THE PRICE OF GOING PUBLIC

EXAMINING IPO UNDERPRICING AND INFORMATION ASYMMETRY DURING THE COVID-19 HOT ISSUE MARKET

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Abstract:

We examine the spike in IPO underpricing during COVID-19 from the perspective of traditional theories of adverse selection, which suggest that underpricing follows from uncertainty about the quality of firms going public. Using a sample of 1,026 U.S. IPOs from 2017 to 2022, we find little evidence of increased dispersion in firm quality during the pandemic. We also analyze certification mechanisms, such as underwriter reputation, and find that while it reduces underpricing, its effect does not intensify during the pandemic. Instead, significant underperformance in longer-term returns for IPOs issued during the pandemic suggests alternative explanations, such as investor sentiment, motivating future research to explore behavioral drivers of the pandemic IPO market.

Keywords:

IPO underpricing, information asymmetry, adverse selection, underwriter reputation, COVID-19, hot issue market

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I. Introduction

The COVID-19 pandemic period saw a substantial increase in IPO activity, with over 300 IPOs being completed on major U.S. exchanges in 2021, compared to slightly over 100 IPOs in 2019. The increase in activity was accompanied by the largest spike in IPO underpricing since the dot-com bubble in the late 1990s (Ritter, 2024). The combination of high IPO volume and underpricing is commonly referred to as a "hot issue market" in the literature (Ljungqvist, 2007). Although counterintuitive, firms seemingly decided to go public when it was the least likely for them to obtain full pricing. The economic magnitude is sizable, with aggregate money left on the table for U.S. IPOs exceeding $25 billion in both 2020 and 2021 (Ritter, 2024). Despite this, apart from a few select papers, the causes of the pandemic underpricing spike remain a largely unexplored topic (Zhang and Neupane, 2024; Panda and Deb, 2023; Baig and Chen, 2022).

There are several theories in the literature aimed at explaining the IPO underpricing phenomenon. These include asymmetric information models, institutional explanations, ownership control mechanisms, and behavioral explanations. Broadly speaking, most empirical evidence supports informational frictions having a first-order effect on underpricing (Ljungqvist, 2007). In this paper, we use U.S. IPO data from the years 2017-2022, and build on traditional information asymmetry explanations to address two research questions. First, we examine whether the pandemic underpricing spike can be attributed to an increase in adverse selection, resulting from higher dispersion in the quality of firms going public. Second, we examine whether certification mechanisms, such as underwriter reputation and VC backing, mitigate underpricing, and to what extent this relationship changed during the pandemic. Our findings suggest that while information asymmetry may play a role in underpricing, these theories are insufficient in explaining trend breaks like the pandemic underpricing spike.

Our theoretical framework originates from Rock (1986). Rock's model consists of informed investors, who have perfect information about the true value of IPOs, and uninformed investors, who cannot distinguish between undervalued and overvalued IPOs. Since informed investors only subscribe to undervalued IPOs, uninformed investors are "crowded out" and receive an over-allocation of overvalued IPOs. This adverse allocation of shares is commonly known as the "winner's curse" (Ljungqvist, 2007). In this framework, undervalued firms rely on underpricing to attract uninformed investors' capital. Ritter (1984) observes that adverse selection models, such as the winner's curse, can explain time-varying underpricing if the risk composition of firms going public changes across time. This is commonly referred to as the "changing risk composition hypothesis". Yung, Çolak, and Wang (2008) extend this hypothesis, building on the empirical evidence that IPO volume and underpricing tend

to be positively correlated. Their model suggests that a positive economic shock increases the NPV of firms' projects, allowing firms of lower quality to go public when valuations are high. As per Rock's (1986) model, dispersion in firm quality intensifies underpricing, as uninformed investors run the risk of more extreme losses and require greater compensation for participating in the IPO market.

Extending Yung, Çolak, and Wang (2008), we examine whether the increase in underpricing during the pandemic can be explained by low-quality firms going public in response to favorable market conditions, leading to increased adverse selection. We argue that this is particularly relevant in the context of COVID-19, which exhibited increased stock market activity following the initial economic shock, driven in part by low interest rates and the Federal Reserve's unprecedented fiscal support of $5.8 trillion (Clarida, Burcu, and Chiara, 2021). Using IPO returns as a proxy for quality, we examine the cross-sectional variance in first-day- and abnormal returns for firms that went public during the pandemic and compare them to firms that went public before and after the pandemic. Contrary to Yung, Çolak, and Wang (2008), we find weak support for increased dispersion in firm quality during COVID. Instead, we observe less dispersion and pronounced underperformance in longer-run abnormal returns of pandemic IPOs.

Further drawing on the adverse selection explanation of underpricing, we examine whether certification mechanisms mitigate underpricing, to further assess the presence of information asymmetry in IPO markets. Carter and Manaster (1990) show that reputable underwriters may reduce information asymmetry by certifying the quality of an IPO, based on the premise that reputable underwriters only underwrite high-quality firms. Similarly, external certification can be achieved through venture capital backing, as shown by Megginson and Weiss (1991). These certification hypotheses form the basis of our second research question. Our results indicate that while reputable underwriters mitigate underpricing, the effect was not amplified during the pandemic. We do not find a significant association between VC backing and underpricing. While these results provide some support for the presence of information frictions, they do not provide support for an increase in such frictions during the pandemic.

We provide a slightly different framework from the immediately related literature. Zhang and Neupane (2024), Panda and Deb (2023), and Baig and Chen (2022) also examine the pandemic hot issue market and find a significant association between the pandemic period and underpricing. These papers attribute this effect to the general volatility brought about by COVID-19 increasing informational frictions. Their reasoning builds on Beatty and Ritter (1986), who extend on Rock's model (1986), showing that ex ante uncertainty about firm values contributes to higher underpricing. However, as per Rock's model, higher uncertainty should only imply higher underpricing if uncertainty increases disproportionally for the uninformed party (Yung, Çolak, and Wang 2008). We propose that this may not be the case for

a systematic shock like the pandemic. Therefore, we do not attempt to link the increase in underpricing to COVID-19 per se, but rather to the economic activity that occurred during this period.

Helwege and Liang (2004) analyze IPO characteristics and performance during hot and cold markets. Consistent with our findings, they report no significant changes in firm characteristics during hot markets, instead observing long-run underperformance of hot market IPOs. Contrary to our paper, the authors focus on observable risk factors, such as firm age and industry. As Yung, Çolak, and Wang (2008) suggest, from an information asymmetry perspective, such observable factors influence underpricing only when they are associated with a higher degree of private information. Our results extend the findings of Helwege and Liang (2004) by confirming similar patterns through a framework that does not rely on observable factors which may not be an adequate proxy for private information. Building on these insights, Ljungqvist, Nanda, and Singh (2006) provide an important related contribution. Consistent with Helwege and Liang (2004) and our findings, the authors develop a behavioral model that explains how investor sentiment can drive underpricing, overvaluation, and subsequent underperformance. In their framework, firms capitalize on investor sentiment, with underpricing serving as compensation to institutional investors who hold overvalued shares and sell them off gradually, bearing the risk that exuberant demand may diminish.

Our paper contributes to the IPO literature by revisiting established theories of underpricing and applying them to a new economic context. Specifically, we add to the literature that documents the changing risk composition of firms as an explanation for underpricing (Yung, Çolak, and Wang, 2008; Helwege and Liang, 2004; Ritter, 1984) and the effect of certification mechanisms in mitigating underpricing (Carter and Manaster, 1990; Megginson and Weiss, 1991). We provide a possible explanation for the increase in underpricing during the pandemic from the perspective of information frictions, but find insufficient evidence to support this being the main cause. Lastly, our results indicate a systematic mispricing that is inconsistent with the theories underpinning this paper. Our findings motivates future research to explore the pandemic hot issue market through behavioral perspectives, such as investor sentiment (Ljungqvist, Nanda, and Singh, 2006; Helwege and Liang, 2004).

II. Theoretical Background

We present a simplified model to reflect the core insights of Yung, Çolak, and Wang (2008) and Rock (1986), serving as our theoretical background. In this model, firms are defined by their privately known quality, q, which represents the ability to realize economic opportunities. For simplicity, firm quality is assumed to be uniformly distributed on $[0, 1]$. Firms

decide to go public when the net present value (NPV) of doing so is non-negative. The NPV is defined as $V = qX - K$, where X is the value of economic opportunities once public, and K is the fixed cost of going public. Therefore, the threshold quality of firms entering the IPO market is defined as:

$$q_{\min} = \frac{K}{X}$$

The first implication of the model is that a positive shock to the economy increases X, lowering $q_{\min}$, causing firms of lower quality to enter the market. Irrespective of market conditions, the expected value of firms in the IPO market is equivalent to the pooling price, defined by the average quality:

$$P_{\text{pool}} = E[q] \cdot X - K = \left(\frac{q_{\min} + 1}{2}\right) X - K$$

Informed investors subscribe exclusively to IPOs that are NPV positive with $V > P_{\text{pool}}$. Uninformed investors cannot distinguish between different firm types and are crowded out, leaving them primarily with NPV negative IPOs and a fraction, α, of NPV positive IPOs. This is the core proposition of Rock's (1986) winner's curse. NPV positive firms, which rely on uninformed investors' participation, must set their price such that the uninformed investors' expected return is zero:

$$E[P_{\text{offer}}] = \frac{1}{2}\left(E[V_{\text{bad}}] + \alpha \cdot E[V_{\text{good}}]\right) \quad [1]$$

A second implication of the model is that for any $q_{\min} < 1$, IPOs are *underpriced in expectation*, as the expected offer price is strictly less than the expected pooling price ($E[P_{\text{offer}}] < E[P_{\text{pool}}] = E[V]$). As $q_{\min}$ decreases, the variance in firm quality increases. Since $V = qX - K$, the variance in valuations is defined as:

$$\text{Var}(V) = X^2 \cdot \text{Var}(q) = \frac{X^2(1 - q_{\min})^2}{12} \quad [2]$$

A third implication is that a positive economic shock, by decreasing $q_{\min}$, increases the dispersion in firm quality, which raises the mean and variance of underpricing. As dispersion in firm quality increases (i.e., $\text{Var}(q)$ rises), firms further from P_{pool} must lower P_{offer} to

[1] The expected offer price combines the expected value of bad firms ($q \leq E[q]$) and uninformed investors' allocation, α, of good firms ($q > E[q]$) such that:

$$E[P_{\text{offer}}] = \frac{1}{2}\left[\left(\frac{q_{\min} + E[q]}{2}\right) X - K + \alpha \cdot \left(\left(\frac{E[q] + 1}{2}\right) X - K\right)\right].$$

[2] The variance of a uniform distribution $U[a, b]$ is given by $\text{Var}(U) = \frac{(b-a)^2}{12}$.

maintain zero expected returns for uninformed investors. This adjustment widens the range of underpricing outcomes, increasing both its mean and variance. This is the core insight of Yung, Çolak, and Wang (2008). The fourth and final implication is that certification may reduce information asymmetry by conveying firm quality q of a particular firm, thereby lowering the need for underpricing for that firm. This follows from the general proposition of the certification hypothesis (Megginson and Wess, 1991; Carter and Manaster, 1990).

III. Data

A. Sample Selection

Our main data source is S&P Capital IQ, from which we obtain 1,150 IPOs from the period January 1st, 2017, to December 31st, 2022. Similar to Ljungqvist and Wilhelm (2003), we include the years leading up to our hot market period of interest to represent more typical market conditions, serving as a control period. Our sample is limited to firms listed on major U.S. exchanges, primarily Nasdaq and NYSE, which are the listing venues for approximately 75% of our sample IPOs. We further apply two additional filters to arrive at our initial sample. First, following Ljungqvist and Wilhelm (2003), we exclude firms with SIC codes 60-63 and 67, as these represent financial institutions with inherently different capital structures and regulatory environments. Second, we omit blank check companies, the majority of which are SPACs. While the exclusion of SPACs is not explicitly addressed in the prior literature (Carter and Manaster, 1990; Carter, Dark, and Singh, 1998; Ljungqvist and Wilhelm, 2003), we argue that excluding them is appropriate for our study. SPACs experienced record-breaking activity in 2021 and are inherently different in nature from regular IPOs in that they lack firm financials at the time of issuance (Gahng, Ritter, and Zhang, 2023). Although ADRs also differ somewhat from regular IPOs, we do not remove them from our sample. Chen, Fauver, and Yang (2009) find that firm- and offer characteristics, including underwriter reputation, have a significant influence on gross spreads for both ADR IPOs and US IPOs. These findings indicate different levels of perceived risk across ADRs from the perspective of the underwriter, making it reasonable to assume that variations in firm- and offer characteristics of ADRs also influence first-day returns, making them relevant for our research.

The firm-specific variables obtained from Capital IQ include the IPO date, year founded, primary sector, first-day return, 3-, 6-, and 12-month return, and gross offering amount. These also include firm financials at the date of issuance (total revenue, net income, total debt, total assets, and total common equity), as well as the names of the underwriters, their role, and compensation. From Capital IQ, we also obtain returns of the S&P sector

indices for each of the 11 primary sectors into which our IPOs are classified, which use to calculate abnormal returns. For the same purpose, we also gather the return on the S&P 500 index, and the 3-month U.S. treasury yield. Given that some IPOs in our sample have more than 20 underwriters, including several co-lead underwriters, we single out the three highest-compensated underwriters for each IPO. We argue that the highest-compensated underwriters are likely the most important to the issuance process and, therefore, provide the strongest signaling effect to investors. For all IPOs in our sample, the lead underwriter is amongst the top three highest compensated. Therefore, our approach mainly serves to extract the most important co-lead underwriters in the cases where there are several of these. To ensure the consistency and replicability of our results, we remove 31 IPOs with missing information about underwriter compensation.

We obtain data on VC-backing for each firm from a dataset provided to us by Professor Jay R. Ritter. The dataset includes U.S. IPOs dating back to 1975, with a dummy variable specifying whether each IPO is VC-backed. 46 IPOs in our initial sample are not included in Ritter's dataset. We note that these are not due to our inclusion of ADRs, as ADRs are also included in Ritter's data. For these IPOs, we manually fill in VC-backing from the respective S-1 prospectuses, which we retrieve from SEC's Edgar database. In these instances, we classify VC-backing as having an owner with above 5% ownership that explicitly identifies as a VC firm. Lastly, we exclude 57 IPOs due to missing data on first-day returns and 36 IPOs due to missing firm-level financial information. We attribute the majority of missing first-day returns to Capital IQ misclassifying seasoned equity offerings as IPOs, and the missing financial data to pre-revenue firms with balance sheets smaller than one million USD. Using a logistic regression, we confirm that neither missing return-data nor missing financial data is significantly associated with any particular year in our sample, minimizing the risk of bias. After these exclusions, our final sample consists of 1,026 IPOs.

B. Reputation Measures

We use two different measures to proxy underwriter reputation: one based on relative prestige as defined by Carter and Manaster (1990), and one based on market share like Megginson and Weiss (1991). The Carter-Manaster ranking is based on tombstone announcements (informational advertisements), which are published ahead of public offerings listing all underwriters. In short, the ranking is done by examining all tombstone announcements for a given period and assigning each underwriter an integer of zero to nine based on the order in which they are mentioned in the tombstones. Within the given period, firms with a rank of nine never have any firms ranked above them, and firms with a rank of zero never have any firms ranked below them. We use Ritter's updated Carter-Manaster ranking for the period 2018-2020 to align with our sample period. Our market share measure is derived from

Bloomberg's Capital Markets League Table, which lists the top U.S. IPO underwriters by market share for 2018, aligning with our sample period. Using a binary variable, we classify underwriters with a top ten market share as reputable and all others as non-reputable.

Our two measures are meant to capture two slightly different aspects of what could constitute an underwriter's reputation. The market share measure assumes an underwriter's deal volume increases either brand awareness or perceived skill and thus the value of its quality certification. The Carter-Manaster ranking is based on the underwriter's ability to defend its position within tombstone announcements, which in turn reflects its power and standing within the industry (Carter, Dark and Singh, 1998; Megginson and Weiss, 1991). These two measures together cover the most commonly used indicators of underwriter reputation in the extant literature.

IV. Methodology

A. Empirical Methodology

Our empirical analysis is designed to test whether the observed increase in IPO activity and underpricing during the pandemic is consistent with the theoretical model presented in Section II. The model predicts that the pandemic underpricing spike is directly related to the increase in IPO activity, driven by favorable market conditions that allowed low-quality firms to go public. Classical theory, first presented by Rock (1986) and extended by Yung, Çolak, and Wang (2008), indicates that an influx of low-quality firms increases information asymmetry and therefore underpricing. Therefore, we focus on two testable implications related to the pandemic hot market period: the dispersion of firm quality and the role of certification in mitigating information asymmetry and reducing underpricing. We structure the analysis in three stages. First, we define the pandemic hot market period based on IPO activity, splitting our sample into a hot and non-hot period. Second, we compare the dispersion in firm quality between these groups, using cross-sectional variance in return measures as a proxy. Third, we use OLS regression to examine the impact of potential certification mechanisms (underwriter reputation and VC backing) on underpricing. As the model suggests the value of certification increases with underpricing, we also add interaction terms to examine if the role of certification changed during the pandemic. In the following three subsections, we present the abovementioned stages of our methodology in further detail.

B. Hot Market Definition

To compare IPOs issued during the pandemic hot issue market with those issued under normal market conditions, we first define the start and end of these periods. Other papers examining underpricing in relation to the pandemic have defined their study periods to align

with the onset of COVID-19 (Zhang & Neupane, 2024; Baig and Chen, 2022). This approach is also used by Ljungqvist and Wilhelm (2003) when studying underpricing during the dot-com bubble. However, following Yung, Çolak, and Wang (2008), we instead define our hot market period by analyzing quarterly IPO activity. This is because we are not attempting to link the increase in underpricing during the pandemic to COVID-19 per se, but rather the increase in economic activity that occurred during this period (Clarida, Burcu and Chiara, 2021). This follows from our theoretical framework, which suggests that increased IPO activity, driven by increased supply of capital, encourages more "bad" firms to go public, thereby heightening adverse selection.

Yung, Çolak, and Wang (2008) calculate a four-quarter moving average and classify quarters with IPO activity exceeding 50% of this average as "hot". Given the much lower number of quarters in our sample, this approach would significantly underfit our hot market definition. Instead, we specify our hot market as the top 25% of quarters in terms of IPO activity. This results in a continuous hot market period from July 1st, 2020, to December 31st, 2021, which also represents the longest consecutive set of quarters exceeding the overall average quarterly IPO activity in our sample. This classification results in 474 IPOs during the hot period and 552 IPOs during the non-hot period. Figure 1 presents a bar chart illustrating quarterly IPO activity in our sample, a line representing the quarterly average first-day return, and our specified hot market period. Consistent with the rest of our analysis, we exclude outliers with a first-day return above 300% and below -50%.

As shown in Figure 1, high first-day returns are generally associated with high IPO activity, however, not without exceptions. These exceptions may be due to several factors influencing underpricing simultaneously (Ljungqvist, 2007). That being said, the average first-day return during our hot market period is 28.8% compared to 17.7% during the non-hot period. Additionally, using a Mann-Whitney test, we conclude that this difference is statistically significant at the 1% level. This indicates that in line with previous literature and our model, IPO activity is associated with higher first-day returns (Yung, Çolak, and Wang, 2008; Helwege and Liang, 2004; Ritter and Welch, 2002). Lastly, we attribute the spike in underpricing during the third quarter of 2022 to two marginal outliers which significantly influences the average, given that there were only 27 IPOs in this quarter. These two IPOs had an underpricing of 275% and 285% respectively.

C. Dispersion in Firm Quality

Following the framework of Rock (1986), and the cyclical extension by Yung, Çolak and Wang (2008), we examine whether the pandemic hot issue market is associated with an increase in dispersion of firm quality. To test this, we follow Yung, Çolak, and Wang (2008) and use cross-sectional return measures as a proxy for quality. Specifically, we examine 3-,

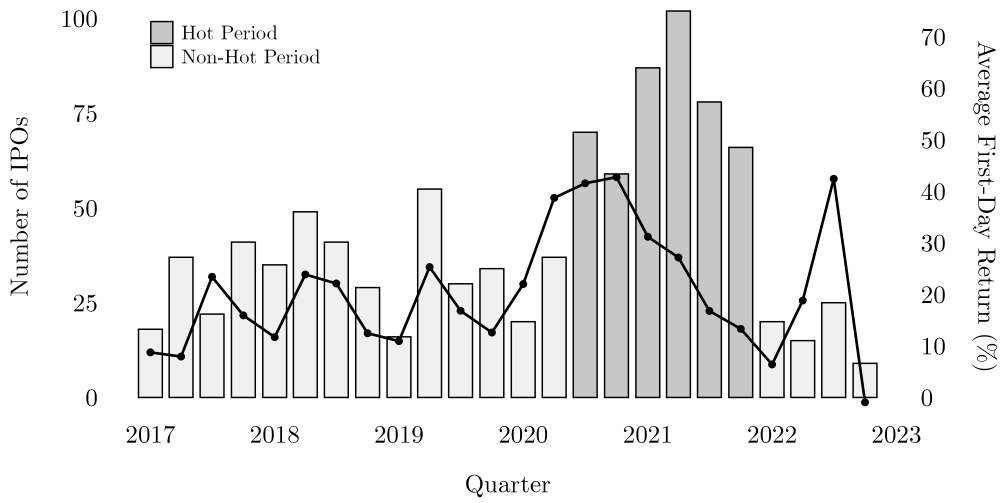

Figure 1. Quarterly Number of IPOs and Average First-Day Return (2017-2022). The combined bar and line chart shows the number of IPOs by quarter on major US exchanges during the years 2017-2022, average quarterly first-day return (%), and our specified hot market period. The hot market period is defined based on the top 25% of quarters in terms of IPO activity, which also represents the longest consecutive period exceeding the overall average number of IPOs.

6- and 12- month buy-and-hold abnormal returns of IPOs from our hot market period and compare them with IPOs from our normal period. Our chosen time frames are based on the assumptions that private information is gradually revealed in the months following the IPO, as lock-up periods end, and the firm releases its first earnings reports. In other words, the privately known firm quality is revealed over time and reflected in the medium- to long-run performance. As the threshold for going public decreases and low-quality firms enter the market, our model predicts increased variance of cross-sectional market-adjusted returns. To examine this, we follow Yung, Çolak and Wang (2008), and employ a simple market model in our baseline tests. Let R_{it} be firm i's stock return for day t, and let R_{mt} be the market return during the same period. We define firm i's buy-and-hold abnormal return (BHAR) across T periods as:

$$BHAR_{i,T}^{\text{Market}} = \prod_{t=1}^{T}(1 + R_{i,t}) - \prod_{t=1}^{T}(1 + R_{m,t}) \tag{1}$$

When measuring long-run returns in event studies it is common to also use a risk-adjusted model such as the Fama-French three-factor or Carhart four-factor model. This is generally difficult for IPO studies as there is no pre-event data on which to estimate factor betas. Yung, Çolak and Wang (2008), address this issue by estimating factor betas using the 5-year

post-IPO period and assume constant factor parameters throughout this time frame. This approach is not viable for our study. Due to the recency of our sample, our estimation period would overlap too much with the analysis period. Additionally, as shown by Neill, Perfect, and Wiles (1999), beta measures in the first months following a firm's IPO result in noisy estimates that are not representative of the long-run systematic risk. To improve the robustness of our results, we instead use a model that adjusts for sector returns, employing the respective S&P Global Industry Classification Standard indices of the eleven sectors into which our sample firms are classified. The COVID-19 pandemic had varying impacts on sector performance across different industries. For example, lockdown measures heightened the demand for information-technology firms, whereas the drop in fuel consumption lowered the demand for energy firms (Curto and Serrasqueiro, 2022). Therefore, to better account for industry-specific differences, we let $R_{s(i)t}$ be the sector return for firm i, and define firm i's sector-adjusted BHAR as:

$$BHAR_{i,T}^{\text{Sector}} = \prod_{t=1}^{T}(1 + R_{i,t}) - \prod_{t=1}^{T}\left(1 + R_{s(i),t}\right) \tag{2}$$

To further ensure a reliable estimate of how firm quality changed during the pandemic hot issue market, we extend Yung, Çolak and Wang's (2008) methodology and examine the distribution of first-day returns. Using first-day returns reduces the need for risk adjustment through an asset pricing model, as the impact of systematic factors over a single trading day is likely negligible compared to the realized idiosyncratic performance. First-day return, i.e. the percentage difference between the offer price and the first day closing price, is the most commonly used proxy for underpricing. This is because the extent of underpricing is quickly reflected in the stock price, especially in well-developed capital markets (Ljungqvist, 2007). In other words, the first-day return is primarily driven by the revelation of firm-specific information—however not to the same extent as in the months following the IPO. In our framework, first-day returns, or underpricing, compensate uninformed investors for facing adverse selection. This risk grows as more bad firms enter the market and the benefit of being informed increases. Since underpricing is dependent on firm quality, and our model predicts higher variance in firm quality, we examine whether the variance in first-day returns is higher in our pandemic hot market period.

Lastly, we use the same four non-parametric tests as Yung, Çolak and Wang (2008) to test for dispersion and composition differences in the return of IPOs from our hot and non-hot period. First, we use the Kolmogorov-Smirnov and Kuiper test to compare differences in overall distribution. Second, we use the Mann-Whitney U test to compare differences in median. Lastly, we use the Siegel-Tukey test for difference in variability between our two groups. The non-parametric characteristics of the tests are important, as we confirm, using

an Anderson-Darling test, that our data does not follow a normal distribution. The results from the Anderson-Darling tests are significant at the 1% level.

D. Underwriter and VC Certification

The certification hypothesis suggests that a positive signal about a firm's true value reduces the need for that firm to underprice. As per our model, such a signal reduces information asymmetry regarding the privately known quality of a firm, and thus the adverse selection problem faced by uninformed investors. The most commonly used quality signals in the literature are underwriter reputation and VC-backing. To examine the explanatory power of underwriter reputation and VC-backing on underpricing, we follow previous papers in the IPO literature and use ordinary least squares regression (Carter and Manaster, 1990; Carter, Dark, and Singh, 1998; Megginson and Weiss, 1991). Also following previous literature, we define underpricing as the first-day return (Ljungqvist, 2007). We regress these first day returns on our independent variables, underwriter reputation and VC-backing.

As previously mentioned, we use two measures for underwriter reputation. The first measure, based on the Carter-Manaster ranking, is treated as a discrete variable ranging from zero to nine. This approach aligns with the methodology used in prior research employing the same ranking system (Ljungqvist and Wilhelm, 2003; Carter, Dark and Singh, 1998; Carter and Manaster, 1990). As the majority of the IPOs in our sample have multiple underwriters, each IPO is assigned the highest rank of the top three underwriters by compensation. Again, we argue that the highest-compensated underwriters are likely the most important to the issuance process, and therefore their reputation has the greatest impact on underpricing. Our second measure, based on market share, is treated as a binary variable. This is a similar, but slightly simplified, approach to Megginson and Weiss (1991), who use relative market share as a continuous variable rather than a dichotomous one. Using a binary variable avoids noise from small variations in market share that are unlikely to be meaningful for this paper. Additionally, this approach allows us to make a broader distinction between reputable and non-reputable underwriters, complementing the Carter-Manaster ranking.

To control for firm-specific characteristics, we again follow previous literature and include variables such as age, sales, size of the offering, and leverage (Carter and Manaster, 1990; Carter, Dark, and Singh, 1998). We take the natural logarithm of all these variables except leverage to handle potential skewness and heteroscedasticity, and to make coefficients interpretable as percentage effects. To control for industry, we follow Ljungqvist and Wilhelm (2003) who include dummy variables for "high-tech" and "internet" companies. However, to better reflect the time period we are examining, we instead control for firms in the healthcare and technology sector, as the number of issuances in these industries increased during the pandemic and may be associated with higher uncertainty (Baig and Chen, 2022). Addition-

ally, like Ljungqvist and Wilhelm (2003), we include a dummy variable for our previously defined hot market period. Lastly, like Zhang and Neupane (2024), we use OLS with interaction terms, to explore the moderating effect of our hot market period on the effect of underwriter reputation and VC-backing. Building on our initial framework, we do not expect observable risk characteristics to influence underpricing unless they are associated with differing degrees of private information. In other words, investors are presumably more uninformed about a young healthcare company compared to a mature retail company.

V. Results and Analysis

A. Dispersion in Firm Quality

In this section, we test our hypothesis that dispersion in firm quality increased during the pandemic, using first-day return and medium- to long-run return measures as proxies for quality. Figure 2, with subfigures A–D, plots the return distributions for first-day returns (FDR) and 3-, 6-, and 12-month buy-and-hold abnormal returns (BHAR) for IPOs from our specified hot and non-hot periods. Table I presents the variance and median for each period and return horizon, along with our four non-parametric tests. These tests evaluate differences in overall distributions, variances, and medians between our hot period and non-hot period for each horizon. To maintain brevity, the BHAR measures presented here are calculated using sector-adjusted BHAR as defined in equation (2). We have included the same tests, using our market-adjusted BHAR as calculated in equation (1), in Table A.I of the appendix. Our results are robust to using the market-adjusted return measure and the exclusion of outliers.

Our analysis reveals three key findings. First, first-day returns during our pandemic hot market period exhibit higher variance than our non-hot period (0.193 vs. 0.155), consistent with our model and Yung, Çolak, and Wang (2008). As confirmed by the Siegel-Tukey test, this is significant at the 5% level. Second, for medium- to long-run returns (3-, 6-, and 12-month BHAR), the evidence is mixed. While 3- and 6-month variances are slightly higher for the hot period, these differences are not statistically significant. By contrast, 12-month BHAR shows significantly lower variance in the hot period (0.376 vs. 0.891). This is significant at the 1% level and indicates less dispersion in firm quality during the pandemic hot issue market. Lastly, the Kolmogorov-Smirnov and Kuiper tests confirm that return distributions differ significantly for our all horizons except 3-month BHAR. Figure 2 shows a pronounced right skew in 6-, and 12-month returns during the hot period. Additionally, the medians for 6- and 12-month BHAR are significantly lower for the hot period, with the Mann-Whitney test confirming statistical significance at the 1% level. This further diverges

Table I
Nonparametric Test Results for the Pandemic Hot Issue Market vs. Non-Hot Period Across Return Horizons

The table presents nonparametric test results comparing return distributions between our hot and non-hot period for each return horizon (FDR, and sector-adjusted BHAR horizons of 3, 6, and 12 months). It reports the variance and median of returns for each period and horizon. The Kolmogorov-Smirnov (K.Smir) and Kuiper tests examine differences in overall distributions, the Mann-Whitney test (M.Whit) assesses differences in medians, and the Siegel-Tukey test (S.Tuk) evaluates differences in variability.

	Variance		Median		Non-Parametric Tests			
	Hot	Non-Hot	Hot	Non-Hot	K.Smir	Kuiper	M.Whit	S.Tuk
FDR	0.193	0.155	0.174	0.09	0***	0.022**	0.001***	0.029**
3-Mo	0.473	0.397	-0.01	0.027	0.359	0.144	0.366	0.399
6-Mo	0.421	0.372	-0.205	-0.023	0***	0***	0***	0.687
12-Mo	0.376	0.891	-0.461	-0.127	0***	0***	0***	0***

Note: *p<0.1; **p<0.05; ***p<0.01

from our theoretical framework, which suggests higher expected returns in hot periods given rational investors and higher underpricing. According to our framework, underpricing sets the starting price below the intrinsic value, theoretically leading to higher subsequent returns as the market adjusts.

Our results contradict Yung, Çolak, and Wang (2008), who find consistent evidence of higher variance in all return measures across hot market periods. Therefore, we find insufficient support for the changing risk composition hypothesis as an explanation for the observed increase in underpricing during the pandemic. The consistently right-skewed distributions and significantly lower medians for our 6- and 12-month BHAR measures indicate that pandemic hot market IPOs underperformed compared to those from the non-hot period. The median 12-month BHAR is -46.1% for hot market IPOs, compared to -12.7% for non-hot market IPOs. The Mann-Whitney test confirms these results are significant at the 1% level. These findings are consistent with Helwege and Liang (2004), who find that IPOs from hot markets are associated with greater underperformance. They observe that hot market IPOs exhibit higher market-to-book ratios and lower operating performance, which they attribute to speculative overvaluation.

Ljungqvist, Nanda, and Singh (2006) provide a complementary theory which could explain the increase in underpricing during the pandemic from a behavioral perspective. The authors assert that, in a market with investor optimism, the optimal strategy from the is-

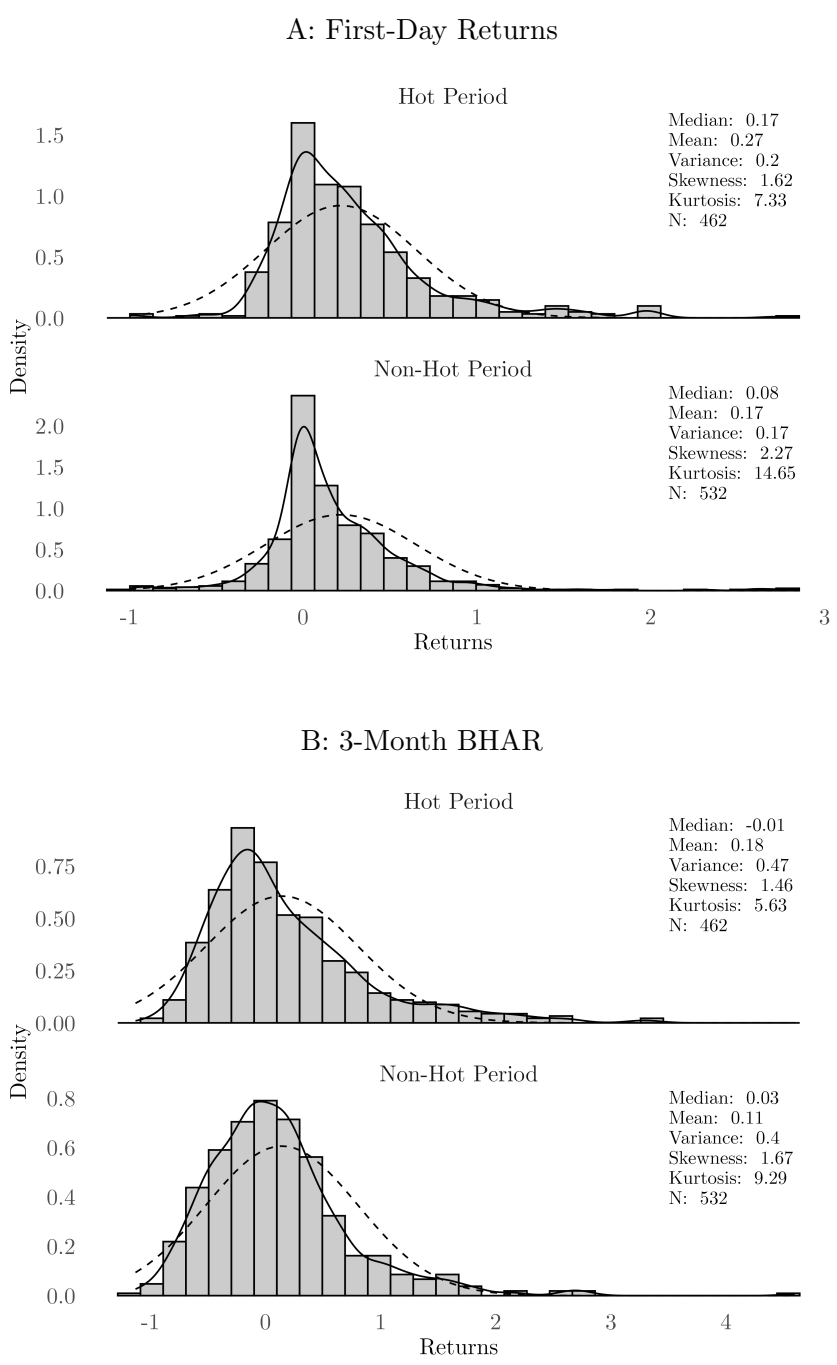

Figure 2. Return distributions for Hot Period and Non-Hot Period IPOs. Subfigure A plots the distribution of first-day returns (FDR) for the hot period and the non-hot period. Only here, we include outliers with FDR below -50% for visual purposes. Subfigure B plots the sector-adjusted BHAR distribution for the hot period and non-hot period over a 3-month holding period. The bars represent the distribution of the return data. The dotted line represents the fitted normal distribution whereas the solid line represents a non-parametric Kernel density plot. We display summary statistics next to each distribution, including median, mean, variance, skewness, kurtosis, and number of data points.

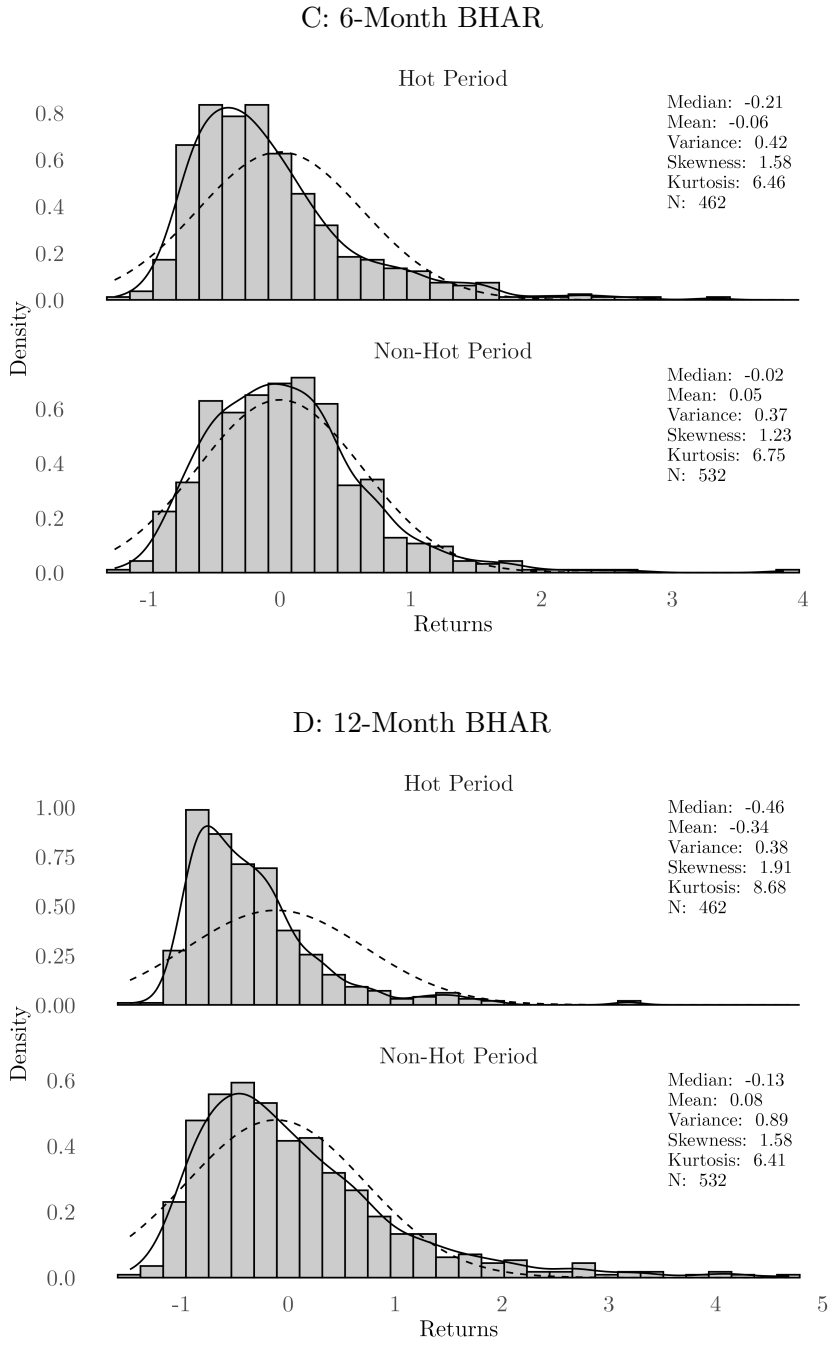

Figure 2. (Continued). Subfigure C plots the sector-adjusted BHAR distribution for the hot period and non-hot period over a 6-month holding period, and Subfigure D over a 12-month holding period. The bars represent the distribution of the return data. The dotted line represents the fitted normal distribution whereas the solid line represents a non-parametric Kernel density plot. We display summary statistics next to each distribution, including median, mean, variance, skewness, kurtosis, and number of data points.

suers point of view is to capture as much as possible of the surplus under the exuberant investors' demand curve. Under these assumptions, value to an issuer is maximized by going public when valuations are high and having underwriters allocate large amounts of stock to institutional investors that offload shares gradually as sentiment investors enter the market. From this perspective, the stylized fact of higher underpricing during hot issue markets can be described as the compensation to institutional investors for acquiring large allocations of shares while risking that sentiment demand may cease. Conclusively, our findings are more indicative of investor sentiment rather than the classical explanations based on information asymmetry.

B. Underwriter and VC Certification

In this section, we test our second hypothesis that certification mechanisms, such as underwriter reputation and VC backing, are negatively associated with underpricing—and whether this relationship changed during the pandemic. We start by testing the effect of underwriter reputation and VC backing on first-day returns and present the results in Table II. We find that underwriter reputation has a significant negative effect on first-day returns, with coefficients of -0.046 (Carter-Manaster ranking, significant at the 1% level) and -0.098 (market share ranking, significant at the 5% level). These results are consistent with the certification hypothesis and indicate the presence of information asymmetry in the IPO market, as shown by Carter and Manaster (1990). To put this into context, our results indicate that having a reputable underwriter, as defined by market share, results in 9.8 percentage points less underpricing on average. This implies an additional $28.7 million in proceeds for an average-sized offering in our sample.

VC backing has a positive, though statistically non-significant, effect on first-day returns. These results differ from Megginson and Weiss (1991) and indicate that either the presence of information asymmetry is less pronounced in our study period, or that the role of venture capital firms and the certification value they provide is more complex. A possible explanation for our findings is the grandstanding hypothesis, first proposed by Gompers (1996), which implies that venture capital firms have an incentive to build a track record of taking companies public to attract more capital and may therefore bear the cost of underpricing. Supporting this, Lee and Wahal (2004) find that future capital inflows into VC firms are positively related to both the number of IPOs they complete and the level of underpricing in those IPOs. This does not discredit the information asymmetry explanation for underpricing, but rather suggests that the role of VCs in underpricing has become more a matter of agency dynamics.

Next, we consider our control variables. The hot market variable is positively associated with first-day returns, consistently significant at the 5% level, again confirming higher un-

Table II
Cross-Sectional Regressions Showing the Effect of Underwriter Reputation and Venture Capital Backing on First-Day Returns

The dependent variable is the first-day return of 995 IPOs issued between January 1, 2017, and December 31, 2022. The OLS sample is slightly smaller than the finalized sample due to the removal of extreme values. First-day returns are regressed on two measures of underwriter reputation—Carter-Manaster ranking (Reputation1) and market share (Reputation2)—and a binary variable for VC-backing (VC). The models control for firm-specific variables such as the natural logarithm of sales (LNSALES), firm age (LNAGE), offering size (LNSIZE), and leverage (debt-to-assets ratio), as well as binary variables for high-risk industries (Healthcare, Technology) and the Covid-19 hot market period, defined based on IPO activity.

	Dependent variable: First Day Return (%)			
	Model 1	Model 2	Model 3	Model 4
Reputation	-0.046^{***}			-0.057^{***}
	(0.013)			(0.017)
Reputation2		-0.098^{**}		0.072
		(0.044)		(0.058)
Venture Capital			0.023	0.026
			(0.025)	(0.025)
Leverage	-0.024^{*}	-0.020^{*}	-0.018^{*}	-0.023^{*}
	(0.014)	(0.011)	(0.011)	(0.014)
Log Size	0.082^{***}	0.048^{***}	0.025^{*}	0.078^{***}
	(0.016)	(0.015)	(0.013)	(0.016)
Log Sales	-0.005	-0.007	-0.007	-0.004
	(0.008)	(0.008)	(0.008)	(0.008)
Log Age	-0.008	-0.009	-0.009	-0.007
	(0.015)	(0.015)	(0.015)	(0.015)
Healthcare	0.064	0.030	0.013	0.063
	(0.044)	(0.045)	(0.046)	(0.044)
Technology	0.077^{**}	0.070^{*}	0.064	0.076^{*}
	(0.039)	(0.039)	(0.039)	(0.039)
Hot Market	0.057^{**}	0.069^{**}	0.076^{***}	0.057^{**}
	(0.027)	(0.027)	(0.026)	(0.027)
Constant	0.173^{*}	0.073	0.111	0.211^{**}
	(0.091)	(0.079)	(0.084)	(0.105)
Observations	995	995	995	995
R^2	0.044	0.027	0.024	0.047
Adjusted R^2	0.037	0.020	0.016	0.037
Note:				*p<0.1; **p<0.05; ***p<0.01

Table III
Cross-Sectional Regressions Showing the Moderating Effect of the Hot Market on Certification Measures

The dependent variable is the first-day return of 995 IPOs issued between January 1, 2017, and December 31, 2022. First-day returns are regressed on two measures of underwriter reputation and a binary variable for VC-backing (VC). We include interaction terms between these certification measures and our hot market variable. These variables are centered to reduce multicollinearity. The models control for firm-specific variables such as the natural logarithm of sales (LNSALES), firm age (LNAGE), offering size (LNSIZE), and leverage (debt-to-assets ratio), as well as binary variables for high-risk industries (Healthcare, Technology) and the Covid-19 hot market period.

	Dependent variable: First Day Return (%)		
	Model 5	Model 6	Model 7
Reputation	−0.046***		
	(0.013)		
Reputation2		−0.097**	
		(0.044)	
Venture Capital			0.023
			(0.025)
Leverage	−0.024*	−0.021*	−0.018
	(0.014)	(0.011)	(0.011)
Log Size	0.082***	0.048***	0.025*
	(0.016)	(0.015)	(0.013)
Log Sales	−0.005	−0.007	−0.007
	(0.008)	(0.008)	(0.008)
Log Age	−0.008	−0.009	−0.009
	(0.015)	(0.015)	(0.014)
Healthcare	0.064	0.029	0.013
	(0.044)	(0.045)	(0.046)
Technology	0.076*	0.069*	0.064
	(0.039)	(0.040)	(0.039)
Hot Market	0.057**	0.068**	0.075***
	(0.027)	(0.027)	(0.026)
Reputation:Hot Market	0.004		
	(0.019)		
Reputation2:Hot Market		0.033	
		(0.077)	
VC:Hot Market			0.020
			(0.052)
Constant	−0.161**	0.031	0.154*
	(0.080)	(0.083)	(0.083)
Observations	995	995	995
R^2	0.044	0.028	0.024
Adjusted R^2	0.036	0.019	0.015
Note:			*p<0.1; **p<0.05; ***p<0.01

derpricing during the pandemic. Among firm-specific characteristics, technology firms show a significant positive association with first-day returns, with coefficients ranging from 0.070 in model 2 (significant at the 10% level and) to 0.077 in Model 1 (significant at the 5% level). Our theoretical framework suggests that observable firm characteristics affect underpricing if they are associated with a certain distribution of private information. For example, technology firms may be associated with higher uncertainty about firm quality (Ljungqvist and Wilhelm, 2003). Leverage is negatively associated with first-day returns, with coefficients of -0.018 (Model 3) to -0.024 (Model 1), significant at the 10% level in model 1 through 4. In line with our framework, leverage may reduce underpricing as highly levered firms are subject to more monitoring (Ghosh, 2007). Lastly, the size of the offering has a significant positive effect on first-day returns, with coefficients ranging from 0.025 (Model 3) to 0.082 (Model 1), significant at the 1% level in most models. This finding contrasts with previous literature, which typically associates larger offerings with reduced underpricing (Carter and Manaster, 1990; Carter, Dark, and Singh, 1998). As per Ljungqvist, Nanda, and Singh (2006), larger offerings require institutional investors to collectively hold more shares in inventory—increasing the overall risk.

To examine whether the impact of underwriter reputation and VC backing on underpricing changed during our hot market period, we include interaction terms between the hot market variable and underwriter reputation, as well as VC backing, and present the results in Table III. We have centered all variables included in the interaction terms to mitigate multicollinearity. None of the interaction terms show a significant moderating effect, indicating that the relationship between the hot market conditions and underwriter reputation or VC backing was not significantly altered during the pandemic hot market. This has two possible implications. First, it could indicate that adverse selection did not increase, resulting in the value of certification not increasing. Alternatively, underwriter's role in mitigating underpricing may not be related to the level of underpricing. Our results provide support for the certification hypothesis, as we find evidence that reputable underwriters are associated with lower underpricing across all our models and both reputation measures. However, the lack of significant moderation in Models 5 through 7 does not provide support that adverse selection increased during the pandemic as per our framework.

C. Robustness and Limitations

We first consider the robustness and limitations of our tests for dispersion in firm quality. One aspect of our methodology that may influence our results is our classification of the hot and non-hot periods. In contrast to Yung, Çolak, and Wang (2008), who explicitly differentiate between cold and normal IPO market periods, we aggregate all non-hot data points into a single benchmark. For the 3-month BHAR measures, where all tests are insignificant,

economic differences in quality may exist but are not as evident as in Yung, Çolak, and Wang (2008), who compare periods with greater heat disparity. The same argument can be applied to the insignificant hot market interaction terms in Table III. However, we argue that our definition aligns with the purpose of this paper, which is to specifically study the pandemic trend break in underpricing from normal market conditions.

Next, we consider the fact that the consistent underperformance of our COVID IPOs may stem from our BHAR measures not being risk-adjusted and therefore picking up systematic movements. Ritter (1991) estimates an average 12-month beta of 1.39 for U.S. IPOs, which we use in a CAPM model to extract 12-month excess returns. We then run the same four non-parametric tests as in Table I and present the results in Table A.II of the appendix. We find that the significantly lower median in our hot period is robust to this adjustment, suggesting that underperformance is not solely due to unadjusted systematic risk. We note that the beta measure serves only to correct for the fact that the firms in our sample likely have a higher beta than one. Additionally, this adjustment renders the variance measures uninformative, as differences in risk exposure between firms are not accounted for.

For our OLS regressions, we use the Variance Inflation Factor (VIF) with a threshold of 5 to identify multicollinearity. We find that our interaction terms exceed this threshold. Therefore, we have applied centering to all interaction terms in Table III to adjust for this. Moreover, we use robust standard errors in all regressions to ensure p-values remain stable under heteroscedasticity. An additional consideration for the robustness of our OLS regressions is the potential issue of simultaneity. Our OLS model assumes that underwriter choice is exogenous. Beatty and Welch (1996) examine underwriter reputation during the 1990s and find that it is positively related to underpricing, suggesting potential endogeneity. In other words, firms anticipating underpricing may seek reputable underwriters to reduce money left on the table. Habib and Ljungqvist (2001) address this potential bias using a 2SLS regression and find that, when controlling for potential endogeneity, reputable underwriters are associated with less underpricing. This supports the robustness of the certification role of reputable underwriters in our results.

Building on these considerations and our discussion of the results, three main limitations of our study should be considered. First, due to the recency of our sample, we are unable to account for firm-specific market exposure using an asset pricing model. Future research could replicate this study in later years to allow for a longer time horizon from which factor loadings can be estimated. Second, our benchmark for the non-hot period may not sufficiently differ from the hot period, potentially limiting the ability to capture differences compared to Yung, Çolak, and Wang (2008). Third, the role of certification agents may not be limited to reducing information frictions between informed and uninformed investors, as they may also pursue other objectives.

VI. Conclusion

The IPO market during the COVID-19 pandemic exhibited a clear trend break in both IPO activity and underpricing. We examine the causes of this phenomenon, building on traditional theories of adverse selection, suggesting that underpricing follows from uncertainty about the quality of firms going public. Our results indicate that these theories are insufficient in explaining the pandemic underpricing spike. While previous literature has documented higher dispersion in IPO firm quality during hot market periods, our results show that the pandemic hot issue market does not follow this pattern. Although the higher dispersion and median of first-day returns during the pandemic follow the theoretical implications of our model, the lower dispersion in medium- to long-run returns is contradictory.

We find that reputable underwriters are associated with less underpricing, but not to a greater extent during the pandemic. Therefore, our results support the presence of information asymmetry in the IPO market but does not support that the pandemic underpricing spike can be attributed to heightened informational frictions. The IPO literature is multifaceted, with several different theoretical frameworks of what drives underpricing which have been proven to various extents. One single framework might not be sufficient to explain the dynamics during the COVID hot market. However, the economic magnitude is sizable and warrants further research. We provide brief examples of how our empirical results could align with the behavioral framework of investor sentiment and encourage future research to test it empirically.

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Appendix A

Table A.I
Non-Parametric Tests of Return Distributions Across Different Horizons for our Hot and Non-Hot Period

The table presents nonparametric test results comparing return distributions between our hot and non-hot period for each return horizon (FDR, and market-adjusted BHAR horizons of 3, 6, and 12 months). It reports the variance and median of returns for each period and horizon. The Kolmogorov-Smirnov (K.Smir) and Kuiper tests examine differences in overall distributions, the Mann-Whitney test (M.Whit) assesses differences in medians, and the Siegel-Tukey test (S.Tuk) evaluates differences in variability.

	Variance		Median		Non-Parametric Tests			
	Hot	Non-Hot	Hot	Non-Hot	K.Smir	Kuiper	M.Whit	S.Tuk
3-Mo	0.491	0.398	-0.008	0.021	0.352	0.152	0.348	0.283
6-Mo	0.423	0.393	-0.242	-0.018	0***	0.006***	0***	0.329
12-Mo	0.361	0.993	-0.483	-0.166	0***	0***	0***	0***

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.II
Non-Parametric Tests of 12-month Excess Return Distributions Across our Hot and Non-Hot Period

The table presents nonparametric test results comparing excess 12-month returns from CAPM, assuming an average beta of 1.39 across all IPOs. It also reports the variance and median of the excess returns for each period. The Kolmogorov-Smirnov (K.Smir) and Kuiper tests examine differences in overall distributions, the Mann-Whitney test (M.Whit) assesses differences in medians, and the Siegel-Tukey test (S.Tuk) evaluates differences in variability.

	Variance		Median		Non-Parametric Tests			
	Hot	Non-Hot	Hot	Non-Hot	K.Smir	Kuiper	M.Whit	S.Tuk
12-Mo	0.374	1.002	-0.510	-0.194	0***	0***	0***	0***

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix B: AI Disclosure

We have used ChatGPT-4 for two purposes. First, to help us resolve issues with our R code and modify the formatting of outputs to enhance their visual appeal in LaTeX. Second, to correct grammar and syntactical errors.