Learning from the Market: The Choice Between IPOs and SPAC Mergers[*]

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Abstract

This paper studies the impact of the SEC's new rule, which makes the PSLRA's safe harbor for forward-looking statements unavailable for SPACs, on private firms. I build a dynamic model of a private firm's optimal timing for going public, featuring two public offering markets: SPACs, which produce more information but are more costly, and IPOs. I simulate the effect of the SEC's new rule on firms that are currently private. Excluding the safe harbor for SPACs causes the option value of private firms to decline and eliminates half the benefit of information production in the SPAC process.

Keywords: Security Issuance, Going Public Decision, Bayesian Learning

JEL classification: G14, G32, G34.

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1 Introduction

A large body of literature explores why and when private firms choose to go public[1]. However, little is known about the decision-making process behind the specific mechanisms firms choose. Since 2016, one out of three private firms has chosen Special Purpose Acquisition Company (SPAC) mergers instead of initial public offerings (IPOs) to go public in the United States. A total of 982 IPOs raised \$308 billion in gross proceeds, averaging \$314 million per deal, whereas 501 SPAC mergers raised \$161 billion, with an average deal value of \$322 million. Despite the importance of SPAC mergers as a major alternative to IPOs, academic understanding of the trade-off between the two is less developed.

The IPO process allows firms to learn about their quality via market demand (e.g., Ritter and Welch 2002; Hanley 1993), but it limits investor access to the firm's future operational strategies due to the "safe harbor" rule. In contrast, SPAC mergers are not bound by this rule, offering investors a more precise assessment of the firm, albeit at a higher cost. Determining which of these forces predominates is an empirical question, which is hard to resolve using reduced-form techniques because the firm's decision-making is endogenous and there is no obvious instrument. Moreover, the answer also depends on unobservables, including the firm's quality and the precision and cost of investors' information production. To address these unobservables and accurately measure the trade-offs, I propose a tractable model where firms optimally choose between remaining private, IPO, and SPAC merger, and empirically estimate it using a simulated method of moments (SMM) technique.

I find that early-stage firms with more uncertainty about their quality choose SPAC mergers. For these firms, the SPAC investor's precise evaluation substantially reduces uncertainty. Upon receiving positive feedback from the SPAC merger, these firms' equity value increases by 34.3% (\$539 million), compared to a modest boost of 17.3% (\$256 million) from

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[1] See Lucas and McDonald (1990); Zingales (1995); Black and Gilson (1998); Pagano, Panetta, and Zingales (1998); Chemmanur and Fulghieri (1999); Subrahmanyam and Titman (1999); Maksimovic and Pichler (2001); Schultz and Zaman (2001); Ritter and Welch (2002); Pástor and Veronesi (2005); Pástor, Taylor, and Veronesi (2009).

an IPO. In contrast, high-quality firms prefer IPOs as the need for precise evaluations is less critical. Additionally, the SEC's new regulation excluding the safe harbor for SPACs would decrease private firms' option value by 30% relative to their current size and eliminate half the benefit of information production in the SPAC merger process.

In the proposed model, firms face uncertainty regarding their growth prospects, which sometimes makes it hard for firms to get financing. To attract financing, a firm can keep producing and prove the market it is conducting a profitable project through good production outcomes. Alternatively, a firm can learn from the financial market by going public through either an IPO or a SPAC merger process. A firm can learn more information in a SPAC merger than in an IPO because of the safe harbor regulation, but the SPAC merger is more costly due to its more complex design. As a result, whether a firm should go public via IPO or SPAC depends on the marginal benefit from the extra information that the SPAC merger produces against the extra cost.

Firms choose the optimal time and way of going public based on prior beliefs of their quality, driven by positive and negative earnings shocks. In the model, the degree of uncertainty regarding the type of firm is highest when the belief is in the middle range, that is, the firm has an equal chance of being high-quality or low-quality. These firms prefer SPAC mergers to IPOs because a more precise evaluation significantly reduces uncertainty and generates larger payoffs. When the uncertainty surrounding the firm's quality fades, the marginal benefits of a more precise evaluation are depressed. Therefore, firms with a stronger prior belief tend to opt for an IPO, while firms with a weaker prior belief tend to retain their private status.

More specifically in the model, the economy consists of entrepreneurs who own private firms. These firms produce projects protected by patents, which can be high-growth or low-growth in nature. The entrepreneur is uncertain about the firm's true quality. The firms generate earnings until the patent exogenously expires, which can be interpreted as the eventual erosion of the firm's abnormal returns due to increased competition. Before the patent expires, all market participants symmetrically update their beliefs about the firm's quality.

Throughout a firm's lifetime, opportunities to go public arise exogenously, representing periods when market conditions are favorable for firms to go public, as in Pástor and Veronesi (2005). When such an opportunity arises, the entrepreneur can choose to take the firm public by selling it to public investors. Part of the capital raised is immediately reinvested in the firm to expand its operations.

During the public selling process, the entrepreneur and investors together produce a binary signal that updates the prior belief about the firm's quality. The evaluation is prone to type-II errors: while high-quality firms are identified accurately, errors may occur in evaluating low-quality firms. A positive signal increases the firm's prior belief, suggesting a higher expected growth rate, while a negative signal indicates a low-growth project. Successfully going public provides two benefits: additional capital for scaling up the firm's production and strengthened belief in its quality, both contributing to a higher valuation of the firm's post-public equity.

Going public generates fixed costs, including direct issuance costs, accounting, legal, and underwriting fees, as well as indirect due diligence costs for producing information. Because investors are compensated with equity, if the process is successful, these costs are offset through underpricing, where the firm intentionally sets a lower price for its shares, known as leaving "money on the table" (MLOT). If the process fails, investors bear the cost. The model assumes that investors break even in expectation: for a successful public offering, the firm needs to underprice its shares enough to compensate for the potential risk of failure.

The entrepreneur has two options for taking the firm public: IPO or SPAC merger.[2] The model assumes a critical difference between the two mechanisms: SPAC investors can

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[2] For a detailed comparison between SPAC and IPO, see Ritter, Gahng, and Zhang (2023).

evaluate the firm more accurately but at a higher cost. This assumption is based on institutional differences between the methods: (1) Under the "safe harbor" rule, SPAC investors have access to the firm's future business plans, a level of detail not permitted in the IPO process, allowing for more informed evaluations. (2) The SPAC merger process is inherently more complex than the IPO process, with more direct costs.

Empirical evidence supports this assumption. First, companies that go public through SPAC mergers on average leave \$149 million "on the table", significantly more than the \$57 million left by firms undergoing IPOs. Second, the communication of future business plans is a key element in the interaction between the firm and SPAC investors. Using a pre-trained Bidirectional Encoder Representations from Transformers (BERT) model, I analyze earnings call transcripts from the merger's announcement to its completion. These calls, similar to IPO roadshows, are vital channels for investors to directly obtain information from the company. The analysis shows that approximately 10% of these discussions focus on the firm's specific future business strategies. This additional information helps SPAC investors make more informed and accurate evaluations than IPO investors.

Building on this assumption, I solve for the private firm's optimal choice based on its current earnings and prior belief. Using a stochastic lumpy adjustments (SLAs) technique, similar to the approaches in Van Binsbergen and Opp (2019); van Binsbergen and Opp (2019); Opp (2019), I derive a tractable global solution to the model. The solution identifies two prerequisites for a private firm to go public: (a) sufficient earnings and (b) a not-too-low prior belief. Adequate earnings ensure that the benefits of scaling up outweigh the costs of investor evaluation, while a not-too-low prior belief ensures that a positive evaluation can indicate a positive NPV for the firm. Without meeting these criteria, investors are likely to forego evaluation, resulting in the firm remaining private in equilibrium.

The model depicts a "U-shaped" entry boundary for going public, based on the required levels of earnings and prior belief. Successful public entry not only expands the firm's production but also increases the firm's belief. The marginal benefit from this expansion increases with the firm's earnings, whereas the marginal increase in the firm's belief is concave in the firm's prior belief. Specifically, firms with the highest uncertainty—those with roughly equal chances of being high-growth or low-growth—gain the most from an investor's positive evaluation. As a firm's prior belief increases from a lower point, the marginal benefit of a positive evaluation rises, thereby reducing the earnings threshold needed for going public. This threshold reaches its lowest point when the firm's prior belief is moderate. As the prior belief continues to increase, the firm's confidence in being high-growth before any evaluation also rises, diminishing the incremental benefit of the evaluation. Consequently, the earnings threshold for going public tightens again, resulting in a "U-shaped" entry boundary.

The model predicts a firm's optimal choice between an IPO and a SPAC merger based on the same logic. Firms with intermediate levels of prior belief, or those facing the greatest uncertainty, aim to generate as much information as possible. These firms favor SPAC mergers, as the precise evaluation significantly reduces the firm's uncertainty and improves its post-public equity value, outweighing the higher costs. Conversely, firms with strong prior beliefs find less value in a more precise evaluation, as their uncertainty is already low. Thus, they tend to choose an IPO, which, despite offering a less precise signal, comes with lower costs.

Next step is to quantify the tradeoff presented in the model: the increase in a firm's equity value due to positive evaluations by SPAC and IPO investors, weighed against the associated costs. However, quantifying these tradeoffs poses a significant challenge. Firms' decisions to go public are endogenous, leading to endogenous patterns in the outcomes of their public offerings. There are no obvious instruments to address this endogeneity. Additionally, several model elements are unobservable, such as the precision and costs of IPO and SPAC investors' evaluations. While reduced-form empirical techniques can indicate the direction of these tradeoffs, accurately measuring their magnitudes requires estimating an economic model.

These challenges naturally lead to a structural estimation approach. This approach infers unobservable variables from the observed endogenous patterns in firms' decisions to go public and the resulting outcomes. Employing a structural approach not only quantifies the magnitudes of these tradeoffs but also allows us to explore counterfactuals for evaluating the SEC's new policy.

I estimate the model parameters using a simulated method of moments (SMM) strategy that utilizes data from firms that sought to go public between 2010 and mid-2023. The parameters I estimate encompass the growth rate for low-growth firms, the differential in growth rates between high- and low-growth firms, the frequency of public offering opportunities, the rate of patent expiration, the precision and costs of IPO and SPAC investors' evaluations, and the initial level of prior belief. The moments simulated from the model align closely with the empirical moments observed in the data, with no significant statistical discrepancies.

I find that SPAC firms benefit significantly from the additional information produced in the SPAC merger process, as they are less mature and face higher uncertainty than IPO firms. Receiving a positive signal from the SPAC merger process increases their equity value by 34%, half of which comes from the additional information that the IPO process does not provide. In contrast, more mature firms benefit less from the additional information, leading them to choose the less costly IPO process.

These estimation results are consistent with the observed characteristics of firms in the empirical data. Firms that merge with SPACs have fewer patents, smaller workforces, longer durations to secure initial financing, and a higher propensity to operate within the information technology sector. Additionally, they need more help elevating their prior belief as they are backed by less reputable venture capitalists.

Using the model estimates, I examine the implications of the SEC's newly adopted rule excluding SPAC mergers from the safe harbor provision. This new rule removes the option for private firms to go public via SPAC mergers, as these do not yield more accurate information despite higher costs compared to an IPO. By comparing a firm's current option value against their counterfactual option value under the new regulation, I find that relatively mature private firms suffer an option value loss of up to 5%. Calculating the option value loss for 409,509 firms that remained private during my sample period, I find the total loss amounts to $335.81 billion. On average, each private firm suffers a loss of $0.82 million, which equals 30.73% of the firm's current size.

Related Literature. My paper is related to the extensive IPO literature. Several factors can influence the timing and success of an IPO, including market conditions, the company's financial performance, and the regulatory environment. Studies have found that market conditions, such as the state of the stock market and the overall economic climate, can significantly impact the timing of IPOs (Ritter, 1987; Pástor and Veronesi, 2005). The financial performance of the company, such as its profitability and growth prospects, also plays a critical role in the success of an IPO (Welch, 1989; Megginson and Weiss, 1991). Additionally, regulatory factors, such as changes to securities laws or accounting regulations, can affect the IPO process and the cost of going public (Kim and Ritter, 1999). My paper contributes to this literature by examining how investors' evaluations of a firm's future growth can affect the entrepreneur's decision to go public.

My research also contributes to the extensive body of work studying the role of institutional investors in producing information during the IPO process. Rock (1986) presents a model where some investors have an informational advantage, leading firms to underprice their shares to attract uninformed investors. Benveniste and Spindt (1989) predict positive average underpricing because investors are rewarded for providing value-relevant information. Yung (2005) models both the investment bank's screening and the investor's evaluation processes. Empirical studies also support the role of public investors in information production, including (Bradley and Jordan, 2002; Lowry and Schwert, 2004). A recent study by Aryal et al. (2022) uses SPACs as an empirical setting to provide evidence on larger investors producing information in SPAC mergers. My study extends this work by modeling the information production cost as a factor in the entrepreneur's decision to take the firm public.

Additionally, I contribute to the nascent literature on SPACs. For instance, Ritter, Gahng, and Zhang (2023) study the costs and benefits of using SPACs to go public; Gofman and Yao (2022) examine conflicts of interest from directors serving on multiple SPAC boards; and Klausner, Ohlrogge, and Ruan (2022) analyze SPAC structures and associated costs. Cumming, Haß, and Schweizer (2014) and Lakicevic and Vulanovic (2013) study the likelihood of SPACs raising money. Fagan and Levmore (2022) and Levmore and Fagan (2022) investigate the role of PIPEs (Private Investor(s) in Public Equity) in the SPAC process. Dimitrova (2012) shows empirical evidence that implicit incentives in SPAC contracts can lead to poor performance. Kolb and Tykvova (2016) find that small, levered firms with low growth opportunities tend to use SPACs to go public. Vulanovic (2017) study how institutional characteristics of SPACs impact post-merger outcomes. Blankespoor et al. (2022) examine financial projections in the SPAC merger process and find highly optimistic projections. Theoretical papers on SPACs include Gryglewicz, Hartman-Glaser, and Mayer (2021), who model a financial sponsor's choice between private equity and sponsoring a SPAC in the presence of adverse selection, and Luo and Sun (2022), who study the incentive misalignment between SPAC sponsors and investors. To my knowledge, my study is the first to model a firm's choice between an IPO and a SPAC merger and use structural estimation to directly quantify the tradeoff.

My paper also relates to the literature on how firms learn from the financial market. Firms can learn from prices when market participants have more information than the firm's management (Hayek, 2013). Bond, Edmans, and Goldstein (2012) introduces a new definition of price informativeness, emphasizing how prices reveal new information to managers, which firms incorporate into their investment decisions (Chen, Goldstein, and Jiang, 2007; Foucault and Gehrig, 2008). The regulatory environment, particularly regarding insider trading (Fernandes and Ferreira, 2009) and disclosure (Jayaraman and Wu, 2019; Blankespoor, deHaan, and Marinovic, 2020), also plays a crucial role in determining price informativeness and influencing firms' investment decisions. Firms can also learn from the prices of other firms in the same industry. Yan (2022) show that private firms increase investment when public firms in the same industry are valued higher. Firms can time their going public decisions based on industry dynamics (Lowry, 2003). My paper contributes to this literature by studying which firms have the strongest incentive to learn from the market and how this affects their going public choice.

Finally, my paper contributes to the literature on investors learning about a firm's profitability and how this learning affects IPO decisions. Pástor and Pietro (2003) provides a framework for evaluating a firm's market value in the presence of investor learning. Pástor and Veronesi (2005) argue that firms strategically time their IPOs based on favorable market conditions. Pástor, Taylor, and Veronesi (2009) focus on the entrepreneur's tradeoff between going public and staying private, showing that going public can be optimal when a firm's expected future profitability is high, as the market value of the firm exceeds its private value. My paper differs by examining the tradeoff between going public through SPACs versus traditional IPOs.

For tractability, my model adopts a stochastic lumpy adjustments (SLAs) technique, which is also used in Van Binsbergen and Opp (2019); van Binsbergen and Opp (2019), and Opp (2019).

2 Institutional Details

IPO and SPAC Merger Process.—The IPO and SPAC merger processes are two major alternatives for a private firm to go public in the US. Since 2010, roughly 70% of private firms that tried to go public chose a traditional IPO, while the remaining 30% opted for a SPAC merger. "SPAC was just a way for us to get listed in the U.S.," said Thuy Le, the

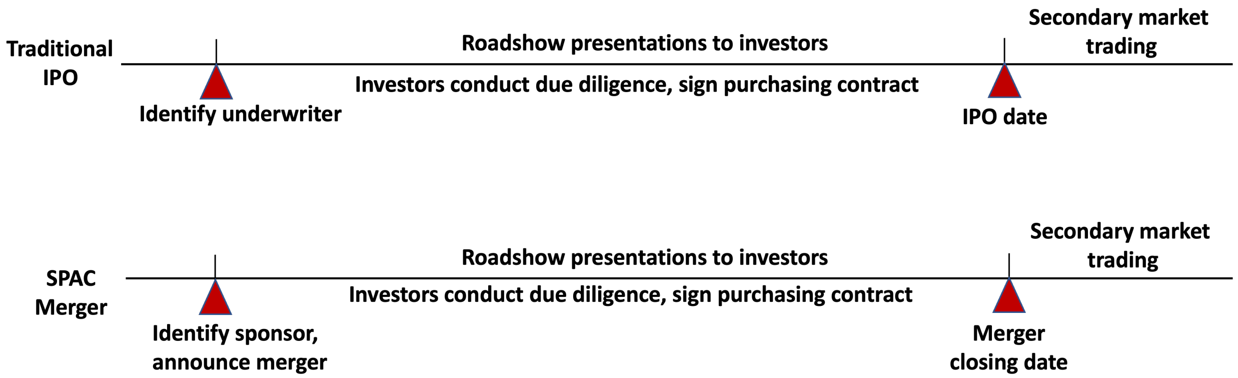

Figure 1: Comparison of IPO and SPAC Merger Processes

This figure compares the traditional IPO process and the SPAC merger process that a private firm needs to go through to get publicly listed.

CEO of Vietnamese electric vehicle maker VinFast, which went public on August 10, 2023.

Figure 1 compares the traditional IPO process and the SPAC merger process that a private firm undergoes to get publicly listed. The traditional IPO process begins with the firm signing an underwriting contract with an investment bank. The investment bank then helps the firm conduct roadshow presentations, where the firm's management team meets with investors to present its business. This interaction helps investors understand the firm's business and determine its selling price. Finally, investors sign purchase contracts with the firm. If there is sufficient demand from investors, the sale is successful, and the firm's shares are publicly listed on the stock exchange on the IPO date, followed by secondary market trading. If demand is insufficient, the sale process fails, the registration is withdrawn from the SEC, and the firm remains private.

The SPAC merger process is similar. A SPAC is a publicly listed shell company with a limited time frame, typically two years, to merge with a private firm to take it public. To go public through a SPAC merger, the private firm first identifies a SPAC sponsor, who plays the role of the underwriter. Since a SPAC is already publicly listed, the merger deal is announced to the SPAC's original shareholders. The sponsor then helps the firm conduct a similar roadshow process and gather investor demand. If there is sufficient demand, the sale is successful, and the private firm becomes publicly listed on the merger closing date. If not, the merger deal fails, and the private firm remains private.

Like IPO investors, SPAC investors are predominantly institutional investors. A SPAC's initial investors often include a group of repeat-playing hedge funds known as the "SPAC Mafia," which accounts for roughly 70% of total SPAC shares (Klausner, Ohlrogge, and Ruan, 2022). At the SPAC merger stage, additional financing is usually necessary to finalize the announced merger, which is typically obtained through a private investment in public equity (PIPE). Because a PIPE is a private placement, securities laws generally restrict investments to accredited investors, meaning that only institutional investors and high-net-worth individuals are permitted to participate. As a result, the entire SPAC process, from IPO to merger with a private company, predominantly involves initial investments from institutional investors, with little to no participation from retail investors (CCMR, 2021).

The two processes also take a similar amount of time, and firms face similar uncertainty regarding the amount of capital raised (Ritter, Gahng, and Zhang, 2023). However, firms going public through a SPAC merger face fewer constraints in terms of communication with their investors during the roadshow due to regulatory differences and incur higher transaction costs because the SPAC merger process is more complex than the traditional IPO process, as discussed in more detail below.

Safe Harbor and Forward-looking Statement.—The safe harbor provision protects qualified companies from legal burdens when making forward-looking statements. While companies that go public through an IPO are not covered by safe harbor, those that merge with SPACs are. This provision provides informational benefits to investors, as communication with the company's management team during roadshow presentations is less constrained. SPAC investors can discuss not only the company's current operations but also its detailed future production plans, which are critical for evaluating the firm's quality and making informed investment decisions.

To illustrate the impact of the safe harbor regulation, consider the roadshow presentation

	Polestar 1	Polestar 2	Polestar 3 Luxury Aero SUV	Polestar 4 Premium Sport SUV	Polestar 5 Luxury Sport GT 4 Door
Price	~$155k	~$50-60k	Porsche Cayenne	Porsche Macan	Porsche Panamera
Start of Production (SoP)	2019	2020	2022E	2023E	2024E
Range	~120km range[1]	~540km range[1]	+600km target range	+600km target range	+600km target range

Info in IPO

Additional info in SPAC merger

Figure 2: IPO and SPAC Merger Roadshow Comparison: Polestar Example

This figure presents the product portfolio introduced during Polestar's investor presentation. Polestar went public in 2022 through a SPAC merger. The two models on the left, Polestar 1 and Polestar 2, would be introduced in a hypothetical IPO roadshow presentation. The three models on the right of the dotted red line, planned for future release, were introduced in the SPAC merger presentation.

of Polestar, a Swedish electric vehicle manufacturer owned by Volvo Cars. Polestar went public through a SPAC merger announced in 2021 and completed in 2022. Figure 2 shows the product portfolio introduced during Polestar's investor presentation. Thomas Ingenlath, CEO of Polestar, first introduced Polestar 1 and Polestar 2, which were already in production and on sale. Because the SPAC merger is protected by safe harbor, Ingenlath also presented three new models projected to be released in the next three years: Polestar 3, a luxury SUV; Polestar 4, a sport SUV; and Polestar 5, a sport GT car.

These detailed future production plans are essential for investors to evaluate the company's prospects. In Polestar's case, investors could ask about suppliers, such as battery manufacturers, to ensure production scalability; targeted markets and competitors for each new model, like luxury car manufacturers such as Porsche; and details about future factory locations. These information are especially valuable in growing markets to identify market competition, production capability, and future capital needs, helping to resolve investor uncertainty.

In contrast, if Polestar had gone public through a traditional IPO, its management team would most likely only present the two models currently in production to avoid legal risks. In practice, firms going through IPOs almost never present detailed future business plans.

Overall, information generated in SPAC roadshow presentations tends to be much more informative than in IPO presentations.

SEC's New Rule.—On January 24, 2024, the Securities and Exchange Commission (SEC) adopted new rules[3], in a 3-2 vote, that eliminate the safe harbor provision for projections included in SPAC mergers. The rules will become effective 125 days after publication in the Federal Register, with registrants having 490 days to comply. Current SPAC IPOs and near-complete de-SPAC transactions will not be subject to the new rules if they close in the next few months.

The new rule is controversial. SEC Chair Gary Gensler, who voted in favor, stated, "Investors are harmed when parties engaged in a de-SPAC transaction over-promise future results regarding the target company. Today's adoption will help ensure that the rules for SPACs are substantially aligned with those of traditional IPOs." Conversely, SEC Commissioner Hester Peirce, who voted against the rule, argued, "De-SPAC transactions are uniquely well-suited to certain types of companies, including smaller companies, those that are both capital-intensive and relatively immature, and companies in specific industries. By layering obligations on the SPAC process, we are effectively removing this option for some companies, which may choose not to go public at all."

This paper contributes to the policy debate by: (1) providing empirical evidence on the extent to which SPAC firms utilize the safe harbor provision to present their business plans during roadshow presentations in Section 3; (2) building a dynamic model that captures the tradeoffs a private firm faces when choosing the timing and method of going public in Section 4; and (3) analyzing policy implications by estimating the model and conducting counterfactual analysis in Section 6 and Section 7.

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[3] https://www.sec.gov/news/press-release/2024-8

3 Data

3.1 Data Sources

To conduct the empirical analysis, this paper uses data on firms that were private between January 2010 and June 2023. I compiled a comprehensive dataset tracking these firms' status during the sample period. Specifically, a firm could remain private throughout the period, or go public via a traditional IPO or a SPAC merger. The dataset provides detailed information on the firm's characteristics during the private stage, public offering outcomes, and financial performance after going public. Below, I introduce the different data sources used.

The Pitchbook database[4] provides financing information for these firms while they are still private. Pitchbook collects detailed data on venture capital, private equity, and M&A—including public and private companies, investors, funds, investments, exits, and people. It is best known for venture capital (VC) and private equity (PE) data. Specifically, Pitchbook provides information such as the firm's first invested financing capital, whether the firm is backed by a VC investor, the firm's operating sector, employee history, and whether the firm exited through a merger and acquisition deal.

For firms that chose to go public through IPO, I obtained IPO outcomes from two data sources. The primary source for IPOs up to December 2022 is the SDC Platinum New Issues database[5]. For IPOs between January and June 2023, data was obtained from Stock Analysis[6]. The sample includes IPOs with an offer price of at least $5.00 but excludes ADRs, unit offers, closed-end funds, REITs, natural resource limited partnerships, small best-efforts offers, banks and S&Ls, and stocks not listed on CRSP. CRSP includes stocks from Amex, NYSE, and NASDAQ.

For firms that chose to go public through a SPAC merger, I compiled SPAC merger out-

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[4] `https://pitchbook.com/`

[5] `https://www.refinitiv.com/en/products/sdc-platinum-financial-securities-data`

[6] `https://stockanalysis.com/`

comes from two main sources: the SPAC Research Database[7] and the PrivateRaise SPAC Search Database[8]. This combined dataset provides a comprehensive list of SPACs registered with the SEC from January 2010 to June 2023, detailing their ticker symbols, target companies, IPO dates, merger dates, and capital raised. Data accuracy was ensured by cross-referencing the datasets and removing duplicates.

For firms that chose SPAC, I manually collected their conference call transcripts related to roadshows to examine communication between the firm and SPAC investors. As SPACs are publicly traded at the time of the roadshow, I found these transcripts in the firms' filings with the SEC, particularly the 8-K statements around the time of the SPAC's merger announcement. I also collected the firms' earnings call transcripts during the SPAC merger process from the SEC's Edgar database.

Post-public financial data for firms was derived from Compustat, with stock pricing data sourced from CRSP.

3.2 Sample construction

This study focuses on the firm's decision to go public versus staying private. The going public sample includes all firms that went public through either IPO or SPAC merger during the sample period of January 2010 to June 2023. The public sample contains 2,744 firms that went public during my sample period. Out of these firms, 802 firms tried to go public through merging with SPACs. Out of the 802 firms, 498 completed the merger process, 134 deals were broken, and 170 have announced targets but have not completed the merger process as of the end date of my sample. During the same sample period, 1,942 firms tried to go public through IPO. 1,737 firms successfully completed the IPO process, and the rest 205 firms eventually withdrew from the IPO process and went back to staying private. As of the second quarter of 2023, there are 215 active SPACs. These SPACs have collectively garnered

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[7] `https://www.spacresearch.com/`

[8] `https://www.privateraise.com/`

$50.5 billion in proceeds, underscoring their substantial financial capability and emphasizing their role in aiding private firms to transition to public status via SPAC mergers.

3.3 Summary Statistics

In Table 1 (Panel A), I present statistics for 1,942 firms that transitioned to the public domain via IPOs. These firms had an average patent count of 0.03 at inception, which increased to a mean of 7.62 patents by the time they went public. They started with an average of 1,102 employees. Of these firms, 13% operate in the information technology sector, 28% are in healthcare, and the average VC reputation is 0.17, where VC reputation is measured as the lead VC's proportion of total investment in the VC industry.

Table 1 (Panel B) delves into the data for 802 firms that chose the SPAC merger route. Compared to firms that went public via IPO, evaluating these firms both at their start and prior to going public can be more challenging. Their average initial patent count is close to zero, increasing only to 0.02 patents before their public listing. They typically commence with fewer employees, averaging 484. Within this group, 20% are associated with the technology sector, 15% belong to healthcare, and the average VC reputation is lower at 0.13.

The post-public equity value for the two sets of firms is comparable. However, SPAC firms grow at a lower rate than IPO firms and choose to access the public market earlier. On the cost side, I use the money left on the table (MLOT) that the firm leaves to investors to measure the information production cost, as in Aryal et al. (2022), which measures the difference in the value of purchased securities at the end of the merger and the offer price. I find that SPAC firms leave around $148 million to investors. In contrast, IPO firms leave only around $57 million on the table.

Table 1
Descriptive Statistics

	Mean	Std.Dev.	p25	p50	p75	Obs.
A. IPO sample						
Firm Characteristics						
Patents at start	0.03	0.18	0.00	0.00	0.00	1,942
Patents pre-public	7.62	283.17	0.00	0.00	0.00	1,942
Employees at start	1,102	9,451	0	15	157	1,942
Years to first finance	5.92	16.36	0	0	3	1,942
VC reputation	0.17	0.38	0.00	0.00	0.17	1,942
Healthcare	0.28	0.45	0.00	0.00	1.00	1,942
IT	0.13	0.34	0.00	0.00	0.00	1,942
HHI	0.03	0.04	0.00	0.00	0.08	1,942
Public Offering Outcome						
MLOT	56.67	148.28	-0.22	10.83	59.24	1,382
Post-public valuation	2,100.68	4,098.73	281.04	697.12	1,913.85	1,211
Years to public	18.16	23.40	6.00	11.00	19.00	1,815
Growth rate	0.19	0.24	0.06	0.12	0.21	786
B. SPAC merger sample						
Firm Characteristics						
Patents at start	0.00	0.00	0.00	0.00	0.00	802
Patents pre-public	0.02	0.33	0.00	0.00	0.00	802
Employees at start	484	2,946	0	16	109	802
Years to first finance	6.64	16.63	0	1	5	802
VC reputation	0.13	0.40	0.00	0.00	0.03	802
Healthcare	0.15	0.36	0.00	0.00	0.00	802
IT	0.20	0.40	0.00	0.00	0.00	802
HHI	0.02	0.05	0.00	0.00	0.00	802
Public Offering Outcome						
MLOT	148.64	252.42	24.94	65.20	139.88	484
Post-public valuation	2,112.20	3,394.18	492.55	1,164.37	2,282.72	438
Years to public	16.94	21.69	6.00	10.00	18.00	595
Growth rate	0.15	0.18	0.04	0.09	0.18	287

This table presents descriptive statistics for firms in my sample. The sample covers the period from 2010 to mid-2023. All variables are winsorized at the 1st and 99th percentiles.

3.4 Safe Harbor and Forward Looking Statements

One distinct feature of the SPAC merger is that SPAC investors can learn about the company's future business plan, thanks to the "Safe Harbor" protections offered by the

Private Securities Litigation Reform Act of 1995 (PSLRA).

To determine if SPAC investors utilize the safe harbor rule during the merger process, I examine the communication between SPACs and investors. After a SPAC merger announcement and before its completion, the private company's top executives can present the company to investors during the SPAC's earnings conference calls, which play a similar role to the IPO roadshow.

Compared to 10-K filings and news sources like the Wall Street Journal, the signal-to-noise ratio in earnings calls is much stronger (Garcia, Hu, and Rohrer, 2023). My approach depends on the relationship between the information investors receive from earnings calls and the quality of the firm. Therefore, a strong signal-to-noise ratio is essential for my analysis.

To extract word embeddings, I use the Bidirectional Encoder Representations from Transformers (BERT), a natural language processing algorithm created by Google AI. BERT offers several advantages over other models. Unlike context-free models such as Word2Vec and GloVe, BERT generates an embedding representation of a word based on its surrounding context. Additionally, unlike unidirectional models like ELMo and ULMFiT, which only consider preceding words, BERT takes into account both preceding and following context to form word embeddings. These features make BERT highly accurate in interpreting texts (Devlin et al., 2018) and it has been increasingly utilized in economic studies (Chava, Du, and Paradkar, 2020; Chava, Du, and Malakar, 2021; Gorodnichenko, Pham, and Talavera, 2023).

For my analysis, I use a pretrained BERT model, FinBERT (Araci, 2019), which can interpret texts, including sentiments (positive, neutral, or negative), and identify forward-looking statements. FinBERT is trained on a large corpus of 4.9 billion tokens from corporate reports (10-K and 10-Q), earnings call transcripts, and analyst reports. For sentiment analysis, I use the finbert-tone model, a version of FinBERT fine-tuned on 10,000 manually annotated sentences (positive, negative, neutral) from analyst reports. This model performs

Table 2
Summary of Forward-looking Statements in SPAC Merger

	Obs.	Mean	Std	P10	P50	P90
Sentence Count	709	183.10	121.68	40.00	167.00	371.20
Forward-Looking Classification						
Forward-looking sentences (FLS)	709	22.17	18.27	0.00	18.00	48.20
Specific FLS	709	15.96	13.75	2.00	12.00	35.00
Non-specific FLS	709	6.73	6.57	0.00	5.00	16.00
% Forward-looking sentences (FLS)	709	12.04	8.35	0.00	10.96	22.59
% Specific FLS	709	9.71	7.52	2.36	7.73	19.67
% Non-specific FLS	709	3.52	2.62	0.00	3.14	6.72

This table provides descriptive statistics for the earnings press release sentence types for the sample of SPAC firms at the merger announcement.

well on financial tone analysis tasks (Huang, Wang, and Yang, 2023). Additionally, I identify forward-looking statements from SPAC firm earnings calls at the merger announcement using FinBERT-FLS, a FinBERT model fine-tuned on 3,500 manually annotated sentences from the Management Discussion and Analysis section of annual reports from Russell 3000 firms.

Using the pretrained FinBERT model, I analyze the text of earnings call transcripts on a sentence-by-sentence basis. After removing boilerplate language, such as standard forward-looking statements, I classify sentences as specific forward-looking statements (Specific-FLS)[9], non-specific forward-looking statements (Non-Specific FLS)[10], and not forward-looking sentences (Not-FLS).

Table 2, Panel A provides descriptive statistics for the earnings announcements in my sample for SPAC firms at the time of their merger announcement. There are 279 SPACs that filed earnings transcripts with the SEC at the time of their merger announcement, resulting in a total of 709 transcript files. Earnings announcements have an average of 183.10 sentences

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[9] An example of a specific forward-looking sentence is "We look forward to providing more detailed information regarding our strategic plans, important milestones, and our progress in the coming quarters for both our Gen 4 vehicles and our Gen 5 ground-up chassis vehicles, which will follow subsequently behind Gen 4."

[10] An example of a non-specific forward-looking sentence is "So we're in the early stages of that, but we're seeing benefits already. And we think as we continue to innovate and create new opportunities to expand with those customers, that strategy is going to pay off."

(after removing boilerplate language and sentences with fewer than 10 words), of which 22.17 (12.04%) are classified as forward-looking. Of those forward-looking statements, an average of 15.96 (9.71%) are classified as relating to the forecast of specific information (specific FLS), and 6.73 (3.52%) are classified as general forecasts (non-specific FLS).[11]

Overall, the data indicate three key points about firms that choose to merge with SPACs. First, when private firms present to investors during SPAC earnings calls, a significant portion of the communication consists of forward-looking statements specific to the firm's future plans. Second, compared to firms that choose IPOs, firms opting for SPAC mergers face greater difficulty resolving their uncertainty while remaining private, as they have fewer patents, fewer employees, operate more in the IT sector, and are backed by less reputable VCs. Third, compared to the IPO process, firms merging with SPACs leave more money on the table for market participants. Motivated by these empirical findings, I build a model in the next section to examine the firm's endogenous choice of the optimal way to go public.

4 Model

I build the model using an SLA technology specification consistent with the principles laid out in Van Binsbergen and Opp (2019), van Binsbergen and Opp (2019), and Opp (2019). I make three specific modeling choices that ensure solving the model involves only inverting sparse matrices.

There are two classes of risk-neutral agents, investors and an entrepreneur, who have identical preferences. I start by describing the firm's earning process.

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[11] Besides future production plans, firms can also make financial projections. Blankespoor et al. (2022) show that the projections are overly optimistic, leaving a lot of room for evaluation during the roadshow process.

4.1 Environment

At time $t = 0$, the entrepreneur is endowed with a private firm implementing a patent-protected technology. There are two possible outcomes of implementing the technology. First, the technology may generate a positive net present value (NPV) project, in which case the firm is denoted as high type ($\theta = h$). Second, the technology may generate a negative NPV project, in which case the firm is denoted as low type ($\theta = l$). The firm's type is not directly observable. At date $t = 0$, nature determines the value of θ, where h is drawn with probability π_0, and l is drawn with complementary probability $1 - \pi_0$.

By implementing the technology, the firm makes earnings at each time, denoted by B_t. The firm's log-earnings process b_t is governed by a stochastic lumpy adjustment (SLA) process with both positive and negative Poisson shocks.

The arrival intensities of shocks to the state b are affected by the firm's type. Let $\lambda_b^+(\theta)$ and $\lambda_b^-(\theta)$ denote the Poisson arrival rates of upward and downward shocks to b, the distribution of the Poisson process can be written as:

$$N_{b,t}^+(\theta) \sim \text{Poisson}(\lambda_b^+(\theta)),$$
$$N_{b,t}^-(\theta) \sim \text{Poisson}(\lambda_b^-(\theta)),$$

where $N_{b,t}^+(\theta)$ and $N_{b,t}^-(\theta)$ denote the Poisson processes of positive and negative earnings shocks within time t for a firm of type θ.

When a positive shock hits, the firm's log-earnings increase by a fixed amount Δ_b, and when a negative shock hits, the firm's log-earnings decrease by the same amount. The dynamics of the firm's log-earnings process can be written as:

$$db_t = \Delta_b \cdot \left[dN_{b,t}^+ - dN_{b,t}^- \right]. \tag{1}$$

Given these dynamics, b_t takes values in a discrete set Ω_b, the elements of which constitute a grid with increments of size $\Delta_b > 0$, and the earnings B_t then follow the jump-diffusion process:

$$\frac{dB_t}{B_t} = \left(e^{\Delta b} - 1\right) dN^+_{b,t} + \left(e^{-\Delta b} - 1\right) dN^-_{b,t}. \tag{2}$$

The firm keeps producing earnings until its patent expires at some future time T. The patent expiration date arrives at a hazard rate η, meaning the firm's patent, on average, lasts for $\frac{1}{\eta}$. The firm is assumed to pay no dividends, reinvest all its earnings, and be financed only by equity. Because b_t follows a random process, B_t also evolves randomly, so B_T is unknown before time T.

I assume that the volatility of b does not contain incremental information about the hidden state θ. This is the case if the total Poisson arrival rate with which any adjustment to b occurs does not depend on the hidden state θ, although it may vary with any observable state or firm characteristic. Specifically, the total jump intensity is given by:

$$\lambda_b \equiv \lambda^+_b(\theta) + \lambda^-_b(\theta) \quad \text{for all } \theta. \tag{3}$$

This specification implies that the mean and the volatility of adjustments to b are given by:

$$\mu_b(\theta) = \Delta_b \left(\lambda^+_b(\theta) - \lambda^-_b(\theta)\right), \tag{4}$$

$$\sigma_b = \Delta_b \sqrt{\lambda_b}. \tag{5}$$

As intended, the drift μ_b depends on the hidden state θ, whereas the volatility σ_b does not. As in models where earnings follow a Brownian motion with hidden drift, the dynamics for b are fully described by the drifts $\mu_b(\theta)$ and the volatilities σ_b; given these parameters, the Poisson intensities $\lambda^+_b(\theta)$ and $\lambda^-_b(\theta)$ are uniquely determined, given any choice for Δ_b. Accordingly, I will estimate the model by directly assigning values for the drifts $\mu_b(\theta)$ and volatilities σ_b, and back out the associated Poisson intensities. This modeling choice implies that beliefs about the state θ exhibit stochastic lumpy adjustments after earnings shocks are realized and stay constant otherwise.

Before the patent's expiration, opportunities to go public emerge at a Poisson rate of ρ. Upon the arrival of such an opportunity, the entrepreneur must choose between taking the company public or maintaining its private status. To enter the public market, the entrepreneur can either undergo the conventional IPO process or merge with a SPAC. In the next subsection, I explain the going public process in detail.

Now consider a firm whose current log-earnings is b_t, and it is considering going public through the traditional IPO process. The IPO process is costly. To complete the IPO, the firm needs to pay fees to the underwriter and investors to prepare all necessary documents and conduct an evaluation of the firm. The total cost is denoted by c_{IPO}. The evaluation process generates an independent signal of the firm's quality. The signal generated by the investor[12] can be either good ($s = H$) or bad ($s = L$), and the signal is independent of the prior information and satisfies

$$\Pr(s = L|\theta = l) = q_{\text{IPO}}, \tag{6}$$

$$\Pr(s = H|\theta = h) = 1. \tag{7}$$

Note that the investor's signal only admits type II errors. By Bayes' rule, given a bad signal, the firm is of low type with probability 1; given a good signal, the firm may be of high or low type. I verify the Martingale condition in Appendix A.2.1.

Using the newly generated signal, market participants update their beliefs about the firm's quality. If the updated belief indicates that the firm is a positive NPV project, the firm signs a sales contract with the investor by selling the firm at price p and reinvests part

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[12] In reality, there are multiple investors. Here one can think of all other investors delegating the information production task to one investor.

of the proceeds back into the firm's production.

Alternatively, the firm can choose to merge with a SPAC. The process is similar to the IPO process, but SPAC investors receive a signal with precision q_{SPAC} at a cost c_{SPAC}.

4.2 Discussion of Model's Assumptions

Signal structure.—This signal structure mimics the due diligence process, aiming to detect significant errors within bad firms. It also simplifies the identification strategy for estimation, which I will explain later in Section 6.1. Choosing an alternative symmetric signal structure would not impact the model's predictions or the identification strategy.

Fixed cost.—The cost of going public includes direct costs of issuance, accounting, legal, and underwriting fees, as well as the information production/due diligence cost. The due diligence process is largely standardized and does not vary significantly based on the issuing firm's scale, whether large or small. Figure 3 plots the average size of firms on the x-axis and the average fees-to-size ratio on the y-axis. The plot shows that the fees-to-size ratio decreases as the size of the firms increases. This trend indicates that the fees grow less than linearly with the size of the firms, meaning larger firms tend to incur lower fees relative to their size compared to smaller firms.

Investment scales with earnings.—Larger firms tend to raise more proceeds in an IPO than smaller firms. IPO proceeds are empirically used as a proxy for firm size, as seen in Switzer, El Meslmani, and Zhai (2022).

Binary types of firms.—In the model, firms are categorized into two types: high growth and low growth. The actual type of a firm is not observable. Investors form beliefs about the firm's type based on realized production outcomes and signals generated during the going public process. These beliefs influence their investment decisions, and since beliefs are continuous, investment amounts are also continuous.

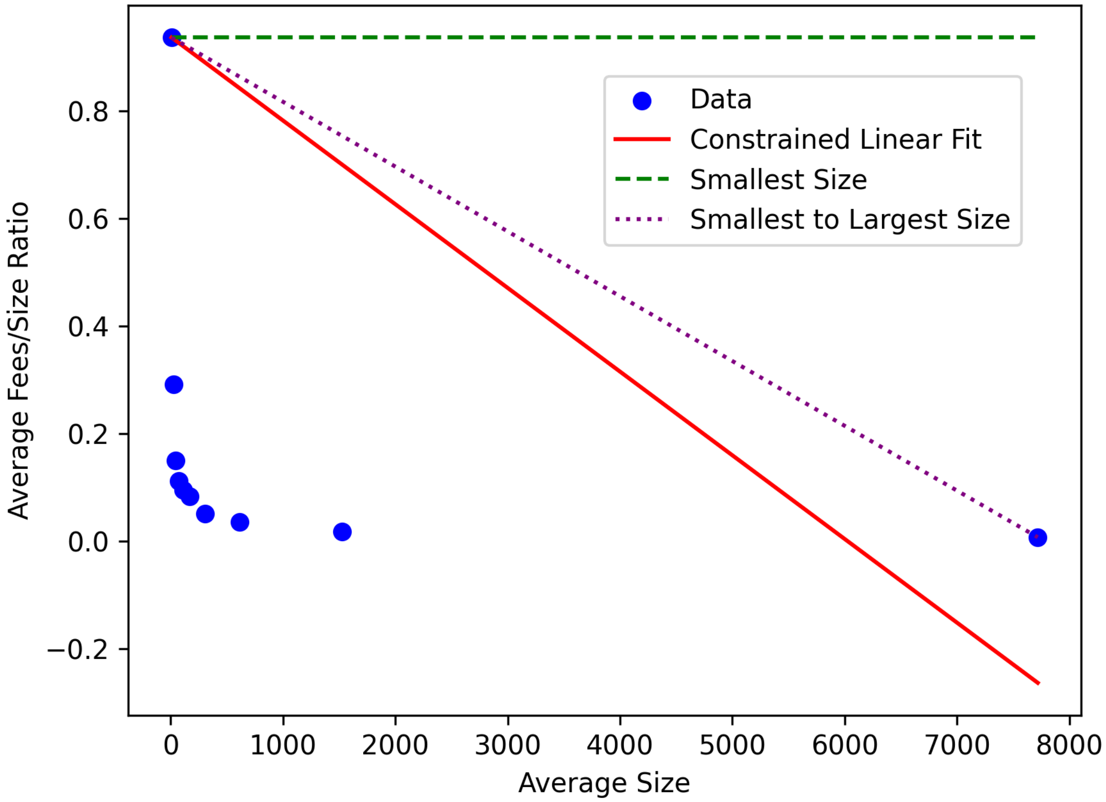


Figure 3: Fees/Size Ratio vs. Average Size of Firm

This figure illustrates the relationship between the average size of firms and the average fees-to-size ratio across ten size-based bins. The x-axis represents the average firm size within each bin, while the y-axis represents the average fees-to-size ratio. The green dashed line shows the average fees-to-size ratio for the smallest size group of firms. The purple dotted line connects the average fees-to-size ratios for the smallest and largest size groups. The red solid line represents the linear fitted line, constrained to start from the first data point corresponding to the smallest size group.

The binary classification implies that when the belief is in the middle range, the uncertainty about the firm's actual type is high. Conversely, when the belief is either low or high, the uncertainty is low. This scenario is similar to a normal distribution, where the firm is less likely to have very low or very high growth rates and more likely to have a middle-range growth rate.

Assume that only firms with high growth rates are mature enough to go public. The high-growth firm in my model serves as a proxy for those with a growth rate exceeding a certain threshold in a model with normally distributed types. Similarly, if the current belief about a firm's high growth rate is in the middle range, the uncertainty remains high. In this sense, the binary classification serves as a proxy for a continuous distribution of firm types. This is akin to approximating the normal distribution with quadrature points, as discussed in Judd (1998) and Tauchen and Hussey (1991).

Perfectly competitive investors.—Although investors are perfectly competitive in the model, this does not conflict with the empirical observation of the money they make. The money made by investors can be seen as the opportunity cost of producing information.

4.3 Analysis

In this section, I characterize the equilibrium dynamics of a perfect Bayesian Nash equilibrium, with a focus on the information updating process.

4.3.1 Information Updating

Investors and the entrepreneur share identical priors regarding the firm-specific hidden state, denoted as θ. They gain insights from the realized earnings, with all other parameters being known. At time t, the agent's belief that the firm is in a good state is represented by π_t, which can be expressed as $\pi_t \equiv \Pr[\theta = h | \mathcal{F}_t]$. Here, $\mathcal{F}_t$ refers to all historical information accessible up to time t.

Before making an investment, it is essential for investors to understand the investment opportunity thoroughly. When a firm has a project with a positive Net Present Value (NPV), there is a clear inclination to upscale. Conversely, if the project has a negative NPV, the firm might be hesitant. Therefore, to secure financing, a firm needs to demonstrate to the market that it is worth investing in.

A firm can learn about its type by remaining private and continuing production. If positive production shocks occur, the belief in the firm being a high-type increases. However, this approach delays the firm's opportunity to go public and scale up its production. Alternatively, the firm can utilize the information produced during the IPO or SPAC merger process. The downside is that going public is costly.

Ultimately, a firm needs to consider the trade-offs, balancing the benefits derived from public signals with the associated costs. Firms with different prior beliefs may benefit differently from these signals. The following lemma explores how a firm's prior belief interacts with a received high signal.

Lemma 1 (Posterior increase with high signal)**.** *Let a firm's posterior belief, after receiving a high-type signal, be denoted as* $\pi(\theta = h|s = H, \mathcal{F}_t)$*, its prior belief be denoted as* $\pi(\theta = h|\mathcal{F}_t)$*, and the precision of the signal be denoted as* q*. We have:*

1. The firm's posterior belief increases upon receipt of a high-type signal, i.e., $\pi(\theta = h|s = H, \mathcal{F}_t) > \pi(\theta = h|\mathcal{F}_t)$*.*

2. The magnitude of the increase in the posterior belief, following the high-type signal, is a function of the firm's prior belief. Specifically, as $\pi(\theta = h|\mathcal{F}_t)$ *increases from a low value, the magnitude of the increase in the posterior first rises and then falls.*

3. The prior belief, $\pi^*(\theta = h|\mathcal{F}_t)$*, that has the maximum increase in the posterior diminishes as the signal's precision,* q*, rises. That is,* $\frac{\partial \pi^*(\theta=h|\mathcal{F}_t)}{\partial q} < 0$*.*

Proof. See Appendix A.2.2. □

Lemma 1, point 1 shows that all firms benefit from a high signal in terms of increasing the belief of being a positive NPV project.

Lemma 1, point 2 illustrates that the marginal value of information is highest when the belief about the firm's quality is in an intermediate range. Given a low prior belief, the company is almost certain that it is a low-growth type. This perspective is too rooted in pessimism, and a positive signal from public investors may yield little increase in optimism. Conversely, with a strong prior belief, the firm already has a high level of confidence that it is a high-growth type. Receiving additional positive news serves merely as confirmation and does not significantly update the belief. When the prior belief is in the middle range, the uncertainty about the firm's type is the highest. In this range, substantial information can serve as a powerful factor in determining the firm's value.

Lemma 1, pint 3 shows a clear relationship: the value a firm gets from a high signal is tied to the precision of that signal. Simply put, the more precise the signal, the lower the prior belief of the firm that benefits the most from it. If we consider a situation where SPAC investors offer more accurate signals than IPO investors, this would mean that firms opting for SPACs typically have a lower prior belief.

Next, I detail the process of information updating with respect to earnings shocks and any public signal generated. Agents update their beliefs based on Bayesian rules when they observe shocks to log-earnings b_t before and after the firm goes public. A positive shock to b increases the log-odds ratio by the log-Bayes factor f^+, while a negative shock decreases it by the log-Bayes factor f^-. The log-Bayes factors are determined by the grid increments Δ_b, the drifts $\mu_b(\theta)$, and the volatility σ_b. As the total arrival intensity λ_b is independent of the hidden state θ, the time elapsed between shocks to b does not provide agents with extra information. Agents also update their beliefs based on Bayesian rules when they observe the signal generated by public investors.

The following lemma characterizes the evolution of these beliefs:

Lemma 2 (Bayesian updating). *The log-odds ratio $o_t \equiv \log[\pi_t/(1-\pi_t)]$ evolves according to the following process:*

$$\begin{aligned} do_t &= f^+ dN^+_{b,t} - f^- dN^-_{b,t} \\ &\quad + \left[(o_t + f_{IPO})\mathbb{1}_{s=H} - \infty\mathbb{1}_{s=L} - o_t\right] dN_{IPO,t} \\ &\quad + \left[(o_t + f_{SPAC})\mathbb{1}_{s=H} - \infty\mathbb{1}_{s=L} - o_t\right] dN_{SPAC,t} \end{aligned} \tag{8}$$

where I define the log-Bayes factors associated with positive and negative shocks to b:

$$f^{+} \equiv \log\left[\frac{\lambda_b^{+}(h)}{\lambda_b^{+}(l)}\right] = \log\left[\frac{1+\Delta_b\frac{\mu_b(h)}{\sigma_b^2}}{1+\Delta_b\frac{\mu_b(l)}{\sigma_b^2}}\right], \tag{9}$$

$$f^{-} \equiv -\log\left[\frac{\lambda_b^{-}(h)}{\lambda_b^{-}(l)}\right] = -\log\left[\frac{1-\Delta_b\frac{\mu_b(h)}{\sigma_b^2}}{1-\Delta_b\frac{\mu_b(l)}{\sigma_b^2}}\right], \tag{10}$$

and the increase in the log-odds ratio associated with a good signal generated by public investors:

$$f_{IPO} = \log\left[\frac{1}{1-q_{IPO}}\right], \tag{11}$$

$$f_{SPAC} = \log\left[\frac{1}{1-q_{SPAC}}\right]. \tag{12}$$

Proof. See Appendix A.2.4. □

To ensure the log-odds ratio only assumes values on a grid with increments of size $\Delta_o > 0$, a mild parameter restriction is imposed. This constraint is the third critical modeling choice for maintaining the model's tractability, enabling the problem of optimal default to be solved using computationally efficient methods.

Assumption 1. *Parameters adhere to the restriction that* $\frac{f^{+}}{\Delta_o}$, $\frac{f^{-}}{\Delta_o}$, $\frac{f_{IPO}}{\Delta_o}$, *and* $\frac{f_{SPAC}}{\Delta_o}$ *are natural numbers.*

While this constraint is vital for ensuring the model's tractability in the presence of learning, it imposes virtually no limitations on the parameter choices determining profitability dynamics, as Δ_o can be set to an arbitrarily small value. By enforcing this constraint, precise global solutions can be obtained, requiring only matrix inversions.

4.3.2 Post-public Equity Value

Employing the principle of backward induction, we initiate the analysis of the company's equity value after its transition to public status. The state vector is symbolized by (b, o). The total number of discrete states is $n = n_b \times n_o$. The entrepreneur's value function, denoted by $V_{post}(b, o)$, satisfies the Hamilton-Jacobi-Bellman (HJB) equations in the following form:

$$\begin{aligned} 0 = & - rV_{post}(b,o) + \eta(e^b - V_{post}(b,o)) \\ & + \mathbb{E}\left[\lambda_b^+|o\right]\left[V_{post}(b+\Delta_b, o+f^+) - V_{post}(b,o)\right] \\ & + \mathbb{E}\left[\lambda_b^-|o\right]\left[V_{post}(b-\Delta_b, o-f^-) - V_{post}(b,o)\right], \end{aligned} \tag{13}$$

where

$$\begin{aligned} \mathbb{E}\left[\lambda_b^+|o\right] &= \pi(o)\lambda_b^+(h) + (1-\pi(o))\lambda_b^+(l) \\ \mathbb{E}\left[\lambda_b^-|o\right] &= \pi(o)\lambda_b^-(h) + (1-\pi(o))\lambda_b^-(l). \end{aligned}$$

In this context, $\pi(o)$ represents the posterior belief of the firm being high type based on the log-odds ratio o. The terms λ_b^+ and λ_b^- are the Poisson arrival rates of positive and negative shocks to b, respectively, and they are conditional on the firm's type. The HJB equation captures the evolution of the firm's value considering the arrival of positive and negative earnings shocks, as well as the potential for the firm's value to adjust when transitioning to a public status.

4.3.3 Equity Value of Going Public

When a firm goes public, it offers a sales contract to the public investor, ensuring that the investor breaks even. The investor then receives the proceeds net of the investment, leading to the following system of equations in the case of an IPO:

$$\Pr(s=H)\left(V_{\text{Post}}(b+k\Delta b, o+f_{\text{IPO}})-p_{\text{IPO}}\right)=c_{\text{IPO}}, \tag{14}$$

$$V_{\text{IPO}}(b,o)=\Pr(s=H)\left(p_{\text{IPO}}-(e^{k\Delta b}-1)e^{b}\right)+\Pr(s=L)V_{\text{Post}}(b,-\infty), \tag{15}$$

Equation (14) articulates that the investor and the underwriter break even ex-ante in expectation, and Equation (15) specifies the total expected equity value for the entrepreneur if the entrepreneur opts to go public through the traditional IPO process.

By substituting $\Pr(s=H)=\pi_t+(1-\pi_t)(1-q_{\text{IPO}})=1-\frac{q_{\text{IPO}}}{1+e^{o_t}}$ into Equation (14), we can derive an expression for the selling price p_{IPO}:

$$p_{\text{IPO}}=V_{\text{Post}}(b+k\Delta b, o+f_{\text{IPO}})-\frac{c_{\text{IPO}}}{1-\frac{q_{\text{IPO}}}{1+e^{o_t}}}. \tag{16}$$

Equation (16) explicates the selling price of the firm, composed of two components. The first component represents the firm's post-merger equity value after considering the newly raised investment and after a positive signal from the IPO investors. The second component refers to the total amount of money left on the table ("MLOT"), i.e., the total dollar amount from underpricing that the firm needs to leave to the underwriter and investor during the IPO process.

If the information production cost c_{IPO} is higher, the firm must underprice its shares more substantially. Furthermore, if the IPO investor's signal is more precise (higher q_{IPO}), the degree of underpricing will also be larger. However, a more accurate signal also amplifies the increase in the firm's log-odds ratio, f_{IPO}, enhancing the post-merger valuation. This means that the firm will likely be a more positive NPV project upon receiving a favorable signal.

Overall, the firm confronts a trade-off from a more precise signal in two significant ways: it heightens the value of a positive signal but also necessitates that the firm compensate the investor by leaving additional money on the table. By substituting Equation (16) into Equation (15), we derive a formal expression for the firm's equity value when going IPO, as follows:

$$V_{\text{IPO}}(b,o) = \left(1 - \frac{q_{\text{IPO}}}{1+e^o}\right)\left[V_{\text{Post}}(b + k\Delta b, o + \log\left[\frac{1}{q_{\text{IPO}}}\right]) - \frac{c_{\text{IPO}}}{1-\frac{q_{\text{IPO}}}{1+e^o}} - (e^{k\Delta b} - 1)e^b\right] + \frac{q_{\text{IPO}}}{1+e^o}V_{\text{Post}}(b, -\infty). \tag{17}$$

Similarly, we can derive the equation for the firm's choice to go public via a SPAC merger as:

$$V_{\text{SPAC}}(b,o) = \left(1 - \frac{q_{\text{SPAC}}}{1+e^o}\right)\left[V_{\text{Post}}(b + k\Delta b, o + \log\left[\frac{1}{q_{\text{SPAC}}}\right]) - \frac{c_{\text{SPAC}}}{1-\frac{q_{\text{SPAC}}}{1+e^o}} - (e^{k\Delta b} - 1)e^b\right] + \frac{q_{\text{SPAC}}}{1+e^o}V_{\text{Post}}(b, -\infty). \tag{18}$$

The break-even function for SPAC investors can be derived too as follows,

$$p_{SPAC} = V_{\text{Post}}(b + k\Delta b, o + f_{\text{SPAC}}) - \frac{c_{\text{SPAC}}}{1-\frac{q_{\text{SPAC}}}{1+e^{o}t}}. \tag{19}$$

4.3.4 Firm's Choice

We can now describe the firm's decision-making process among staying private, going public through an IPO, and going public through a SPAC merger using the following HJB equation:

$$\begin{aligned} 0 = &- rV(b,o) + \rho\left[\max\{V_{\text{IPO}}(b,o), V_{\text{SPAC}}(b,o), V(b,o)\} - V(b,o)\right] \\ &+ \eta(e^b - V(b,o)) \\ &+ \mathbb{E}\left[\lambda_b^+ | o\right]\left[V(b + \Delta_b, o + f^+) - V(b,o)\right] \\ &+ \mathbb{E}\left[\lambda_b^- | o\right]\left[V(b - \Delta_b, o - f^-) - V(b,o)\right], \end{aligned} \tag{20}$$

where V_{IPO} and V_{SPAC} are defined in Equations (17) and (18), respectively.

In Equation (20), $V(b, o)$ represents the expected value from keeping the firm private. If this value is less than the expected value of taking the firm public through either an IPO ($V_{\text{IPO}}(b, o)$) or a SPAC merger ($V_{\text{SPAC}}(b, o)$), the firm will elect to go public. This decision-making process encapsulates the trade-offs and strategic considerations involved in determining the optimal path for the firm.

5 Model Solution and Predictions

The firm's earnings and posterior belief about its type fluctuate over time as earnings shocks arrive. The firm goes public as soon as the earnings and the posterior belief surpass an endogenous threshold, which depends on all model parameters. Additionally, the thresholds for IPO and SPAC can differ.

To analyze the firm's optimal decisions for going public, I solve the model numerically, using the parameters from Section 6. Figure 4 plots the pairs of probability belief (π_t) and the firm's earnings (B_t) for which the firm optimally decides to stay private, go public through a SPAC, or go public through an IPO.

Firms go public through SPACs when B_t and π_t lie within the "entry region" in the middle green area, and go public through IPOs when B_t and π_t lie within the entry region in the northeast orange area. If the firm is endowed with a project where B_t and π_t fall within either of the two entry regions, the firm goes public immediately through the respective method. Otherwise, the firm stays private until it matures and goes public as soon as either of the two entry boundaries is reached. If neither of the two boundaries is reached before the patent expires, the firm never goes public.

First, consider the trade-off between staying private and going public. From the entrepreneur's point of view, a successful going-public process allows the entrepreneur to cash

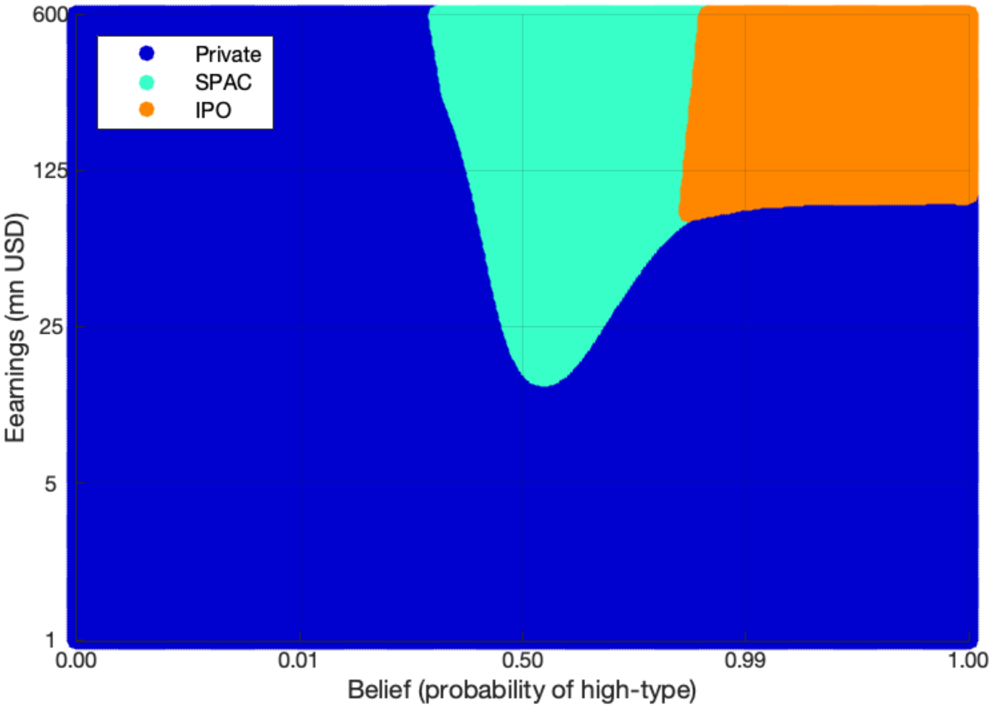


Figure 4: Going Public Decision

This figure plots the firm's optimal decision: the set of pairs of probability belief (horizontal axis) and earnings (vertical axis) that is optimal for the firm to stay private (blue), go public through a SPAC merger (green), and go public through an IPO (orange).

out by selling the firm to the investor. Using the money raised, the firm scales up by a factor of K. Additionally, the firm's posterior belief increases. Both factors enhance the firm's post-public equity value. After the purchase, the investor receives the firm's future cash flows. Thus, the starting point of a successful public sale is that the firm's posterior NPV needs to be positive, given a positive public signal. Otherwise, the investor will not be willing to make the purchase. The firm's posterior NPV is calculated as follows:

$$\text{Firm's posterior NPV}|_{s=H} = V_{\text{Post}}(b + k\Delta b, o + f_{\text{SPAC/IPO}}) - Ke^{b}.$$

In Appendix A.2.3, I show that the firm's posterior value is scalable in the firm's earnings

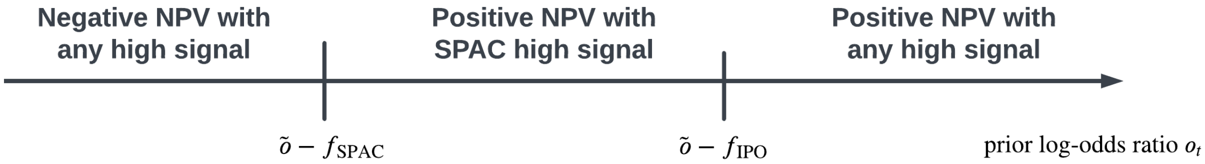


Figure 5: Evaluation Result Given a Positive Signal

This figure plots the evaluation result given a positive signal from the public investor based on the firm's prior belief. $\tilde{o}$ is the threshold log-odds ratio that makes the firm's posterior project with zero NPV. f_{IPO} is the amount of increase in the firm's log-odds ratio with a positive IPO signal, and f_{SPAC} is the amount of increase in the firm's log-odds ratio with a positive SPAC signal.

level, i.e., $V_{\text{Post}}(b, o) = e^b \tilde{V}_{\text{Post}}$. This allows us to rewrite the equation above as:

$$\text{Firm's posterior NPV}|_{s=H} = Ke^b(\tilde{V}_{\text{Post}}(o + f_{\text{SPAC/IPO}}) - 1).$$

For a private firm to have a positive NPV after the public sale, the condition $\tilde{V}_{\text{Post}}(o + f_{\text{SPAC/IPO}}) \geq 1$ must be satisfied. There exists a threshold log-odds ratio, $\tilde{o}$, such that $\tilde{V}_{\text{Post}}(\tilde{o}) = 1$. Since $\tilde{V}_{\text{Post}}(o)$ is an increasing function in o, we derive the following lemma:

Lemma 3 (Posterior increase with high signal)**.** *Private firms can be classified based on their prior beliefs and the resulting evaluations:*

1. *Private firms with a prior belief below $\tilde{o} - f_{SPAC}$ will be evaluated as negative NPV projects with any positive signal from public investors.*

2. *Private firms with a prior belief within $(\tilde{o} - f_{SPAC}, \tilde{o} - f_{IPO})$ will be evaluated as positive NPV projects upon receiving a positive signal from SPAC investors but as negative NPV projects upon receiving a positive signal from IPO investors.*

3. *Private firms with a prior belief above $\tilde{o} - f_{IPO}$ will be evaluated as positive NPV projects upon receiving either a positive SPAC or IPO signal.*

Figure 5 visualizes the evaluation results illustrated in Lemma 3. This lemma predicts a firm's optimal decision based on its prior belief:

Lemma 3, point 1 states that firms that are currently most likely a low-type will be evaluated as negative NPV projects even with positive signals from public investors. For such firms, the investor will not be willing to make the purchase, and thus in equilibrium, these firms stay private.

Lemma 3, point 2 states that firms with a prior belief in the middle range face the highest uncertainty regarding their true type. For these firms, a high signal from a SPAC investor will result in a positive NPV evaluation, but a high signal from an IPO investor will still yield a negative NPV evaluation. These firms benefit the most from a more precise signal from SPAC investors; without SPAC, they would not have the opportunity to access the public market.

Lemma 3, point 2 states that firms with a high prior belief will be evaluated as positive NPV projects with either a SPAC or an IPO high signal. These firms are less inclined to pay extra costs for a SPAC in exchange for a more precise signal and will likely choose to go public through an IPO if possible.

The solution in Figure 4 aligns with Lemma 3's predictions. In equilibrium, firms with low prior belief remain private (left blue region). Firms facing the highest uncertainty choose to access the public market through SPAC (middle green region around the prior belief of 0.5). Firms with high prior belief opt to go public through IPO (northeast orange region).

Lemma 3 represents the first-best scenario: positive NPV projects go public and scale up, while negative NPV projects stay private. However, the firm's ultimate decision to go public also depends on the relative cost of going IPO and SPAC. Specifically, the cost comes from the investor's effort to evaluate the firm. With this evaluation cost, some positive NPV firms may still choose to stay private if the benefit of scaling up is relatively small after compensating the investor by leaving a lot of money on the table.

The benefit of going public lies in the scaling-up effect: using the money raised in the public offering, the firm reinvests part of the money back into production and scales up the

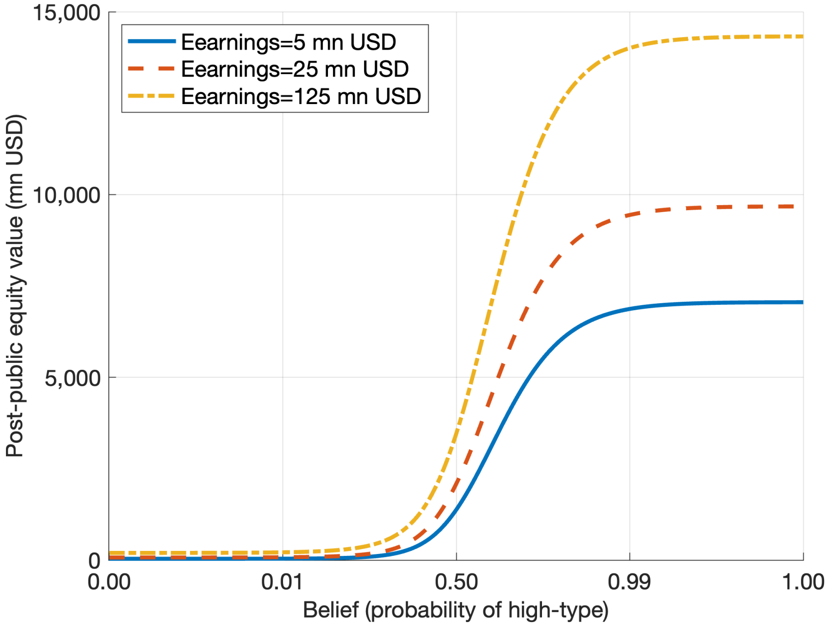


Figure 6: Post-Public Equity Value

This figure plots the firm's post-public equity value as a function of the firm's belief, at three different earnings levels.

firm's production by a fixed factor K. Thus, this scaling-up effect is larger when the firm is larger in size, i.e., b_t is larger. If we fix the firm's prior belief at a constant level, as we increase the firm's earnings level, the firm's value of going public becomes larger, and eventually, it is optimal for the firm to access the public market. This aligns with the fact that small firms in equilibrium stay private, corresponding to the bottom blue regions in Figure 4.

Going public successfully not only scales up the firm's production but also increases the firm's posterior belief, both of which contribute to the firm's post-public valuation, as seen from $V_{\text{Post}}(b_t+k\Delta b, o_t+f_{\text{SPAC/IPO}}) = Ke^b\tilde{V}_{\text{Post}}(o_t+f_{\text{SPAC/IPO}})$. On the other hand, if the firm chooses to stay private, aside from the option value of going public in the future, the firm's valuation can be approximated by $V_{\text{Post}}(b_t, o_t) = e^b\tilde{V}_{\text{Post}}(o_t)$. Thus, the marginal benefit from going public versus staying private depends on both the firm's size and the increase in the firm's unit post-public value $\tilde{V}_{\text{Post}}$ with a positive SPAC or IPO signal.

Lemma 1 shows that firms facing the highest uncertainty regarding their type, i.e., firms with prior belief in the middle, experience the largest increase in their posterior beliefs in response to a positive signal. Correspondingly, the unit post-public equity value also increases the most when the firm's prior belief is in the middle. Consider the following dynamics: as a firm's prior belief increases from $\tilde{o} - f_{\text{SPAC}}$ in Figure 5, the uncertainty with respect to its type becomes larger, and the benefit from going public in terms of the increase in the firm's unit post-public value also becomes larger. Thus, it allows smaller firms to access the public market. This explains the negative slope of the entry boundary in the SPAC (green) area on the left in Figure 4. Now, if we keep increasing the firm's prior belief after a cutoff point, the benefit from the increase in the unit shrinks, resulting in the entry boundary requiring the firm to be larger in size. To better understand this point, Figure 6 plots the firm's post-public equity value at different values of size and belief, showing that the firm's post-public value has the sharpest increase around the middle area of belief.

In economic terms, firms with prior beliefs in the middle range face the highest uncertainty about their growth. The investor's signal will significantly decrease their uncertainty, resulting in the highest marginal benefit from the evaluation. Consequently, these firms are willing to access the public market at a smaller size, even when the scaling-up effect is smaller.

6 Estimation

I structurally estimate most of the parameters of my model using a simulated minimum distance estimator, discussed below. Before estimating the model, I set the value of the constant interest rate parameter r to 0.05, leading to a discount factor of 0.95. This value aligns with the typical annual discount factors observed among investors.

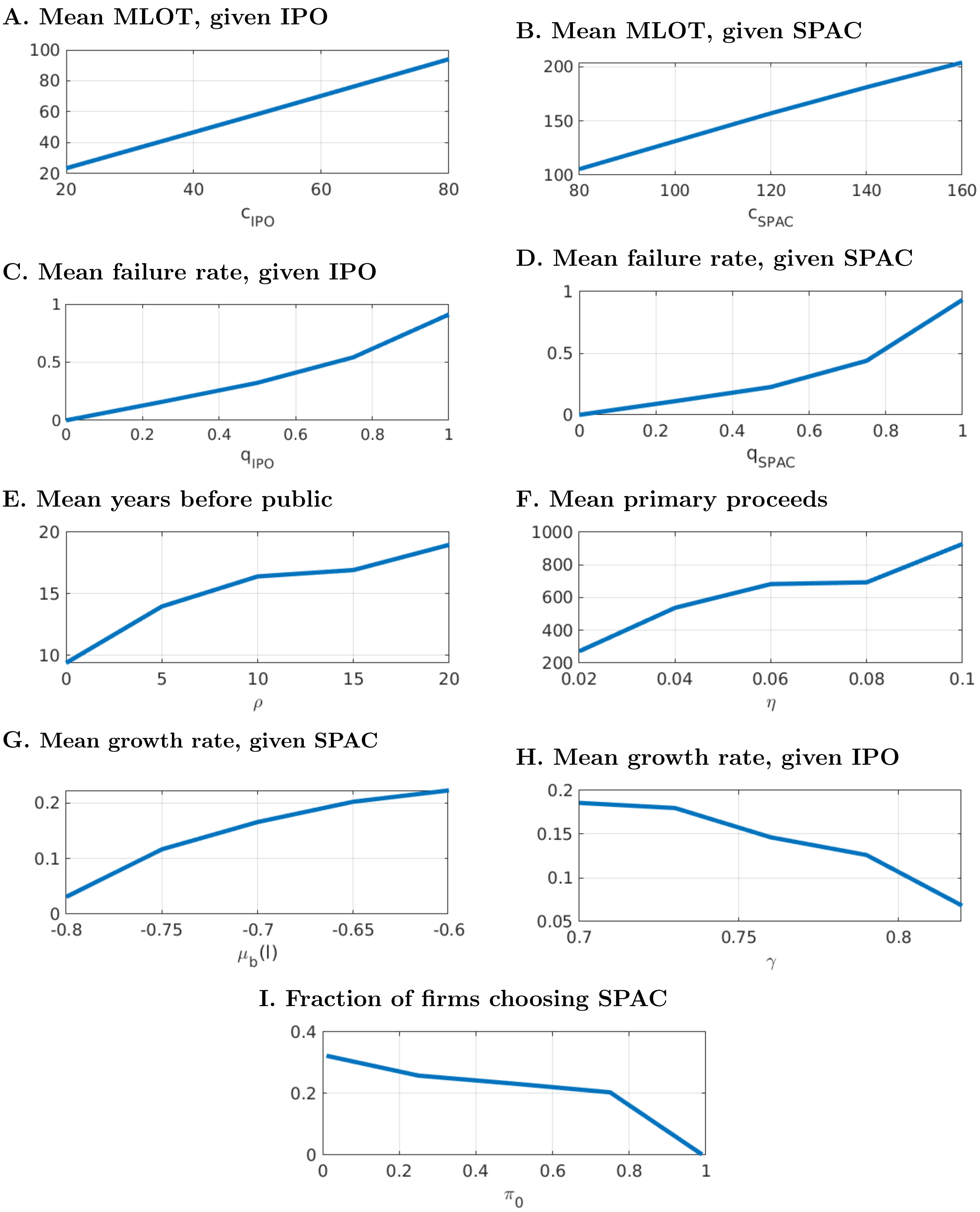
I also estimate several parameters separately. First, I estimate the firm's initial earnings level, B_0, using the firm's capital raised in its first financing. Next, I estimate the scaling factor K. By definition, K is the ratio of capital after and before the firm goes public. I use the firm's asset level after the going public process and the difference between the firm's asset level and the capital raised in the public process through issuing primary shares to estimate K. Lastly, I estimate the firm's volatility σ using the firm's stock return volatility after it went public. The underlying assumption is that the firm's volatility does not change before and after the going public process.

6.1 Identification

I estimate the remaining parameters (c_{IPO}, c_{SPAC}, q_{IPO}, q_{SPAC}, ρ, η, π_0, $\mu_b(l)$, γ) using a simulated minimum distance estimator. Similar estimation procedures are widely used (see Bazdresch, Kahn, and Whited (2018)). Given a set of parameters, I solve the model and use the solution to generate a simulated panel of firms with a comparable number of time periods but with many firms relative to my empirical sample (Michaelides and Ng (2000)). Next, I calculate a set of statistics, which are either moments or functions of moments. I then choose parameter estimates to minimize the distance between the model-generated statistics and their empirical counterparts. To gauge this distance, I use the inverse covariance matrix of the empirical moments. To minimize the econometric objective function, I use a global stochastic optimization routine.

To identify these parameters, I use 10 moment conditions, which I describe in detail below. While each of these moments is related to nearly all model parameters, some moments have strong monotonic relations with certain parameters and are thus particularly useful for identifying those parameters. To ascertain the strength of these relations, I perform a battery of comparative statistics exercises, which I then use to justify my moment choices. The most relevant of these exercises are shown in Figure 7.

The costs of generating signals for IPO (c_{IPO}) and SPAC (c_{SPAC}) investors are mainly identified by the average of the Money Left On the Table (MLOT) when firms go through the IPO and SPAC processes. The higher the cost of the signal-generating process, the more



A. Mean MLOT, given IPO

B. Mean MLOT, given SPAC

C. Mean failure rate, given IPO

D. Mean failure rate, given SPAC

E. Mean years before public

F. Mean primary proceeds

G. Mean growth rate, given SPAC

H. Mean growth rate, given IPO

I. Fraction of firms choosing SPAC

Figure 7: Comparative Statistics

Each panel of this figure plots the relation between a moment on the y-axis and a parameter on the x-axis.

the firm needs to compensate the public investors by leaving more money on the table.

The precisions of signals generated by the IPO (q_{IPO}) and SPAC (q_{SPAC}) investors are mainly identified by the failure rate of going IPO and SPAC. A more precise signal means that more low-type firms are successfully identified by the public signal. Thus, more firms that go public through SPAC will fail the process. In terms of going IPO, it means that more firms that filed an S-1 filing will eventually withdraw from IPO. In terms of going SPAC, it means that more firms that initially signed a contract with a sponsor will eventually terminate the merger process.

The arrival rate of going public opportunities, ρ, is mainly identified by the average time it takes for firms to go public. If going public opportunities arrive more frequently, then waiting for the next opportunity is less costly, thus the average time to go public becomes longer.

The arrival rate of patent expiration, η, measures the frequency at which the founder of the firm can cash out by taking the firm's current earnings. It is mainly identified by the average primary proceeds the firm gets from primary issuance. The intuition is as follows: by taking the firm public, the founder faces a trade-off. If it goes public, raises additional investment, and scales up by a factor of K, it must compensate investors by leaving a certain amount of money on the table today. η here plays the role of discounting the terminal earnings. For a fixed earnings level, the scaling-up effect is larger if the discount rate η is smaller. Thus, when η is larger, the founder understands that the continuation value increase by scaling up is smaller. As a result, the firm is less willing to go public unless the proceeds raised are large enough to make the scaling effect significant. Consequently, when η is larger, the average level of proceeds raised is larger.

The probability that a firm is a high-type firm at the time of founding, π_0, is mainly identified by the fraction of firms choosing SPAC over IPO. The third point of Lemma 1 shows that firms preferring SPACs on average have a lower prior belief than firms preferring

IPOs. If the initial belief is lower, firms have a higher chance of first hitting the boundary where the current belief indicates that the firm benefits most from SPACs. Conversely, if π_0 is higher, firms have a higher chance of hitting the boundary where the current belief is high enough that IPO benefits the firm most. Hence, a higher π_0 predicts that more firms will choose IPO over SPAC.

The average growth rate of low-type firms, $\mu_b(l)$, is mainly identified by the average growth rate of firms that remained private. Firms that choose to remain private on average have lower beliefs when they go public and thus contain more low-type firms compared to those that choose to go public. For the same reason, the difference in growth rates for high-type and low-type firms, γ, is mainly identified by the average growth rate of firms that chose to go IPO.

In addition to the above moments, I also include the average post-public equity value as an additional moment.

6.2 Estimation Results

The baseline estimation results are presented in Table 3. Panel A shows the actual data moments, model-simulated moments, and the t-statistics for each paired moment's equality. There is no significant difference between the empirical and simulated values for the 10 moments the model addresses, indicating a good model fit.

In Panel B, the parameter estimates reveal the following: The estimated $\mu_b(l) \approx -0.69$ suggests that low-type firms have a poor average growth rate. This highlights the importance of scaling decisions for private firms. The estimated γ indicates a 4.5% annual average growth rate for high-type firms, aligning with the growth observed during economic booms as in Opp (2019).

The results include two Poisson rates. First, η is estimated at 0.048, implying that patents expire approximately every 20 years, consistent with the rate in Pástor and Veronesi

Table 3
Estimation Results

A. Moments

	Data moments	Simulated moments	t-stat
Fraction of firms choosing SPAC	0.292	0.264	-0.40
Failure rate of SPAC	0.166	0.168	0.98
Failure rate of IPO	0.106	0.092	-0.61
Time to going public	17.860	16.991	-0.50
Mean post-public equity value	2,118.400	2,006.800	-0.67
Mean MLOT for SPAC firms	154.780	157.990	1.53
Mean MLOT for IPO firms	56.667	56.456	-1.62
Mean proceeds from primary share selling	240.500	242.31	1.75
Mean growth rate for SPAC firms	0.147	0.157	1.01
Mean growth rate for IPO firms	0.188	0.183	-0.84

B. Parameter estimates

$\mu_b(l)$	γ	η	ρ	q_{IPO}	q_{SPAC}	c_{IPO}	c_{SPAC}	π_0
-0.686	0.731	0.048	15.864	0.167	0.293	51.717	121.475	0.083
(0.023)	(0.024)	(0.000)	(0.535)	(0.001)	(0.000)	(0.444)	(1.666)	(0.007)

The estimation is done with a simulated minimum distance estimator, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data. Panel A reports the simulated and actual moments and the t-statistics for the differences between the corresponding moments. Panel B reports the estimated structural parameters with standard errors in parentheses.

(2005). The second Poisson rate relates to the frequency of going public opportunities, with the estimated $\rho \approx 16$, suggesting frequent openings in the going public window.

IPO investors detect low-type firms with an accuracy of about 0.16, while SPAC investors have an accuracy of about 0.29. This represents a 75% increase in the precision of the SPAC investor's signal compared to the IPO investor's signal.

The model's estimates show that at the point of going public, the prior belief for IPO firms is approximately 0.90, indicating a 90% probability of being a high-growth firm. This belief marginally increases to 0.91 following positive evaluations by the IPO investor, leading to a 4.1% raise in the firm's valuation, or \$83 million. In return, the firm leaves the IPO investor \$56 million, of which 93% (\$52 million) covers the investor's actual cost, and the remaining amount is a risk markup. In contrast, SPAC investor evaluations play a more substantial role: firms opting for SPAC mergers have a lower prior belief of 0.72 at the time of going public. This belief elevates to 0.78 after receiving positive evaluations, increasing the firm's equity value by 34.3%, or \$539 million. In return, the firm leaves \$158 million to investors, of which 76% covers the investor's actual cost, and the remaining amount is a risk markup.

Finally, the estimated $\pi_0 \approx 0.08$ shows that firm success rates at inception are below 10%, aligning with typical startup trajectories. Firms often remain private initially, building earnings and investor confidence before entering the market.

7 Policy Implications

Using the model estimates, I examine the implications of the SEC's newly adopted rule excluding SPAC mergers from the safe harbor provision. This new rule removes the option for private firms to go public via SPAC mergers, as these do not yield more accurate information despite higher costs compared to an IPO. Consequently, firms may generally suffer due to the loss of the SPAC merger option.

To understand the impact on firms at different stages, I compare their option values under the counterfactual policy and the current one. I first solve the model in a counterfactual scenario where the SPAC investor's signal matches the precision of an IPO investor's signal. I calculate the percentage decrease in value as follows:

$$\text{Decrease in value (\%)} = \frac{V^{actual} - V^{counterfactual}}{V^{actual}} \times 100\%,$$

where V^{actual} is the entrepreneur's actual value function, and $V^{counterfactual}$ reflects the value under the new rule.

Figure 8 plots the percentage decrease in option value under the new rule compared to the current rule for firms that stay private, merge through a SPAC, or go public via an IPO. The left panel, with fixed earnings of \$25 million, shows that under the new regulation,

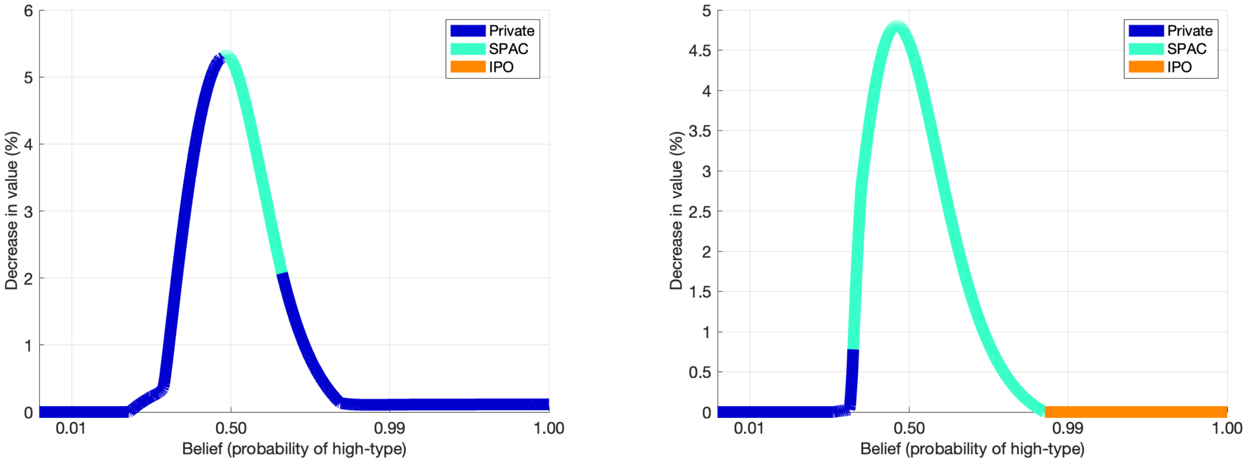


Figure 8: Decrease in Entrepreneur's Option Value Under New Regulation

This figure plots the expected loss of the entrepreneur's value under the new regulation. The left panel fixes earnings at 25 million dollars, and the right panel fixes the earnings at 125 million dollars.

entrepreneurs experience up to a 5.3% loss in option value. Notably, even those opting to stay private encounter a decrease because they lose the opportunity for a SPAC merger. The right panel, with earnings fixed at $125 million, reveals a similar pattern of loss, up to 4.8%. However, the impact on private firms is less pronounced here, likely because the IPO becomes a more feasible alternative at this earnings level. Firms choosing IPOs are unaffected.

Further, I calculate the total option value loss for 409,509 firms that remained private during my sample period. First, I estimate the loss in option value under the new SEC rule for each firm. To get a proxy for the firm's current belief value, I simulate a private firm of the same size and record its log-odds ratio. I then calculate the difference in value functions for each firm under the current and new SEC rules. Aggregating these differences, I find that the total option value loss for private firms is \$335.81 billion, meaning each private firm, on average, suffers a loss of \$0.82 million, which equals 30.73% of the firm's current size.

8 Conclusion

This paper develops a dynamic model to analyze the optimal choice between IPO and SPAC merger for firms going public, examines the model's predictions, and structurally estimates the model's parameters. In the model, entrepreneurs face uncertainty about the quality of their projects and can learn about their type through realized production outcomes or information produced during the IPO or SPAC merger process. The SPAC merger process produces more information because it is exempt from liability for making forward-looking statements under the current SEC rule, but it is also more costly due to its complexity.

The model predicts that firms with high uncertainty—those with prior beliefs in the middle range—favor SPAC mergers over IPOs as they aim to produce as much information as possible, even at a higher cost. A firm remains private when the prior belief is low, due to a lack of investor interest in evaluating it. A firm prefers an IPO when it is confident in being high-growth and faces low uncertainty, as it requires less precise evaluation.

The model generates simulated moments that closely match empirical data moments. According to the model's estimates, for firms opting for SPAC mergers, positive evaluation increases the firm's value by 34%, half of which comes from the additional information produced in the SPAC process compared to a traditional IPO process.

Using the model's parameter estimates, counterfactual analysis shows that the SEC's new rule excluding safe harbor for SPACs would eliminate half the benefits from SPAC mergers and decrease private firms' option value by an amount equal to 30% of their current earnings level.

This paper contributes to the policy debate on whether SPACs should allow firms to make forward-looking statements. Specifically, it focuses on the benefits arising from the potentially more precise information produced in the SPAC merger process and the option value loss after the introduction of the SEC's new regulation. Future work may consider adding a group of less sophisticated investors to address the SEC's concern that overly optimistic information conveyed in these forward-looking statements might mislead these investors.

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Appendices

A.1 Variable Definition

Table A1
Variables Definition

Variable	Definition
Panel A: Model Parameters	
π_0	Initial probability of high-quality firms
B_t	Firm earnings in year t
b_t	Firm-specific log-earnings in year t
o_t	Firm-specific log-odds ratio in year t
$\mu_b(h)$	Drift of b in high firm state ($\theta = h$)
$\mu_b(l)$	Drift of b in low firm state ($\theta = l$)
γ	Difference between $\mu_b(h)$ and $\mu_b(l)$
σ_b	Volatility of b
η	Arrival rate of patent expiration
ρ	Arrival rate of going-public opportunity
K	Scale of post-public earnings
k	Log scale of post-public earnings
c_{IPO}	Information production cost in IPO
c_{SPAC}	Information production cost in SPAC
q_{IPO}	Probability of detecting low type in IPO
q_{SPAC}	Probability of detecting low type in SPAC
r	Interest rate
Panel B: Empirical Variables	
first financing size	Transaction amount of the first financing event. Amounts in millions.
Healthcare	1 if the company operates in the healthcare industry and zero otherwise.
IT	1 if the company operates in the informational technology industry and zero otherwise.
VC reputation	The VC firm's proportion of total investment in the VC industry.
initial employee count	Count of employees that is first available.
industry HHI	The Herfindahl-Hirschman Index.

This table contains defitions of the variables, parameters, and empirical measures used most frequently thoughout the paper. The text contains more detailed defitions

A.2 Proofs

A.2.1 Martingale Condition of Public Investor's Signal

Here I verify the Martingale condition. At time t, the prior belief about the firm's type is $\Pr(\theta = h|\mathcal{F}_t) = \pi_t$. The Martingale condition is as follows,

$$\Pr(\theta = h|s = H, \mathcal{F}_t) \Pr(s = H) + \Pr(\theta = h|s = L, \mathcal{F}_t) \Pr(s = L) = \Pr(\theta = h|\mathcal{F}_t). \tag{A.1}$$

I can write out each term in the above equation as follows,

$$\begin{aligned}
&\text{Posterior blief with a high signal}\\
=&\Pr(\theta = h|s = H, \mathcal{F}_t)\\
=&\frac{\Pr(\theta = h, s = H|\mathcal{F}_t)}{\Pr(s = H)}\\
=&\frac{\Pr(s = H|\theta = h, \mathcal{F}_t) \Pr(\theta = h|\mathcal{F}_t)}{\Pr(s = H|\theta = h, \mathcal{F}_t) \Pr(\theta = h|\mathcal{F}_t) + \Pr(s = H|\theta = l, \mathcal{F}_t) \Pr(\theta = l|\mathcal{F}_t)}\\
=&\frac{1 \cdot \pi_t}{1 \cdot \pi_t + (1 - q)(1 - \pi_t)},
\end{aligned} \tag{A.2}$$

$$\begin{aligned}
&\text{Posterior blief with a low signal}\\
=&\Pr(\theta = h|s = L, \mathcal{F}_t)\\
=&\frac{\Pr(\theta = h, s = L|\mathcal{F}_t)}{\Pr(s = L)}\\
=&\frac{\Pr(s = L|\theta = h, \mathcal{F}_t) \Pr(\theta = h|\mathcal{F}_t)}{\Pr(s = L|\theta = h, \mathcal{F}_t) \Pr(\theta = h|\mathcal{F}_t) + \Pr(s = L|\theta = l, \mathcal{F}_t) \Pr(\theta = l|\mathcal{F}_t)}\\
=&0,
\end{aligned} \tag{A.3}$$

$$\begin{aligned}
&\text{Probability of generating a high signal}\\
=&\Pr(s = H)
\end{aligned}$$

$$
\begin{aligned}
&= \Pr(s = H|\theta = h, \mathcal{F}_t) \Pr(\theta = h|\mathcal{F}_t) + \Pr(s = H|\theta = l, \mathcal{F}_t) \Pr(\theta = l|\mathcal{F}_t) \\
&=1 \cdot \pi_t + (1-q)(1-\pi_t), \qquad \text{(A.4)}
\end{aligned}
$$

$$
\begin{aligned}
&\text{Probability of generating a low signal} \\
&= \Pr(s = L) \\
&= \Pr(s = L|\theta = h, \mathcal{F}_t) \Pr(\theta = h|\mathcal{F}_t) + \Pr(s = L|\theta = l, \mathcal{F}_t) \Pr(\theta = l|\mathcal{F}_t) \\
&=0 + q(1-\pi_t), \qquad \text{(A.5)}
\end{aligned}
$$

I can now verify the Martigale condition by calculating the LHS of equation (A.1),

$$
\begin{aligned}
&\Pr(\theta = h|s = H, \mathcal{F}_t) \Pr(s = H) + \Pr(\theta = h|s = L, \mathcal{F}_t) \Pr(s = L) \qquad \text{(A.6)} \\
&=\pi_t \qquad \text{(A.7)} \\
&= \Pr(\theta = h|\mathcal{F}_t) \qquad \text{(A.8)}
\end{aligned}
$$

A.2.2 Lemma 1

The increase in the posterior belief with a high signal can be represented as the difference in the posterior belief in Equation (A.2) and the prior belief π_t as follows,

$$
\begin{aligned}
&\text{Increase in posterior belief with a high signal} \qquad \text{(A.9)} \\
&= \Pr(\theta = h|s = H, \mathcal{F}_t) - \Pr(\theta = h|\mathcal{F}_t) \\
&=\frac{1 \cdot \pi_t}{1 \cdot \pi_t + (1-q)(1-\pi_t)} - \pi_t \qquad \text{(A.10)}
\end{aligned}
$$

It can be shown that the above equation is maximized at $\pi_t^* = \sqrt{\frac{1-q}{q}} - \frac{1-q}{q}$. Moreover, it can be show that π_t^* is decreasing in the signal's precision q, with $\pi_t^* = 0.5$ at $q = 0$, and $\pi_t^* = 0$ at $q = 1$.

A.2.3 Scalablility of HJB of Post-public Equity

Here we show that the HJB equation (13) scales with $B = e^b$. Conjecture that $V_{\text{Post}}(b, o) = e^b \tilde{V}_{\text{Post}}(o)$ and substitues it into equation (13):

$$\begin{aligned} 0 = & - re^b \tilde{V}_{\text{Post}}(o) + \eta(e^b - e^b \tilde{V}_{\text{Post}}(o)) \\ & + \mathbb{E}\left[\lambda_b^+ | o\right] \left[e^{b+\Delta_b} \tilde{V}_{\text{Post}}(o + f^+) - e^b \tilde{V}_{\text{Post}}(o)\right] \\ & + \mathbb{E}\left[\lambda_b^- | o\right] \left[e^{b-\Delta_b} \tilde{V}_{\text{Post}}(o - f^-) - e^b \tilde{V}_{\text{Post}}(o)\right]. \end{aligned} \tag{A.11}$$

Factor out e^b:

$$\begin{aligned} 0 = & e^b \Big(-r\tilde{V}_{\text{Post}}(o) + \eta(1 - \tilde{V}_{\text{Post}}(o)) \\ & + \mathbb{E}\left[\lambda_b^+ | o\right] \left[e^{\Delta_b} \tilde{V}_{\text{Post}}(o + f^+) - \tilde{V}_{\text{Post}}(o)\right] \\ & + \mathbb{E}\left[\lambda_b^- | o\right] \left[e^{-\Delta_b} \tilde{V}_{\text{Post}}(o - f^-) - \tilde{V}_{\text{Post}}(o)\right]\Big). \end{aligned} \tag{A.12}$$

Since e^b is never zero, we can divide both sides by e^b:

$$\begin{aligned} 0 = & - r\tilde{V}_{\text{Post}}(o) + \eta(1 - \tilde{V}_{\text{Post}}(o)) \\ & + \mathbb{E}\left[\lambda_b^+ | o\right] \left[e^{\Delta_b} \tilde{V}_{\text{Post}}(o + f^+) - \tilde{V}_{\text{Post}}(o)\right] \\ & + \mathbb{E}\left[\lambda_b^- | o\right] \left[e^{-\Delta_b} \tilde{V}_{\text{Post}}(o - f^-) - \tilde{V}_{\text{Post}}(o)\right]. \end{aligned} \tag{A.13}$$

The expression inside the parentheses is now a function of o only. We can multiply both sides by e^{kb} and get

$$\begin{aligned} 0 = & e^{kb} \Big(-r\tilde{V}_{\text{Post}}(o) + \eta(1 - \tilde{V}_{\text{Post}}(o)) \\ & + \mathbb{E}\left[\lambda_b^+ | o\right] \left[e^{\Delta_b} \tilde{V}(o + f^+) - \tilde{V}_{\text{Post}}(o)\right] \\ & + \mathbb{E}\left[\lambda_b^- | o\right] \left[e^{-\Delta_b} \tilde{V}_{\text{Post}}(o - f^-) - \tilde{V}_{\text{Post}}(o)\right]\Big). \end{aligned} \tag{A.14}$$

This indicates that $V_{\text{Post}}(kb, o)$ also solves the HJB equation.

A.2.4 Lemma 2

I first derive the Bayesian updating formula associated with the earnings shocks.

Restriction (3) implies the following equations:

$$\lambda_b = \lambda_b^+(h) + \lambda_b^-(h), \tag{A.15}$$

$$\lambda_b = \lambda_b^+(l) + \lambda_b^-(l), \tag{A.16}$$

Combining the above equations with the formulas for $\mu_b(\theta)$ and σ_b provided in equations (4) and (5), we can express Poisson intensities as follows

$$\begin{aligned}
\lambda_b^+(h) =& \frac{\sigma_b^2}{2\Delta_b^2}\left(1 + \Delta_b \frac{\mu_b(h)}{\sigma_b^2}\right) \\
\lambda_b^+(l) =& \frac{\sigma_b^2}{2\Delta_b^2}\left(1 + \Delta_b \frac{\mu_b(l)}{\sigma_b^2}\right) \\
\lambda_b^-(h) =& \frac{\sigma_b^2}{2\Delta_b^2}\left(1 - \Delta_b \frac{\mu_b(h)}{\sigma_b^2}\right) \\
\lambda_b^-(l) =& \frac{\sigma_b^2}{2\Delta_b^2}\left(1 - \Delta_b \frac{\mu_b(l)}{\sigma_b^2}\right)
\end{aligned}$$

By definition, Bayes factors associated with positive and negative innovations are given by

$$e^{f^+} \equiv \frac{\lambda_b^+(h)}{\lambda_b^+(l)} = \frac{1 + \Delta_b \frac{\mu_b(h)}{\sigma_b^2}}{1 + \Delta_b \frac{\mu_b(l)}{\sigma_b^2}}, \tag{A.17}$$

$$e^{f^-} \equiv \frac{\lambda_b^-(h)}{\lambda_b^-(l)} = \frac{1 - \Delta_b \frac{\mu_b(h)}{\sigma_b^2}}{1 - \Delta_b \frac{\mu_b(l)}{\sigma_b^2}}. \tag{A.18}$$

Next, I examine the updating of the log-odds ratio with the incorporation of a signal generated by the public investor. The objective is to compute the log-odds ratio based on posterior probabilities. I start with calculating the posterior log-odds ratio when the generated signal is good:

$$
\begin{aligned}
&\log\left[\frac{\Pr(\theta=h|s=H,\mathcal{F}_t)}{\Pr(\theta=l|s=H,\mathcal{F}_t)}\right]\\
=&\log\left[\frac{\frac{1\cdot\pi_t}{1\cdot\pi_t+(1-q)(1-\pi_t)}}{1-\frac{1\cdot\pi_t}{1\cdot\pi_t+(1-q)(1-\pi_t)}}\right]\\
=&\log\left[\frac{\pi_t}{(1-q)(1-\pi_t)}\right]\\
=&\log\left[\frac{\pi_t}{1-\pi_t}\right]+\log\left[\frac{1}{1-q}\right]\\
=&o_t+\log\left[\frac{1}{1-q}\right]\\
\equiv&o_t+f \qquad\qquad ,
\end{aligned}
\tag{A.19}
$$

where

$$
\begin{aligned}
o_t &= \log\left[\frac{\Pr(\theta=h|\mathcal{F}_t)}{\Pr(\theta=l|\mathcal{F}_t)}\right]=\log\left[\frac{\pi_t}{1-\pi_t}\right],\\
f &\equiv \log\left[\frac{1}{1-q}\right].
\end{aligned}
$$

Subsequently, I compute the posterior log-odds ratio when the generated signal is bad:

$$
\begin{aligned}
&\log\left[\frac{\Pr(\theta=h|s=L,\mathcal{F}_t)}{\Pr(\theta=l|s=L,\mathcal{F}_t)}\right]\\
=&\log\left[\frac{0}{1-0}\right]\\
=&-\infty.
\end{aligned}
\tag{A.20}
$$

The above results reveal that when the public investor receives a good signal, the log-odds ratio increases by $f=\log\left[\frac{1}{1-q}\right]$. Conversely, when the public investor receives a bad signal, the log-odds ratio declines to $-\infty$.

A.3 Solution Alogorithm

A.3.1 Example of Solving HJB in Matrix Form

In this section, I give a simple example explaining how to solve a HJB. Consider the simpliest case with one state variable. The current state is s, and the next state can take two possible values, $s+f^+$ and $s-f^-$, with probabilities λ^+ and λ^-. we can write out the HJB function for each of the state variable.

$$rW(s) = \psi(s) + \lambda^+[W(s+f^+) - W(s)] + \lambda^-[W(s-f^-) - W(s)],$$

We assume the simpliest case that $f^+ = f^- = \Delta_s$, and s takes values of $\{0, \Delta_s, 2\Delta_s\}$. We can write out of a linear system of equations as follows,

$$\begin{aligned}
rW(0) &= \psi(0) + \lambda^+[W(\Delta_s) - W(0)] + \lambda^-[W(0) - W(0)],\\
rW(\Delta_s) &= \psi(\Delta_s) + \lambda^+[W(2\Delta_s) - W(\Delta_s)] + \lambda^-[W(0) - W(\Delta_s)],\\
rW(2\Delta_s) &= \psi(2\Delta_s) + \lambda^+[W(2\Delta_s) - W(2\Delta_s)] + \lambda^-[W(\Delta_s) - W(2\Delta_s)].
\end{aligned}$$

Now we can change notation and write the above system of equations in matrix form as

$$r\begin{bmatrix} W(0) \\ W(\Delta_s) \\ W(2\Delta_s) \end{bmatrix} = \begin{bmatrix} \psi(0) \\ \psi(\Delta_s) \\ \psi(2\Delta_s) \end{bmatrix} + \begin{bmatrix} \lambda_{0,0} & \lambda_{0,\Delta_s} & \lambda_{0,2\Delta_s} \\ \lambda_{\Delta_s,0} & \lambda_{\Delta_s,\Delta_s} & \lambda_{\Delta_s,2\Delta_s} \\ \lambda_{2\Delta_s,0} & \lambda_{2\Delta_s,\Delta_s} & \lambda_{2\Delta_s,2\Delta_s} \end{bmatrix} \begin{bmatrix} W(0) \\ W(\Delta_s) \\ W(2\Delta_s) \end{bmatrix}.$$

Filling in the transition rates, we have,

$$r\begin{bmatrix} W(0) \\ W(\Delta_s) \\ W(2\Delta_s) \end{bmatrix} = \begin{bmatrix} \psi(0) \\ \psi(\Delta_s) \\ \psi(2\Delta_s) \end{bmatrix} + \begin{bmatrix} -\lambda^+ & \lambda^+ & 0 \\ \lambda^- & -\lambda^+ - \lambda^- & \lambda^+ \\ 0 & \lambda^- & -\lambda^- \end{bmatrix} \begin{bmatrix} W(0) \\ W(\Delta_s) \\ W(2\Delta_s) \end{bmatrix}.$$

Now we can group the value functions together and put it on the right, and put the cash flows on the left, and rewrite as follows,

$$-\begin{bmatrix} \psi(0) \\ \psi(\Delta_s) \\ \psi(2\Delta_s) \end{bmatrix} = \begin{bmatrix} -r-\lambda^{+} & \lambda^{+} & 0 \\ \lambda^{-} & -r-\lambda^{+}-\lambda^{-} & \lambda^{+} \\ 0 & \lambda^{-} & -r-\lambda^{-} \end{bmatrix} \begin{bmatrix} W(0) \\ W(\Delta_s) \\ W(2\Delta_s) \end{bmatrix}.$$

Finally, using matrix inverting, we can solve for the value functions as

$$\begin{bmatrix} W(0) \\ W(\Delta_s) \\ W(2\Delta_s) \end{bmatrix} = \begin{bmatrix} -r-\lambda^{+} & \lambda^{+} & 0 \\ \lambda^{-} & -r-\lambda^{+}-\lambda^{-} & \lambda^{+} \\ 0 & \lambda^{-} & -r-\lambda^{-} \end{bmatrix}^{-1} \left(-\begin{bmatrix} \psi(0) \\ \psi(\Delta_s) \\ \psi(2\Delta_s) \end{bmatrix} \right).$$

Chaning notation, we have,

$$\mathbf{W} = \mathbf{Q}^{-1}\left(-\boldsymbol{\psi}\right)$$

Solution algorithm:

1. Define $\mathbf{Q}$ as an empty sparse matrix of size $n \times n$.
2. Populate the matrix $\mathbf{Q}$ with transitions and discount rates.
3. Compute the vector $\boldsymbol{\psi}$ given the state vector.
4. Compute $\mathbf{W}$ using matrix inversion.

A.4 Solving Post-Public Value Function

The system of HJB equations can be represented as follows:

$$0 = -\psi_1(b,o) - (\eta + r)W(b,o) + \Lambda\mathbf{W},$$

where Λ is an $n \times n$ transition matrix, and $\mathbf{W}$ is an $n \times 1$ vector of value function values, and where the local expected value at the expiration date is $\psi_1(b, o) = \eta e^b$.

We can further rewrite the system of HJB equations as follows:

$$-\boldsymbol{\psi}_1 = Q_1 \cdot \mathbf{W},$$

where Q_1 is a matrix that is equal to the transition matrix Λ except that it includes discounting by r and η on the disagonal. The value functions $\mathbf{W}$ solve the following linear system for any given set of state vectors:

$$\mathbf{W} = Q_1^{-1} \cdot (-\boldsymbol{\psi}_1) \tag{A.21}$$

Solution algorithm:

1. Define Q_1 as an empty sparse matrix of size $n \times n$.
2. Populate the matrix Q_1 with exogenous transitions and discount rates.
    (a) For positive earnings shocks, map (b, o) to $(b + \Delta_b, o + f^+)$ using transition rates $\mathbb{E}\left[\lambda_b^+ | o\right] = \pi(o)\lambda_b^+(h) + (1 - \pi(o))\lambda_b^+(l)$, where $f^+ = \alpha^+\Delta_o$, and α^+ is a natural number by Assumption 1.
    (b) For negative earnings shocks, map (b, o) to $(b - \Delta_b, o - f^-)$ using transition rates $\mathbb{E}\left[\lambda_b^- | o\right] = \pi(o)\lambda_b^-(h) + (1 - \pi(o))\lambda_b^-(l)$, where $f^- = \alpha^-\Delta_o$, and α^- is a natural number by Assumption 1.
    (c) Add discounting rates r and η to the diagonal terms.
3. Compute the vector $\boldsymbol{\psi}_1$ given the state vector.
4. Compute $\mathbf{W}$ based on equation (A.21).

A.4.1 Solving Going-Public Value Function

The system of HJB equations can be represented as follows:

$$0 = -\psi_2(b,o) - (\rho + \eta + r)V(b,o) + \Lambda \mathbf{V},$$

where Λ is an $n \times n$ transition matrix, and $\mathbf{V}$ is an $n \times 1$ vector of value function values, and where the local expected value at the expiration date is $\psi_2(b,o) = \eta e^b + \rho V_{max}(b,o)$, where V_{max} is as follows,

$$V_{max}(b,o) = \max\{V_{Public}(b,o), V(b,o)\},$$

where

$$V_{Public}(b,o) = [\pi(o) + (1-q)\pi(o)]\left[p(b,o)(1-\alpha) - \left(e^{k\Delta_b} - 1\right)e^b\right] + [q(1-\pi(o))]\,V(b,-\infty),$$

and where

$$p(b,o) = W(o+f, b+k\Delta_b) - \frac{c}{\pi(o) + (1-q)(1-\pi(o))}.$$

We can further rewrite the system of HJB equations as follows:

$$\boldsymbol{\psi}_2 = Q_2 \cdot \mathbf{V},$$

where Q_2 is a matrix that is equal to the transition matrix Λ except that it includes discounting by r, η, and ρ on the disagonal. The value functions $\mathbf{V}$ solve the following linear system for any given set of state vectors:

$$\mathbf{V} = Q_2^{-1} \cdot (-\boldsymbol{\psi}_2) \tag{A.22}$$

Solution algorithm:

1. Define Q_2 as an empty sparse matrix of size $n \times n$.
2. Populate the matrix Q_2 with exogenous transitions and discount rates.
   (a) For positive earnings shocks, map (b, o) to $(b + \Delta_b, o + f^+)$ using transition rates $\mathbb{E}\left[\lambda_b^+ | o\right] = \pi(o)\lambda_b^+(h) + (1 - \pi(o))\lambda_b^+(l)$, where $f^+ = \alpha^+\Delta_o$, and α^+ is a natural number by Assumption 1.
   (b) For negative earnings shocks, map (b, o) to $(b - \Delta_b, o - f^-)$ using transition rates $\mathbb{E}\left[\lambda_b^- | o\right] = \pi(o)\lambda_b^-(h) + (1 - \pi(o))\lambda_b^-(l)$, where $f^- = \alpha^-\Delta_o$, and α^- is a natural number by Assumption 1.
   (c) Add discounting rates r, η, and ρ to the diagonal terms.
3. Compute the vector $\boldsymbol{\psi}_2$ given the state vector.
4. Compute $\mathbf{V}$ based on equation (A.22).

A.5 Robustness on Estimation Results

The baseline estimation method uses a sample of firms that attempted to go public. For robustness, this section incorporates an additional moment into the SMM estimation: the growth rate of firms that remained private during the sample period.

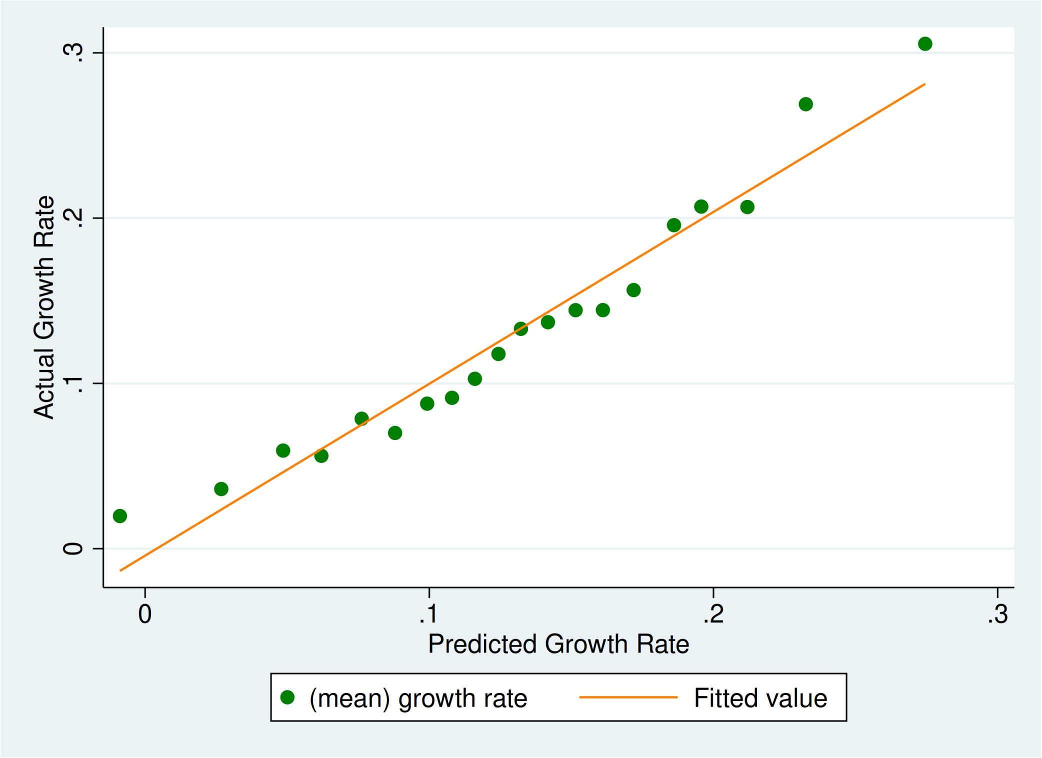

Figure A1: Fitness of Growth Rate Prediction

This figure plots the scatter-binned plot for the growth rate prediction regression using the public firms sample. The x-axis represents the predicted growth rate, and the y-axis represents the actual growth rate.

Private firms often lack comprehensive data on asset levels during their private phase, making it difficult to measure growth rates directly. To estimate private firms' growth rates, I first run a predictive regression on public firms' growth rates. Regressors include the firm's employee growth rate, growth rate of capital raised privately, number of years to obtain the first private financing, initial number of employees, and initial amount of capital, along with several fixed effects including founding year, primary industry, and first and current financing type. The regression has an R^2 of 0.70, indicating a good explanation of the variation in firms' growth rates in my sample. Figure A1 plots the actual growth rate against the predicted

Table A2
Estimation Results: Robustness

A. Moments

	Data moments	Simulated moments	*t*-stat
Fraction of firms choosing SPAC	0.292	0.283	-1.91
Failure rate of SPAC	0.166	0.153	-1.82
Failure rate of IPO	0.106	0.091	-1.72
Time to going public	17.860	16.555	-1.95
Mean post-public equity value	2118.400	2025.300	-1.81
Mean MLOT for SPAC firms	154.780	160.510	1.96
Mean MLOT for IPO firms	56.667	59.582	1.73
Mean proceeds from primary share selling	240.500	234.830	-2.17
Mean growth rate for SPAC firms	0.147	0.151	1.49
Mean growth rate for IPO firms	0.188	0.175	-1.80
Mean growth rate for private firms	-0.023	-0.023	-0.89

B. Parameter estimates

$\mu_b(l)$	γ	η	ρ	q_{IPO}	q_{SPAC}	c_{IPO}	c_{SPAC}	π_0
-0.678	0.723	0.040	19.39	0.134	0.251	53.075	139.319	0.120
(0.011)	(0.028)	(0.002)	(0.697)	(0.005)	(0.012)	(1.303)	(4.476)	(0.004)

The estimation is done with a simulated minimum distance estimator, which chooses structural model parameters by matching the moments from a simulated panel of firms to the corresponding moments from the data. Panel A reports the simulated and actual moments and the t-statistics for the differences between the corresponding moments. Panel B reports the estimated structural parameters with standard errors in parentheses.

growth rate in 20 equally split bins. Overall, the predicted growth rates align with the actual growth rates along a 45-degree line, indicating a good fit for the data.

I then use the estimated coefficients to predict the private firms' growth rates. I add the mean of the private firms' growth rates as an additional moment in the SMM estimation[13]. The estimation results are presented in Table A2. Panel A displays the actual data moments, model-simulated moments, and the t-statistics for each paired moment's equality. Compared to the baseline estimation, the t-statistics of the comparison between data moments and simulated moments are slightly larger but still show no significant discrepancies. The only exception is the mean proceeds from primary share selling, which is an additional moment that does not directly relate to the identification of the model's parameters. Over-

---

[13] In the estimation exercise, public firms and private firms start from the same point in the state variable space. To address the concern that the private firms may start at a less mature stage in the data, I employ propensity score matching and construct a sample of private firms with similar capital and founding dates to those in the public sample before calculating the moments.

all, it indicates a good model fit. Panel B lists the estimated parameter values, which are largely consistent with those from the baseline estimation, affirming the robustness of the parameters.