Acquisitions as a Venture Scaling Strategy:
Adolescent Firms and Innovation Outcomes*

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Abstract: When adolescent ventures choose their scaling strategy for longer-run innovation outcomes, is organic- or acquisition-led-growth preferable? The multifaceted reasons managers may choose an acquisitive path, only some of which are observed and measured, makes this question difficult to address. We study U.S. firms undergoing an initial public offering (IPO) between 1975 and 2016 and track the extent to which they conduct acquisitions, pre- and post-IPO. We use firms' patenting activity as proxies for innovation. We address endogenous selection of acquisition strategies by employing difference-in-differences and instrumental variable methods and estimate a 6 - 10% boost in innovation for acquisition relative to organic scaling. These results contrast with naïve analyses, which suggests a negative or null effect of acquisitions on innovation.

Managerial summary. Should managers choose organic or acquisition-led venture scaling strategies when innovation is important? Organic growth may be slower but organizational culture is preserved. Acquisitions involve paying for products and personnel rather than for effort (as would be the case with organic growth). We empirically investigate this choice by studying the innovation and acquisition behavior of US firms going public between 1975 and 2016. Using methods to control for managerial selection, we find that the acquisition pathway, on average, is more desirable for longer-run innovation. We discuss managerial implications.

Keywords: venture scaling; organic growth; acquisitions; innovation outcomes; endogenous strategic choices.

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INTRODUCTION

As ventures find product-market fit, often following experimentation, they start scaling their businesses (Contigiani & Levinthal, 2019). This scaling phase represents organizational "adolescence," yet has only recently received limited academic attention (e.g., DeSantola & Gulati 2017), despite its theoretical and phenomenological significance.

One setting which illustrates a key strategic decision for adolescent firms is the choice between growing organically or pursuing acquisitions (M&A) when the goal is innovation. While there has been extensive work on M&A and its impact on firm outcomes such as innovation, the focal acquirers are typically mature firms. The question then becomes the generalizability of those findings to adolescent organizations. Since the effects of incumbent firm M&A on innovation run the gamut (e.g., Hitt et al., 1990; Ahuja & Katila, 2001; Puranam, et al., 2006), contingencies such as knowledge bases, firm sizes, and integration strategies are clearly important.

Not only are those factors and others different between established and adolescent firms, but their alternatives to an acquisition-enabled scaling approach may also be distinct. For example, owing to their more developed reputations and organizational structures, established firms may more easily scale across geographies, vertical organizational boundaries (backward or forward-integration), and/or horizontal boundaries (product or service categories) as compared to adolescent ventures. Organic growth for innovation by adolescent firms, for example, may be more slow-paced, as they transition from founder- to institution-centric (DeSantola & Gulati, 2017).

This motivates our central research question: is an organic growth or acquisition pathway better for adolescent firms in shaping their long-run innovation outcomes? To empirically address this question, our study focuses on a specific subset of adolescent firms, those that are newly public. This design choice allows us to both eliminate undesirable heterogeneity from our sample ("lifestyle" firms which are unmotivated to scale) and to control for other firm differences by dint of their public disclosures. The empirical context also suits our research question since newly public ventures face the choice of either deploying the capital raised through the initial public offering (IPO) towards organic growth or pursuing an acquisition route. The latter scaling strategy is enabled by IPOs creating a non-cash currency for acquisition, their own stock (Celikyurt, et al., 2010).

We construct and analyze a firm-year data panel of 4,300 firms that went public between 1975 and 2016, tracking their acquisitions and patenting activity (our proxies for innovation) over a 10-year period spanning their IPO window. Recognizing that the choice of engaging in acquisitions is a (at times, unobserved) purposeful managerial choice, our empirical approach uses a variety of methods to improve inference, including matching, a difference-in-differences approach, as well as an instrumental variable-based identification strategy. Across these methods, we find a robust and economically significant positive, causal relationship between newly public firms undertaking acquisitions and long-run innovation. Our work therefore contributes to entrepreneurship and strategy research by investigating M&A as a mode of scaling for innovation by adolescent firms.

LITERATURE AND MAIN HYPOTHESIS

While there is extensive work on M&A and innovation outcomes, that work mainly focuses on incumbent firms. It is hard to know how the many differences with the adolescent firm context affects the applicability of those results. First, incumbents and emerging newly public firms pursue acquisitions for different reasons. Mature firms that face stagnating revenue growth or innovation may use acquisitions to consolidate market share, enter new geographies, offer new products, vertically integrate, or engage in defensive acquisitions (Chatterjee 1991; Anand & Singh, 1997; Graebner et al., 2010; Cunningham, et al., 2021). Moreover, emerging firms are often analyzed as acquisition targets in the literature (e.g., Stuart & Sorenson, 2003) rather than the acquiring entity attempting to scale. Second, adolescent firms are often first-time acquirers with limited experience (in this and other business development domains). Incumbents are seasoned acquirers (with professional managers) who drive better performance through experience accumulation, knowledge articulation and codification (Zollo & Winter, 2002; Haleblian & Finkelstein 1999). They also have corporate development teams and integration processes to help improve M&A outcomes (Haleblian et al., 2009; Trichternborn et al., 2016). Adolescent firms by contrast generally lack the organizational learning gained from those assets and experiences (Helfat & Winter, 2011).

Recent work on M&A and innovation has leveraged the knowledge-based approach. Acquisitions expand the acquirer's knowledge base and set the stage for potential idea recombination (Ahuja & Katila 2001; Henderson and Cockburn, 1996). Prior work has found that these processes can drive positive effects on innovation under certain contingencies such as larger knowledge bases and knowledge relatedness (Ahuja & Katila 2001; Makri, et al., 2010). Unlike more circumscribed interorganizational collaborations such as alliances, which can also facilitate recombination, the magnitude of acquisitions is an occasion for large-scale recombination in both the technical and home organization innovation routine domains. As such, the potential for novel idea combinations is greater under acquisition-based scaling.

By contrast, a challenge of organic growth is scaling fast enough, particularly in the presence of competitors in technology markets often characterized by network effects. As an example, Google, upon going public and rapidly building their business, faced well-documented challenges in hiring quickly enough (while also maintaining an organizational culture of innovation, a challenge like that faced in the acquisition scaling strategy, albeit with a different antecedent). Since the ability to recombine ideas importantly rests on the size of the knowledge pool (often modeled as an exponential process), the slower pace of human resource scaling under organic growth could negatively impact relative innovation outcomes.

Acquisitions, however, can entail disruption in organizational routines caused by integrating the acquired firms, especially those early on in their innovation trajectories, leading to lower innovation output (Puranam et al., 2006), though this pattern can be reversed in the longer run (Kapoor & Lim, 2007). Although adolescent firms are typically less experienced in integration, we posit that these firms, because of their age, stage and scale may be better equipped to handle integration with young (and typically small) acquiree firms. First, adolescent firms' acquisitions may be disproportionately of younger start-ups which are early in their innovation trajectory. As a result, the acquirer's motivations for retaining and leveraging the acquired inventors' knowledge capabilities may be stronger, thus improving the acquirer-acquiree fit in terms of organizational routines (Kapoor & Lim, 2007). This is especially the case since adolescent firms may provide a more exploration-centric, autonomy-friendly environment for such acquiree inventors to innovate (as compared to incumbent firm acquisitions), compounded by more financial and professional growth opportunities. Therefore, we anticipate that adolescent firms can mitigate any potential disruption caused by acquisitions through greater fit with target firms to drive better inventor retention and favorable innovation outcomes.

By comparison, organic adolescent growth, which is the alternative to acquisition-fueled scaling strategies, is not likely to be as organizationally disruptive. This is also due to not having to identify and resolve organizational and staff redundancies, as would be the case with acquisition. However, prior work has also pointed to innovation novelty declines in newly public firms, at least partly attributed to the lower quality of inventors who remain with the organization (Bernstein, 2015). As the firm moves through adolescence and scales, innovation quality may deteriorate due to this trajectory. By contrast, when adolescent firms undertake acquisitions, the culture of the combined organization may be altered toward greater experimentation. This results from the relative size of the target to the adolescent acquirer, which makes the situation akin to a "merger of equals."

Because adolescent acquisitions facilitate inventor retention, continued experimentation and knowledge recombination as compared to organic scaling strategies, our core hypothesis is therefore: *Adolescent firm acquisition strategy is causally related to innovation outcomes.*

DATA AND METHODS

Data Sources

We combine several data sources to enable our hypothesis test. We utilize patent data sourced from the U.S. Patent and Trademark Office's (USPTO) PatentsView database. We condition our sample on firms with at least one patent in our relevant time window (signaling innovation orientation and important for measuring our outcomes) and match that list with firms going public, identified using a common data source for IPO studies: Jay Ritter's list of over 10,000 firms that went public in the US, 1975-2016.[1] Doing so allows us to make the sample more uniform by excluding firms which may have different (lower) ambitions for their development trajectory. We further match financial and corporate governance data for firms in the sample using Compustat and Wharton Research Development Services (WRDS), allowing us to include such controls and to construct our instrumental variable for endogenous acquisition activity, IPO underpricing (details below). Next, we used the Securities Data Corporation (SDC) M&A database, a standard source, for transactional data on acquirers (to construct the main independent variable, acquisition activity). The result is a panel dataset organized at the firm-year unit of analysis, centered around each firm's IPO year. We select a

[1] https://site.warrington.ufl.edu/ritter/ipo-data/

10-year time window (three years pre-IPO to seven years post-IPO) for analysis, resulting in a more balanced panel dataset of 46,634 observations over 4,347 firms.

Key Variables

The outcomes we examine are standard proxies in the literature for innovation. In addition to *patent counts*, we also use *forward patent citations* since this measure has been validated as a proxy for the innovation's economic importance (Hall et al., 2005). To measure the nature of innovation, we employ measures of the degree to which patents exhibit *originality* and *generality*, measured by the Herfindahl indices of backward citing- and forward citing-patent class span, respectively (Trajtenberg et al., 1997).

Our main explanatory variable is the *aggregate number of acquisitions* the focal firm has conducted in a 3-year window, post-IPO. This window provides a lag for us to study outcomes plausibly due to acquisitions without being so long as to capture confounding effects. It is also consistent with our instrumental variable strategy of using IPO underpricing to instrument for endogenous acquisitions (Celikyurt et al., 2010).

Our control variables are mainly at the firm level. A first set includes *firm age* in the focal year, a *venture capital* (VC) indicator, *VC investor count*, and *inventor count at IPO*. VC characteristics are strongly related to going public and innovation, so it is important to control for them (Gompers & Lerner, 2004).[2] Since managerial control and corporate governance can influence M&A and innovation outcomes (Cao et al., 2020), we include another set of controls: *dual class shares* and *staggered board* are both indicator variables and means for firms to retain power. We also include *analyst coverage* to control for market coverage as it can influence innovation (Hsu & Aggarwal, 2014). For industry characteristics, we use Fama-French industry dummy variables, which control for industry differences in returns, and an IPO year

[2] *R&D expenses* and *firm revenues* are used only in our robustness checks, as those data are quite incomplete. *Inventor count* is a strong proxy for R&D expenses.

dummy is used to control for timing-related heterogeneity. Descriptive statistics of all variables are summarized in Table 1.

Figure 1 shows overall descriptive patterns. There is a surge in post-IPO innovation output and M&A volume: while 38% of firms filed at least one patent pre-IPO, that grows to almost 80% post-IPO (panel A) with average patenting activity expanding about four-fold (panel B). Similarly, newly public firms make acquisitions at a fast pace, exceeding incumbent activity in many industries (Celikyurt et al. 2010). While 10% of firms engaged in M&A pre-IPO, 50% do so five years after IPO. M&A volume increases seven-fold post-IPO. Firms in our dataset have average revenues of about \$360M with R&D expenses of \$19M, median age of 8 years (mean of 14 years).

Empirical Strategy

Our baseline (panel) specification is provided by equation (1):

$$Y_{it}^{Post-IPO} = \beta_0 + \beta_1 X_{it}(Acq) + \gamma_1 Y_i^{Pre-IPO} + \gamma_2 X_{it}{}' + r_i + \theta_t + \varepsilon_{it} \qquad (1)$$

$Y_i^{Post-IPO}$ is the innovation performance over time *t* after IPO, $X_{it}(Acq)$ represents the post-IPO acquisition activity of the focal firm, $Y_i^{Pre-IPO}$ the pre-IPO innovation outcomes. We include industry, firm (r_i) and IPO-year (θ_t) fixed effects. While firm fixed effects helps address some unobservable heterogeneity, it does not account for time-varying within-group changes (newly public firms may undergo unobservable lifecycle changes). Further methods therefore help triangulate our results: pre-processing the data to remove undesirable heterogeneity via a coarsened exact matching (CEM) procedure, using a difference-in-differences (DiD) specification, as well as an instrumental variables (IV) approach to address potentially endogenous acquisition processes. We describe each in turn below.

Matching. We use CEM (Iacus et al. 2011, 2012) to match on a set of observed pre-treatment covariates and discard unmatched observations. The objective of the process is to ensure that the treated and control groups are balanced by key covariates. The "treatment" here is defined as a dummy variable that takes the value of 0 (control) when the focal firm has done no M&A deals for the 5-year post-IPO period and 1 (treated) otherwise. We use six key pre-treatment characteristics for our matching procedure: *pre-IPO Patents*, *pre-IPO M&A activity*, *VC backing*, *Firm Age*, *Industry and Inventor Count (IPO)*. They represent key observable characteristics that are expected to be strongly correlated with the propensity for treatment and are used for balance in constructing the treatment and control samples. We also match on the pre-treatment versions of the key independent and dependent variables, which approaches a synthetic control method (Athey & Imbens, 2016). Table 2 presents the results from the matching, which results in 33,448 observations and 3,202 firms. Pre-CEM subsamples are significantly different (columns (1), (2)) while post-CEM covariates (columns (4), (5)) are considerably more balanced across groups.

Difference-in-differences (DiD). We also employ a DiD approach to estimate the average treatment effects of using an M&A scaling strategy. The time dimension we use is pre- and post-IPO since IPO timing can vary among ventures. Firms that never engage in M&A in the 5-year post-IPO period are the control group while the treatment group includes acquisitive firms.[3] Figure 2 shows no significant parallel pre-trends for the key outcomes.

Instrumental variable (IV). Matching and DiD approaches do not solve the issue of unobserved or unmeasured factors which threaten causal interpretation. To do so, we employ an IV strategy, which requires identifying a variable which satisfies two criteria: it is correlated with the endogenous variable (undertaking acquisition(s) in our case) and at the same time uncorrelated with the ultimate outcome of interest (innovation in our case). Our instrument is

[3] We employ a classic difference-in-difference (with two-way fixed effects) as well as a CS-DiD, developed by Rios-Avila, et al. (2023), which implements suggestions of Callaway & Sant'Anna (2021). CS-DiD exploits the timing heterogeneity of acquisitions utilizing not-yet acquired firms. These methods help address issues that can arise from using never-treated firms as the control group.

IPO stock underpricing. Underpricing measures the percentage change in the equity price from its beginning of public-trading debut to closing price at the end the first day public listing. Since the security issuer only raises funds at the price at the beginning of the trading day, if the stock price increases by the end of the trading day, such a positive "pop" suggests the issuer left funds on the table (in hindsight), and the offering is therefore "underpriced." Celikyurt et al. (2010) show that an important rationale for companies going public is to pursue acquisitions, which is enabled via stock underpricing. Specifically, firms which go public create a new "currency" for acquisition, their own stock. If the offering is underpriced, this newly minted currency has an inflated value compared to using cash for acquisitions, so managers may be eager to pay for acquisitions using their overvalued stock. Additionally, IPO underpricing is positively correlated with widely dispersed ownership, which helps managers maintain corporate control and avoid getting acquired themselves (Pagano, et al., 1998). As to the exclusion restriction, the second requirement of an instrumental variable, there should be no relation between a firm's first day of trading price and subsequent innovation in general (except through the acquisition variable). We believe this condition is satisfied, as underpricing is unlikely to broadly shape firms' forward strategy (Appendix B).

RESULTS

Main Results – M&A and Innovation outcomes

We use a difference-in-difference (DiD) specification on post-CEM data to estimate our hypothesized effects of M&A on post-IPO innovation outcomes. Figure 2 shows that there are no pre-trend innovation effects prior to IPO, while Table 3 presents the average treatment effects (treatment being M&A). Columns (1) to (2) use a classic DiD estimation whereas columns (3) to (4) employ the CS-DiD with heterogenous treatment timing. Overall, these results show a robust positive relation between the focal independent variable, *M&A x post-*

IPO, and the innovation measures. The economic significance of M&A on innovation outcomes suggests a 6-10%[4] increase in patents and citations.

Table 4 reports the instrumental variables-2SLS (IV-2SLS) analysis of the relationship between M&A and aggregate innovation outcomes for 5 years post-IPO, again following pre-processing the data via CEM. Column (1) presents the first stage estimates which demonstrate the effect of the instrumental variable - IPO underpricing on M&A activity. We find that the coefficient is positive and significant ($p < 0.01$). A firm experiencing IPO underpricing translates into an average 20% increase in likelihood of doing an M&A deal (see appendix figure A1). Moreover, the F-statistic in the first stage exceeds the recommended higher threshold of 20 for a strong instrument (Staiger & Stock, 1997; Olea & Pflueger, 2013).

Table 4, columns (2) and (3) report the second stage IV-2SLS coefficients for innovation outcomes, which are positive and significant. The results strongly support the hypothesis that innovation quantity and quality significantly improve for firms engaging in M&A, accounting for endogenous M&A activity. The estimated economic effects are slightly higher than those of DiD specifications from Table 4, which might be the result of over-estimation from IV. For robustness checks, we ran IV-2SLS on 4-year M&A transactions for 5-year post-IPO innovation outcomes (appendix table A1) as well as additional control variables such as firm revenues. The findings are consistent with the main results.

As a naïve comparison to these results, Table 5 (columns (1) and (2)) uses a cross-sectional specification (aggregating variables over the time horizon), using OLS (after CEM matching). This results in a negative estimated relation ($p < 0.05$) between *M&A deals* and the innovation outcomes. However, columns (3) and (4), using panel methods at the firm-year level and

[4] Economic significance indicates percentage change in individual year patent and citation measures based on average treatment effects estimated through a DiD specification for a change in M&A x Post-IPO by 1 unit. All other variables are held constant (at their means) for this calculation.

including fixed effects for firm, finds a (weakly) positive relation with *patents* and *forward citations*. Our methods, which correct for endogenous firm self-selection of scaling strategy, therefore can translate into substantial differences in result inference.

Mechanisms

We also find support for our suggested mechanism that adolescent firms use M&A to acquire promising resources in the form of inventors who then engage in knowledge recombination activities that drive superior innovation outcomes. Table 6 panel A presents the influence of M&A transactions on inventor count, accounting for the endogenous nature of these decisions. We find that M&A activity has a clear positive effect on inventor headcount (controlling for pre-M&A numbers). This demonstrates that despite acquisition-driven organizational disruptions, inventor retention is enhanced. Next, we study whether this increased retention necessarily influences a proxy for innovation recombination. Table 6 panel B presents the evolving impact of individual year acquisitions on patent *generality* over time. *Generality*, which is based on the breadth (Herfindahl) of technology classes of forward citations, reflects the knowledge recombination potential of the innovation activity generated from the focal patent(s), with higher values suggesting broader applicability. We find that acquisitive firms witness significantly more generality over time. Meanwhile, we also find that *originality* (measured on the same Herfindahl measure, but on backward patent citations), which reflects pre-transaction recombination, is not affected by acquisitive activity (results available on request). These findings help support our argument that it may be the collaboration of retained inventors post-M&A that drives long-run innovation outcomes.

DISCUSSION & CONCLUSION

We examine M&A, as compared to organic growth, as a mode of scaling by newly public adolescent firms and their effects on innovation outcomes. Using a variety of empirical methods to mitigate the confound of unobserved managerial selection of pursuing acquisitions, we find that adolescent firm with an acquisition strategy experience a significant increase in innovation output and quality. Our work contributes to entrepreneurship and strategy research by investigating M&A as a mode of scaling by adolescent firms. We believe that our work is among the first to investigate newly public adolescent firms which are typically first-time acquirers and quite distinct from their mature counterparts. Furthermore, these strategy choices and their outcomes may have long-run path-dependence implications as firms mature. Our results suggest that firms may benefit from engaging in M&A at early stages of their lifecycles.

Our study has limitations, however, which represent opportunities for future research. While our work sheds preliminary light on the associated mechanisms (large-scale retention and knowledge recombination), further work is clearly necessary. For example, it is likely that each scaling modality is accompanied by associated organizational investments, priorities, and even structures. A better understanding of these areas, together with how such scaling pathways might affect non-innovation outcomes, would be welcome. Additionally, the antecedents to the acquisitive behavior of these adolescent firms are not as well understood and merit further work. To examine the causal relationship between acquisitions (as compared to organic growth) and innovation outcomes, we relied on a source of exogenous variation. However, are there differences among adolescent firms more generally in the domains of top management or business environment which systematically impact acquisition-led scaling strategies? Finally, we have characterized average effects in organic versus acquisition-led scaling strategies. Future work would ideally explore conditions under which each scaling modality is particularly effective or ineffective. While these and many other questions remain open, our hope is that the study presented here illustrates how an important adolescent firm strategic choice can contribute to its scaling when innovation is a key objective.

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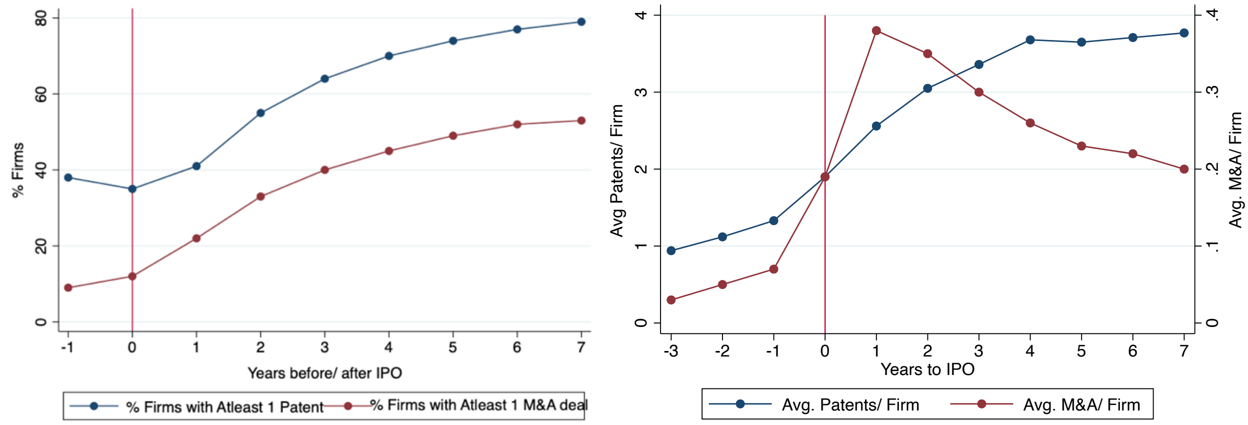
Table 1. Summary statistics

Variable	Definition	Mean	St. Dev.
Innovation Outcomes (Dependent Variables):			
AggPatents (5Y PostIPO)	Aggregate patent stock, 5 Years after IPO	16.3	116.95
AggCitations (5Y PostIPO)	Aggregate 4-year forward citations, 5 Years after IPO	84.67	592.38
Avg Originality (5Y PostIPO)	Average Originality (based on backward citations), 5 Years after IPO	.13	.15
Avg Generality (5Y PostIPO)	Average Generality (based on forward citations), 5 Years after IPO	.08	.11
M&A/ Inorganic Strategy (Independent Variables):			
AggM&A Deals (3Y PostIPO)	Aggregate M&A Transactions, 3 Years after IPO	1.0	2.49
Instrumental Variable:			
IPO Underpricing	Dummy=1 if IPO was underpriced (stock price increase on first day of trading)	.71	.45
Control Variables:			
AggPatents (3Y PreIPO)	Aggregate patent stock, 3 Years prior to IPO	3.39	21.82
AggM&A Trans (3Y PreIPO)	Aggregate M&A Transactions, 3 Years prior to IPO	.14	.72
VC-backed (PreIPO)	Dummy=1 if firm had VC investments prior to IPO	.52	.5
VC Investor Count	Number of VC Investors	4.07	5.87
Inventor Count (IPO)	Number of Inventors at IPO	6.84	38.81
Dual Class Shares	Dummy=1 if firm has dual share classes post IPO	.07	.25
Equity Analyst Coverage	Number of unique analysts covering the firm	1.62	2.7
Firm Age (IPO)	Firm Age at IPO (Years)	14.58	20.13
Industry	Fama-French Industry Dummy	23.6	13.57
R&D (IPO)	Research & Development Expenses in IPO Year ($ Mn)	18.6	162.46
Revenue (IPO)	Revenue in IPO Year ($ Mn)	357.81	3215.25

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Patents (5Y PostIPO)	1.00														
(2) Citations (5Y PostIPO)	0.87	1.00													
(3) Originality (5Y PostIPO)	0.13	0.15	1.00												
(4) Generality (5Y PostIPO)	0.12	0.16	0.74	1.00											
(5) M&A Deals (3Y PostIPO)	0.11	0.12	-0.05	-0.04	1.00										
(6) IPO Underpricing	0.02	0.03	0.04	0.08	0.09	1.00									
(7) Patents (PreIPO)	0.29	0.18	0.13	0.09	-0.01	-0.01	1.00								
(8) M&A Deals (PreIPO)	0.05	0.05	-0.01	-0.01	0.23	0.03	0.03	1.00							
(9) Inventor Count (IPO)	0.91	0.82	0.15	0.12	0.13	0.04	0.18	0.13	1.00						
(10) VC backed	-0.02	0.01	0.16	0.17	-0.03	0.08	-0.02	0.00	0.00	1.00					
(11) Firm Age (IPO)	0.07	0.04	-0.01	-0.05	0.07	-0.04	0.12	0.05	0.09	-0.30	1.00				
(12) Industry	0.03	0.01	-0.10	-0.03	0.07	0.06	0.01	0.03	0.02	-0.13	0.07	1.00			
(13) R&D (IPO)	0.45	0.39	0.05	0.05	0.07	0.03	0.71	0.11	0.48	-0.03	0.14	0.02	1.00		
(14) Revenue (IPO)	0.16	0.12	0.04	0.02	0.05	0.03	0.64	0.02	0.17	-0.09	0.20	0.03	0.85	1.00	
(15) Dual Shares	0.05	0.04	-0.03	-0.05	0.10	-0.00	0.02	0.11	0.10	-0.09	0.14	0.08	0.05	0.06	1.00

Figure 1. M&A and innovation activity around the IPO

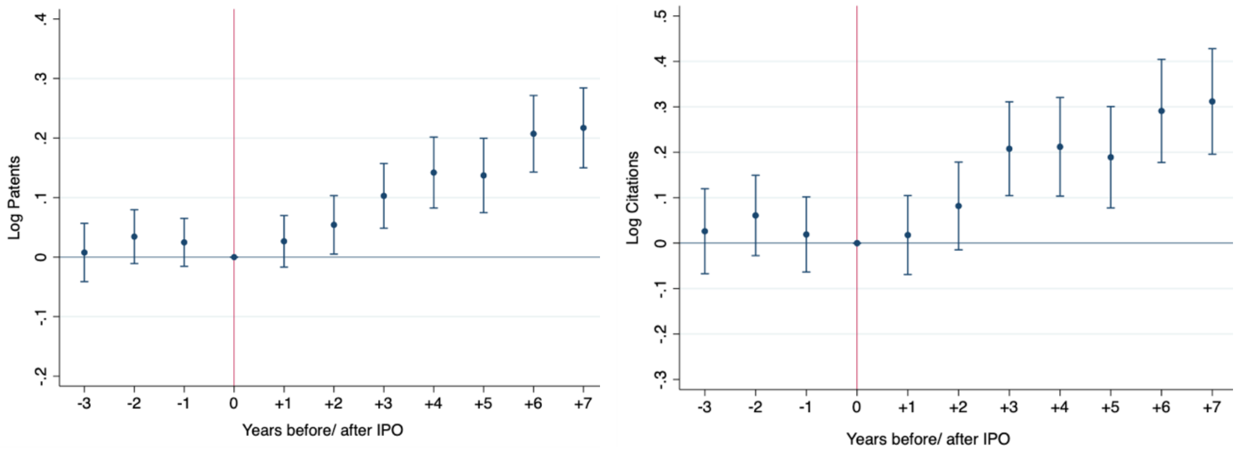
Panel A: % Firms with at least 1 Patent, M&A **Panel B: Average M&A and Patenting activity**



Panel A illustrates the percentage of firms in the dataset that have conducted at least one acquisition or have at least one patent in each year from pre-IPO to 7 years post-IPO. Panel B represents the average patenting and acquisition activity per firm for the years leading up to and after IPO.

Figure 2. Pre-trends in innovation (event study of treated versus control groups)

Panel A: Patents **Panel B: Citations**



This figure presents the event study estimates of innovation outcomes for the organic versus the inorganic group with 95% confidence interval. Sample observations are at the firm-year level. Each year relative to the IPO is treated as a dummy variable to show the dynamic effects. Year 0 is omitted as the reference point. Robust standard errors are clustered at the firm level. Underlying linear regressions include firm and year fixed effects.

Table 2. Coarsened Exact Matching: Pre-CEM vs. Post-CEM Covariates

	(1)	(2)	(3)	(4)
Treatment (Organic vs. Inorganic Strategy)	**Pre-CEM**		**Post-CEM**	
	Control	Treated	Control	Treated
Pre-treatment				
Agg Patents (PreIPO)	3	3.85	2.08	2.06
VC invested (PreIPO)	.53	.51	.50	.50
Firm Age (IPO)	12.78	16.46	12.85	13.13
Industry	22.31	24.89	24.14	24.10
Inventor Count (IPO)	5.18	8.39	4.04	4.5
Agg M&A (PreIPO)	.07	.23	.07	.09
Observations	23,632	23,002	16,724	16,724
Firms	2215	2132	1601	1601

This table reports the covariates prior to the treatment period on which the data has been matched using the coarsened exact matching (CEM) method and the key post-treatment variables. Treatment represents 0 when the number of aggregate M&A transactions done by a focal firm for 5 years post IPO is zero and 1 when the number of aggregate M&A transactions is non-zero.

Table 3. M&A vs. Innovation: Difference-in-Difference (DiD) analyses (following CEM)

	(1)	(2)	(3)	(4)
	DiD		CS-DiD	
Dependent Variables	Log Patents	Log Citations	Log Patents	Log Citations
M&A x Post-IPO	0.057***	0.077**	0.084***	0.119***
	(0.020)	(0.035)	(0.020)	(0.036)
Post-IPO	0.135***	0.294***		
	(0.016)	(0.029)		
Observations	33,411	33,411	30,178	30,178
Firm FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

*This table reports the estimates of Average Treatment Effects for panel data. Dependent variables are individual year innovation outcomes generated by the firm, the independent variables are Post and Treatment x Post. Post represents 1 for the post-IPO period, 0 otherwise. Treated (M&A) represents 0 when the number of aggregate M&A transactions conducted by a focal firm for 5-years post IPO is zero and 1 when the number transactions is non-zero. In columns (1) to (2), the estimation uses two-way fixed effects difference-in-differences (DiD) whereas columns (3) to (4) employ the CSDID method developed by Rios-Avila, et al. (2023). All variables have been processed using CEM. Robust standard errors clustered at firm-level are presented in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.*

Table 4. M&A vs. Innovation Outcomes Instrumental Variable-Regression (2SLS following CEM)

Dependent Variable	(1) Log M&A Trans	(2) Log Patent	(3) Log Citation
	2SLS – 1st stage	2SLS – 2nd Stage	2SLS – 2nd Stage
IPO Under-pricing	0.109***		
	(0.021)		
Log M&A Trans		0.596**	1.255**
		(0.302)	(0.545)
Observations	3,192	3,192	3,192
R-squared	0.153	0.500	0.289
F-statistic	25.533		
Firm Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

*This table reports the IV-2SLS regression estimates of cross-sectional data where the dependent variables are aggregate innovation outcomes generated by the firm for 5 years post-IPO. Columns (2), (3) show the 2nd stage-2SLS results with independent variable as the log of aggregate M&A transactions 3 years post-IPO. Other control variables included in the specification but have unreported coefficient estimates are: Log(Pre-IPO Patents), VC dummy, Log(Firm Age), Log(InventorCount at IPO), Log (pre-IPO M&A), Dual Class shares dummy, US-HQ dummy. All data has been processed using CEM. The model is estimated using 2SLS, and robust standard errors clustered at the firm-level are presented in parentheses. Column (1) presents the first stage 2SLS regression estimates with IPO underpricing as the instrumental variable with Kleibergen-Paap rk Wald F Statistic. The corresponding Cragg-Donald Wald F statistic is 22.439. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% levels.*

Table 5. M&A vs. Innovation Outcomes (naïve OLS following CEM)

	(1)	**(2)**	**(3)**	**(4)**
	Cross-sectional Data - OLS		Panel Data – FE OLS	
Dependent Variable	Log Patents	Log Citations	Log Patent	Log Citation
Log M&A Trans	-0.030	-0.094**	0.028*	0.062**
	(0.025)	(0.043)	(0.014)	(0.025)
Log Prior Patent	0.224***	0.188***	0.090***	0.053***
	(0.021)	(0.034)	(0.012)	(0.014)
Observations (Firms)	3,194	3,194	32,349 (4114)	32,349 (4114)
R-squared	0.677	0.585	0.675	0.619
Firm FE	No	No	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Industry Controls	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes

*This table reports naïve least square regression estimates. Columns (1), (2) use cross-sectional data with the dependent variable as aggregate innovation outcomes over 5 years post-IPO. The independent variable is aggregate number of M&A transactions for 3 years post-IPO. Columns (3), (4) use panel data with individual year variables. Control variables included in the specification but have unreported coefficient estimates are: Log(Pre-IPO Patents), VC dummy, Log(Firm Age), Log(InventorCount at IPO), Log (pre-IPO M&A), Dual Class shares dummy, US-HQ dummy. All data has been processed using CEM. Industry and Firm level controls are applied. Robust standard errors clustered at the firm and industry levels are presented in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.*

Table 6. Potential Mechanisms

Panel A: Inventor Count

VARIABLES	(1) Log Yr 3 Inventors IV-2SLS	(2) Log Yr 4 Inventors IV-2SLS	(3) Log Yr 5 Inventors IV-2SLS
Log Year 3 M&A Trans.	0.988**	1.388**	1.402**
	(0.458)	(0.565)	(0.599)
Observations	3,192	3,192	3,192
R-squared	0.663	0.499	0.444
Firm-level Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

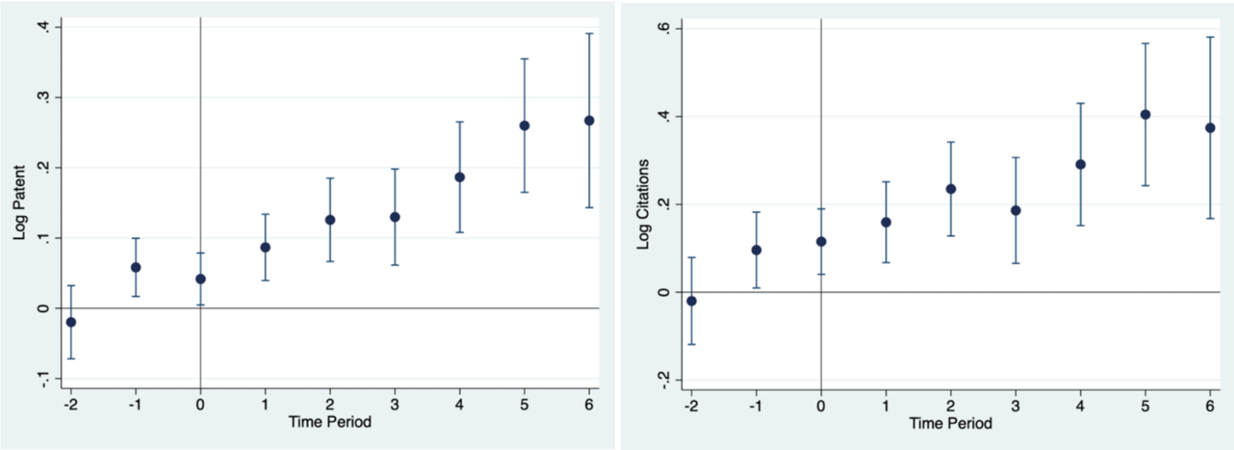
Panel B: Generality as a proxy for Knowledge recombination

VARIABLES	(1) Yr 3 Generality IV-2SLS	(2) Yr 4 Generality IV-2SLS	(3) Yr 5 Generality IV-2SLS	(4) Yr 6 Generality IV-2SLS	(5) Yr 7 Generality IV-2SLS
Log Year 3 M&A Trans.	0.064	0.172	0.318**	0.330**	0.408**
	(0.128)	(0.134)	(0.150)	(0.152)	(0.170)
Observations	3,040	2,982	2,948	2,917	2,880
R-squared	0.095	-0.058	-0.363	-0.426	-0.868
Firm-level Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

*This table reports regression tests to explore the mechanisms driving innovation outcomes from the adolescent M&A strategy. Panel A shows IV-2SLS estimates with columns (1) through (5) using the corresponding year Generality as the outcome variable with Year 3 M&A transactions as the independent variable. Panel B presents IV-2SLS regression with the corresponding year inventor count as outcome variables. Control variables included in the specification but have unreported coefficient estimates are: Log(Pre-IPO Patents), VC dummy, Log(Firm Age), Log(InventorCount at IPO, Prior years), Log (pre-IPO M&A), Dual Class shares dummy, US-HQ dummy. All data has been processed using CEM. Robust standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.*

APPENDIX A: Robustness

Figure A1. Heterogenous Treatment Effects - Event Study Estimates from CSDiD



This figure presents event study estimates for time periods before and after treatment from DiD estimates adjusting for heterogeneity in the treatment effects occurring at multiple time periods using the CSDID method developed by Rios-Avila, et al. (2023). Observations are at the firm-year level.

Table A1. M&A vs. Innovation Outcomes: IV-2SLS Regression (following CEM)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Log M&A Trans	Log Patent	Log Patent	Log Citation	Log Citation
	2SLS – 1st stage	2SLS – 2nd Stage	2SLS – 2nd Stage	2SLS – 2nd Stage	2SLS – 2nd Stage
IPO Under-pricing	0.124***				
	(0.024)				
Log M&A Trans		0.523**	0.966**	1.101**	1.978**
		(0.263)	(0.490)	(0.473)	(0.892)
Observations	3,192	3,192	1,965	3,192	1,965
R-squared	0.150	0.510	0.378	0.304	0.033
F-statistic	27.169				
Firm Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

*The dependent variables are aggregate innovation outcomes generated by the firm for 5 years post-IPO. Columns (2) through (5) show the 2nd stage-2SLS results with independent variable as the log of aggregate M&A transactions 4 years post-IPO. Columns (2) and (3) have log patents as the dependent variable and are similar except that (3) has Log Firm Revenue as an additional control variable. Columns (4) and (5) have log citations as the dependent variable and are similar except that (5) also has Log Firm Revenue as an additional control variable. Other control variables included in the specification but have unreported coefficient estimates are: Log(Pre-IPO Patents), VC dummy, Log(Firm Age), Log(InventorCount at IPO), Log (pre-IPO M&A), Dual Class shares dummy, US-HQ dummy. All data has been processed using CEM. Robust standard errors clustered at firm-level are presented in parentheses. Column (1) presents the first stage 2SLS regression estimates with IPO underpricing as the instrumental variable with Kleibergen-Paap rk Wald F Statistic. The corresponding Cragg-Donald Wald F statistic is 24.404. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.*

Appendix B: Details on Validating the Instrumental Variable

Relevance condition. Appendix figure B1 represents the non-parametric relationship between IPO underpricing and likelihood of the firm doing M&A. When the underpricing is negative (stock under-performance), the likelihood of an acquisition dips below 0.5. On the other hand, with positive underpricing (overperformance or "pop") the probability of an acquisition increases over 0.5 and stabilizes to 1. Panel A of appendix table B1 shows the first stage IV-2SLS results with F-statistics for 3- and 4-year M&A. Columns (1) and (3) present the results without control variables while columns (2) and (4) display estimates with the full array of controls. The coefficient/ F-statistic remains statistically significant suggesting that the instrument is orthogonal to the controls included. The positive relationship between underpricing and M&A is in line with acquisition currency motives from IPO (Celikyurt et al., 2010).

Exclusion restriction. For the instrument to be valid, underpricing should have no direct effect on innovation outcomes other than through the acquisition variable. While it is not possible to directly demonstrate the validity of the exclusion restriction, we use economic arguments to do so. Prior research on IPO stock phenomena found varied explanations for underpricing from information asymmetry to pre-IPO firm characteristics (Ritter & Welch, 2002; Certo, 2003). However, recent studies have found that the above mechanisms do not conclusively explain underpricing (Park, Borah & Kotha, 2016). Underpricing behavior is influenced by misaligned incentives that causes principal-agent conflict between issuers i.e., the firms and investment bankers who underwrite the IPO (Loughran & Ritter, 2004; Ritter, 2022). Underwriters have an incentive to underprice the IPO to induce institutional shareholders to the pre-IPO book-building process. Though this move seems counter-intuitive (lower IPO proceeds mean lower fees), underwriters stand to gain in other ways as allocating more equity to institutional shareholders can drive alternate revenue streams. Additionally, "hotter" IPOs can signal can influence secondary stock purchases, increased commissions, and brokerage revenues. As far as the focal firms are concerned, management may choose to focus on the larger wealth creation rather than the incremental "money left on the table" as per prospect theory (Ritter, 2022). The larger point is that IPO underpricing is driven mainly by ephemeral mechanisms that do not have extensive strategic or managerial antecedents. Appendix Table B1 (Panel B) illustrates this point. Even with no controls, the coefficients show null correlation between key pre-IPO firm characteristics and IPO underpricing. Extending this argument, underpricing is unlikely to have long-term implications on the firm strategy (other than through the acquisition channel).

Additionally, a potential mechanism through which the exclusion restriction condition could be violated is through the influence of the IPO "pop" on inventors in organic firms either by incentivizing them to innovate more or by providing labor market signals that attract more productive inventors. However, for long-tenured employees that held pre-IPO equity, a normally valued stock would already be significantly higher than their strike price and a temporary "pop" is unlikely to cause a significant change in their expected wealth and therefore their long-term productivity. While first-day performance may act as a labor market signal for incoming inventors hired after IPO, it would be hard to disentangle those effects from that of the IPO event itself. Our dataset consists only of IPO firms that are all subject to this signaling mechanism and hence it is ceteris paribus to some extent. Finally, our level of analysis is at the firm-year level and not at the individual level. With that said, we do control for inventor count and presence of dual class shares in our analysis to account for these heterogeneities, to the extent possible.

Figure B1: Non-Parametric Association of %IPO Under-pricing and M&A Likelihood

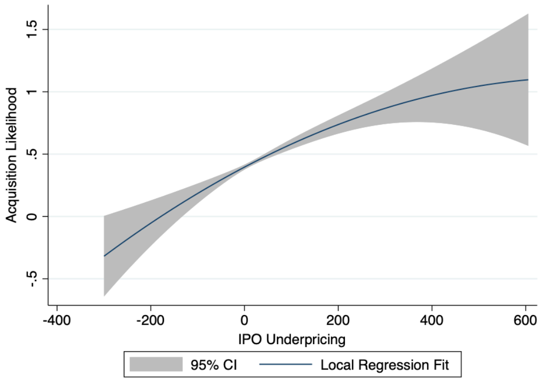


Table B1 Analysis of Instrumental Variable (IPO Underpricing)
Panel A: First-stage 2SLS Regression – IPO Under-pricing vs. M&A

		(2)	(3)	(4)
VARIABLES	M&A Trans 3rd Year post-IPO	M&A Trans 3rd Year post-IPO	M&A Trans 4th Year post-IPO	M&A Trans 4th Year post-IPO
IPO Under-pricing	0.173***	0.109***	0.190***	0.124***
	(0.023)	(0.022)	(0.025)	(0.023)
Observations	3,200	3,192	3,200	3,192
R-squared	0.017	0.153	0.018	0.150
F-Stat	67.216	25.533	65.792	27.169
Firm-level Controls	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

Panel B: Correlation of Pre-IPO Patents and M&A to IPO Under-pricing

	(1)	(2)	(3)	(4)
VARIABLES	IPO Under-pricing	IPO Under-pricing	IPO Under-pricing	IPO Under-pricing
Log Pre-IPO Patent	0.004		-0.003	
	(0.003)		(0.006)	
Log M&A Trans		0.023		-0.000
		(0.015)		(0.015)
Observations	3,200	3,200	3,192	3,192
R-squared	0.000	0.001	0.165	0.165
Firm-level Controls	No	No	Yes	Yes
Industry FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes

*This table reports tests to assess the validity of the instrumental variable. Panel A presents the first-stage regressions with F-stat with (columns (1) and (3) and without control variables (columns (2) and (4). Panel B presents the absence of association linking pre-IPO firm activity and IPO under-pricing. The dependent variable is IPO under-pricing and independent variable pre-IPO M&A and Patent count. Columns (1) and (2) are baseline regressions while (3) and (4) include firm, industry and year controls. Robust standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.*