*	0.007**	0.007**	0.007**
	[0.386]	[0.248]	[0.394]	[0.070]	[0.080]	[0.058]	[0.026]	[0.013]	[0.021]
Log Relative size	-0.005	-0.003	-0.005	-0.014	-0.019	-0.013	-0.016***	-0.015***	-0.016***
	[0.218]	[0.440]	[0.218]	[0.410]	[0.275]	[0.433]	[0.000]	[0.000]	[0.000]
Stock	-0.044***	-0.043***	-0.044***	0.004	0.001	0.005	-0.037***	-0.035***	-0.036***
	[0.000]	[0.000]	[0.000]	[0.925]	[0.984]	[0.898]	[0.000]	[0.000]	[0.000]
VC	-0.009	-0.009	-0.009	-0.011	-0.010	-0.007	-0.004	-0.003	-0.004
	[0.321]	[0.346]	[0.320]	[0.791]	[0.809]	[0.857]	[0.589]	[0.700]	[0.648]
Hostile	-0.081***	-0.077***	-0.081***	0.294***	0.285***	0.302***	0.045*	0.051**	0.047*
	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.087]	[0.049]	[0.073]
Tender	0.000	0.001	0.000	0.107**	0.106**	0.108**	0.007	0.007	0.007
	[0.994]	[0.927]	[0.995]	[0.015]	[0.017]	[0.015]	[0.581]	[0.552]	[0.579]
Adjusted R^2	0.1408	0.1347	0.1408	0.0868	0.0840	0.0881	0.1927	0.1890	0.1939
Observations	537	537	537	524	524	524	524	524	524

Table 7

Regression results controlling for target's return volatility

The dependent variable is *Log Acquirer CAR* in columns 1 and 2 and *Log Target premium* in columns 3 and 4. "*Log*" in front of the variable name indicates the natural logarithm of the variable or, if appropriate, of (1 + the variable). Columns 1 and 3 use our entire sample while columns 2 and 4 only include acquisitions that occur within three years of the target's IPO. All regressions contain intercepts, industry target indicator variables based on 2-digit SIC codes, and acquisition year indicator variables. Appendix B defines all variables. *p*-values, based on heteroskedasticity adjusted standard errors clustered at the acquirer level, are in brackets. ***, **, * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

Table 7 (continued)

	Log Acquirer CAR		Log Target premium	
	Entire sample	Acquired within 3 years	Entire sample	Acquired within 3 years
	(1)	(2)	(3)	(4)
Time since IPO	-0.092**	-0.299*	0.344*	1.927**
	[0.045]	[0.055]	[0.067]	[0.013]
Log Target return stdev	0.009	-0.006	0.110**	0.070
	[0.542]	[0.759]	[0.032]	[0.422]
Target pre-acquisition performance				
Log Target prior return	0.000	-0.003	-0.016	0.007
	[0.985]	[0.763]	[0.409]	[0.872]
Log Prior market return	0.016	0.057	-0.140**	-0.483**
	[0.329]	[0.243]	[0.050]	[0.033]
Target cash burn	0.031***	0.031*	-0.104	0.020
	[0.008]	[0.059]	[0.110]	[0.847]
Target net income/ assets	-0.024*	-0.040*	-0.041	-0.114
	[0.056]	[0.079]	[0.520]	[0.238]
M&A characteristics				
Log Acquirer market-to-book	-0.019***	-0.016	-0.025	-0.027
	[0.007]	[0.118]	[0.341]	[0.498]
Log Acquirer market value	0.002	-0.003	0.023**	-0.008
	[0.463]	[0.577]	[0.043]	[0.657]
Log Relative size	-0.008**	-0.073**	-0.019	-0.398**
	[0.015]	[0.021]	[0.154]	[0.012]
Stock	-0.025***	-0.007	-0.001	-0.055
	[0.001]	[0.620]	[0.972]	[0.369]
VC	-0.013*	-0.010	-0.046	-0.084
	[0.094]	[0.404]	[0.169]	[0.137]
Hostile	0.041	-0.012	0.189*	-0.034
	[0.103]	[0.685]	[0.059]	[0.856]
Tender	0.005	0.004	0.114***	0.122**
	[0.614]	[0.832]	[0.001]	[0.032]
Adjusted R^2	0.1306	0.1975	0.0972	0.1853
Observations	781	354	764	354

Table 8

Regression results for acquirer announcement returns and target premiums

The dependent variables are *Acquirer CAR* and *Target premium*. In contrast to Table 4, we are not taking logarithms of the dependent variables. Appendix B defines all variables. All regressions contain intercepts, target industry indicator variables based on 2-digit SIC codes, and acquisition year indicator variables. *p*-values, based on heteroskedasticity adjusted standard errors clustered at the acquirer level, are in brackets. ***, **, * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

	Acquirer CAR		Target premium	
	Entire sample	Acquired within 3 years	Entire sample	Acquired within 3 years
	(1)	(2)	(3)	(4)
Time since IPO	-0.090**	-0.294*	0.462**	1.614**
	[0.042]	[0.054]	[0.037]	[0.028]
Target pre-acquisition performance				
Log Target prior return	-0.001	-0.003	-0.063***	-0.045
	[0.798]	[0.806]	[0.002]	[0.263]
Log Prior market return	0.017	0.058	-0.199**	-0.398*
	[0.282]	[0.235]	[0.026]	[0.090]
Target cash burn	0.029**	0.030*	-0.063	0.098
	[0.013]	[0.075]	[0.319]	[0.254]
Target net income/ assets	-0.027*	-0.043*	-0.059	-0.123
	[0.052]	[0.085]	[0.383]	[0.136]
M&A characteristics				
Log Acquirer market-to-book	-0.017**	-0.016	-0.009	-0.017
	[0.012]	[0.109]	[0.754]	[0.681]
Log Acquirer market value	0.001	-0.003	0.016	-0.025
	[0.739]	[0.569]	[0.268]	[0.278]
Log Relative size	-0.007**	-0.062**	-0.027	-0.406***
	[0.026]	[0.028]	[0.120]	[0.000]
Stock	-0.024***	-0.006	0.026	-0.072
	[0.001]	[0.695]	[0.531]	[0.313]
VC	-0.011	-0.010	-0.019	-0.057
	[0.129]	[0.400]	[0.620]	[0.285]
Hostile	0.040	-0.015	0.302**	0.021
	[0.121]	[0.587]	[0.031]	[0.933]
Tender	0.004	0.005	0.073*	0.090
	[0.641]	[0.769]	[0.090]	[0.191]
Adjusted R^2	0.1288	0.2004	0.1165	0.2757
Observations	781	354	764	354

Table 9
Acquirer share of gains
Acq rel gain/ combined MV is the dependent variable in columns 1 and 2 while *Acq abs gain/ synergy* is the dependent variable in columns 3 and 4. Appendix B defines all variables. All columns have intercepts, target industry indicator variables based on 2-digit SIC codes, and acquisition year indicator variables. *p*-values, based on heteroskedasticity adjusted standard errors clustered at the acquirer level, are in brackets. ***, **, * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

	Acq rel gain/ combined MV		Acq abs gain/ synergy	
	Entire sample	Acquired within 3 years	Entire sample	Acquired within 3 years
	(1)	(2)	(3)	(4)
Time since IPO	-0.157***	-0.368**	-3.676*	-3.994
	[0.000]	[0.010]	[0.068]	[0.554]
Target pre-acquisition performance				
Log Target prior return	-0.012***	-0.016*	-0.030	0.118
	[0.003]	[0.057]	[0.841]	[0.655]
Log Prior market return	0.026*	0.080*	1.189*	1.373
	[0.080]	[0.074]	[0.071]	[0.520]
Target cash burn	0.017	0.014	0.523	0.779
	[0.151]	[0.408]	[0.199]	[0.216]
Target net income/ assets	-0.013	-0.010	-0.563*	-0.796*
	[0.349]	[0.546]	[0.093]	[0.072]
M&A characteristics				
Log Acquirer market-to-book	-0.008	-0.009	0.059	0.410
	[0.169]	[0.235]	[0.760]	[0.147]
Log Acquirer market value	0.007***	-0.001	0.023	-0.077
	[0.008]	[0.844]	[0.859]	[0.748]
Log Relative size	-0.022***	-0.136***	-0.269	-0.977
	[0.000]	[0.000]	[0.112]	[0.363]
Stock	-0.017**	-0.011	0.015	0.805
	[0.024]	[0.410]	[0.970]	[0.313]
VC	-0.008	-0.008	0.193	0.501
	[0.255]	[0.468]	[0.565]	[0.359]
Hostile	-0.016	0.025	1.526**	0.404
	[0.547]	[0.575]	[0.038]	[0.720]
Tender	0.013	0.009	0.080	0.315
	[0.152]	[0.569]	[0.862]	[0.739]
Adjusted R^2	0.1973	0.2955	0.0502	0.0932
Observations	763	354	763	354

Table 10
Regression results controlling for IPO market conditions
This table adds *IPO bubble*, *Hot IPO market*, *Cold IPO market*, and their interactions with *Time since IPO* to the estimations. The dependent variables are *Log Acquirer CAR* and *Log Target premium*. Panel A uses our entire sample and Panel B only acquisitions that occur within three years after the target's IPO. Appendix B defines all variables. All regressions contain intercepts, target industry indicator variables based on 2-digit SIC codes, and acquisition year indicator variables. *p*-values, based on heteroskedasticity adjusted standard errors clustered at the acquirer level, are in brackets. ***, **, * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

Panel A: Entire sample

	Log Acquirer CAR		Log Target premium	
	(1)	(2)	(3)	(4)
Time since IPO	-0.078	-0.107**	0.369*	0.552**
	[0.106]	[0.034]	[0.057]	[0.014]
IPO bubble	0.030		0.002	
	[0.226]		[0.990]	
Hot IPO market		0.008		0.160*
		[0.617]		[0.073]
Cold IPO market		-0.037*		0.154*
		[0.085]		[0.080]
IPO bubble X				
Time since IPO	-0.056		-0.109	
	[0.244]		[0.613]	
Hot IPO market X				
Time since IPO		-0.019		-0.349**
		[0.530]		[0.028]
Cold IPO market X				
Time since IPO		0.027		-0.350**
		[0.588]		[0.035]
Target pre-acquisition performance	Yes	Yes	Yes	Yes
M&A characteristics	Yes	Yes	Yes	Yes
Adjusted R^2	0.1328	0.1353	0.0935	0.1015
Observations	781	781	764	764

Table 10 (continued)

Panel B: Only acquisitions occurring within three years after target's IPO

	Log Acquirer CAR		Log Target Premium	
	(1)	(2)	(3)	(4)
Time since IPO	-0.468***	-0.412*	1.684**	3.030***
	[0.003]	[0.056]	[0.026]	[0.005]
IPO bubble	-0.080*		-0.047	
	[0.092]		[0.846]	
Hot IPO market		0.009		0.397*
		[0.806]		[0.057]
Cold IPO market		-0.051		0.551***
		[0.280]		[0.010]
IPO bubble X Time since IPO	0.591**		0.803	
	[0.038]		[0.548]	
Hot IPO market X Time since IPO		0.047		-1.667*
		[0.803]		[0.087]
Cold IPO market X Time since IPO		0.001		-2.533**
		[0.997]		[0.020]
Target pre-acquisition performance:	Yes	Yes	Yes	Yes
M&A characteristics:	Yes	Yes	Yes	Yes
Adjusted R^2	0.2114	0.2134	0.1855	0.2090
Observations	354	354	354	354

Figure 1
Takeover premiums for low and high uncertainty targets over time
The figure shows how over time the uncertainty declines for both a low-uncertainty and a high-uncertainty target while the takeover premiums increase for both firms.