

# **FOREIGN IPOs ON STAR SPANGLED EXCHANGES**

---

**A STUDY OF IPO UNDERPRICING FROM 2005 TO 2020**

**ADELE SVEGER**

**JULIA HERLOGSSON**

Bachelor Thesis

Stockholm School of Economics

2021



# **Foreign IPOs on star spangled exchanges: A study of IPO underpricing from 2005 to 2020**

## **Abstract:**

The phenomenon of IPO underpricing has captured the interest of academics for decades and is, to date, continuing to be widely debated. However, little research has been carried out to ascertain whether companies going public in foreign markets are more likely to be underpriced compared to their domestic counterparts and, most importantly, the findings of the existing papers are inconsistent. This study examines US domestic and foreign IPOs on US stock exchanges from 2005 to 2020 and investigate which firm-specific factors that influence IPO initial returns. This study concludes that firms with larger size, older, operating in a high-tech industry and VC-backed have a positive relationship with mean and volatility of initial returns, whereas firms that opt to list on the NYSE are instead characterized by a negative relationship. We extend and complement existing research by investigating whether foreign firms that list on a US stock exchange experience more or less underpricing compared to US domestic firms. In the time period 2005 to 2012, we find equivalent degrees of IPO underpricing for foreign and US domestic IPOs. Whereas in the time period 2013 to 2020, we find that foreign firms experience less underpricing than domestic firms. We assume that the foreign firms may pick up even larger firm-and offer-specific characteristics effects with less information asymmetry than controlled for in our study.

## **Keywords:**

IPO, Initial Public Offering, Information asymmetry, Underpricing, Foreign IPOs

## **Authors:**

Adele Sveger (24319)

Julia Herlogsson (24483)

## **Tutors:**

Peter Aleksziew, Visiting Teacher, Department of Finance

## **Examiner:**

Adrien d' Avernas, Assistant Professor, Department of Finance

Bachelor Thesis

Bachelor Program in Business and Economics

Stockholm School of Economics

© Adele Sveger and Julia Herlogsson, 2021

# 1. Introduction

In 2010, in the aftermath of the financial crisis that led to a severe dip in financial activity, more than a third of Initial Public Offerings (IPOs) in the US are performed by foreign companies (Ritter, 2021). Such statistics supports a continued trend of an ever-increasing number of non-US based companies wanting to list on “star spangled” exchanges. In the period of 2005 to 2020 the ratio of foreign-to-domestic IPOs in the US has increased by almost 50% (Ritter, 2021). The phenomenon is most visible in, but not limited to the US, given its attractiveness for foreign firms. Indeed, past studies in the field of cross-border IPOs have shown a growing tendency for companies turning to global markets to raise capital. For instance, Henderson et al. (2006) estimated that between 1990 and 2001, a mere 12% of total new capital raised through public equity offerings was conducted cross-border. Caglio et al. (2016) estimated that this number increased to 20% in the period from 1995 to 2007.

Previous research (Pagano et al., 2002; Caglio et al., 2016) has focused on understanding what incentivizes companies to prefer listing in foreign versus domestic markets and why these reasons may vary depending on time period and geographies. Doidge et al. (2013) points to financial globalization as the catalyst for the exodus. Our paper is however not concerned with assessing the causes of such trends, but more to its consequences: do companies effectively gain from performing IPOs in foreign markets?

One of the main possible costs a company can incur as a result of performing an IPO is “underpricing costs” (Rock, 1986; Beatty and Ritter, 1986; Lowry et al., 2010). A company faces underpricing costs when the difference between the closing price of the first day of trading and offer price is positive. For this reason, IPO underpricing is also commonly referred to as “positive initial return” (Rock, 1986; Beatty and Ritter, 1986; Lowry et al., 2010). Incurring underpricing costs implies that IPO underwriters have either deliberately or accidentally, underestimated the value of the company.

A large extent of research shows that most IPOs are on average subject to underpricing (Rock, 1986; Beatty and Ritter, 1986; Lowry et al., 2010). While most studies agree on this conclusion, the causes leading to underpricing and possible predictors are largely ambiguous and debated. Overall, it seems clear that asymmetry of information plays a determining role. Although, limited amount of research has been carried out to ascertain whether companies going public in foreign markets are more likely to be underpriced compared to their domestic counterparts and, most importantly, the results of the existing papers are inconsistent (Francis et al., 2001; Ejara and Ghosh, 2004; Bruner et al., 2004). The contradicting findings of these papers call for further research on differences of IPO underpricing between US domestic and foreign firms.

In 2010, Lowry et al.’s comprehensive and detailed study was published, outlining a thorough methodology to predict IPO underpricing. The study accounts for firm- and offering-specific factors to control for different levels of information asymmetry, time-patterns and market volatility as variables to explain IPO underpricing for US domestic firms. The paper reveals that, in the US, a high level of information asymmetry predicts a higher degree of IPO underpricing. The results of the study proved to be more conclusive and accurate compared to previous research in the field and the paper is thus considered a benchmark study in the field of IPO literature. However, the study does not include foreign firms.

The purpose of this paper is therefore to extend and complement previous research by investigating which firm- and offer-specific factors influence IPO initial returns, and by assessing whether the origination of a firm that list on a US stock exchange affects information asymmetry and, consequently, underpricing to a statistically significant extent. More specifically, the research questions that we aim to answer are the following:

*What firm- and offer-specific characteristics determine underpricing on US stock exchanges? Are foreign firms going public in the US more likely to be underpriced compared to US domestic firms?*

To answer these questions, we investigate initial returns and volatility of initial returns of both foreign and US domestic IPOs performed on US stock exchanges, in the period between 2005 and 2020. We assess two different types of IPOs as specified by Caglio et al. (2013), namely: domestic IPOs, defined by a company going public in its home country; foreign IPOs, defined by a company going public outside its home market. Additionally, we exclude firms that previously have been listed on any other stock exchange. As a result of a prior listing process, there is generally a greater amount of information available for these firms which could result in biased observations (Bruner et al., 2004). Lastly, US legislation allows for different IPO procedures. For the purpose of our study, we exclusively evaluate companies that underwent an IPO through either American Depositary Receipts (ADRs) level 3 procedure or issuing of ordinary shares.

We find that firms with the characteristics of being larger, older, in a high-tech industry and VC-backed have a positive relationship with mean and volatility of initial returns whereas firms that decide to list on the NYSE have a negative relationship. We extend and complement existing research by investigating whether foreign firms that list on a US stock exchange experience more or less underpricing than US domestic firms. In the time period 2005 to 2012, we find equivalent degrees of IPO underpricing for foreign and US domestic IPOs. Whereas in the time period 2013 to 2020 we find that foreign firms experience less underpricing than domestic firms. We assume that the foreign firms may pick up even larger firm-and offer-specific characteristics effects with less information asymmetry than controlled for in our study.

The remainder of this paper is organized as follows, section two presents the existing literature in the field of IPO underpricing and foreign IPOs, section three describes our data and data collection process, section four demonstrates our used method, section five shows the descriptive statistics of our data, section six shows our results and section seven summarizes our final conclusions and further research.

## **2. Literature review**

This section provides a comprehensive overview of the existing literature for the two fields of focus of the study: IPO underpricing and foreign IPOs. To begin with, we demonstrate the fundamental theories and relevant research surrounding the phenomenon of IPO underpricing. The focus narrows down to demonstrate the literature on the firm-specific characteristics used as proxies to estimate the level of information asymmetry in our study. Lastly, we define the research gap in the field of IPO underpricing and outline how our study advances the already existing research on the topic.

### **2.1 The IPO underpricing phenomenon**

The phenomenon of IPO underpricing has captured the interest of academics for decades and is, to date, continuing to be widely debated. A firm undergoing an IPO mainly faces two different types of transaction costs, namely: direct costs, including investment banking fees and initial listing fees; indirect costs, including the cost of underpricing (Loughran and Ritter, 2002). Early studies in the field of IPO underpricing, focused on finding supporting evidence for the existence of IPO underpricing. Reilly and Hatfield (1967)'s research on new equity issues in the US during the 1960s is one of the first studies to provide evidence of the existence of IPO underpricing. Later, both Ibbotson (1975) and McDonald and Fisher (1972) provide similar evidence with data from the 1960s in the US, confirming that IPOs on average experience positive initial returns. Additionally, Loughran et al. (1994) find support for the existence of IPO underpricing worldwide, not merely on US exchanges. To date, the existence of IPO underpricing globally and its persistence across time, have been broadly documented and studied (Dong et al., 2011).

While most studies agree on the existence of IPO underpricing, the driving forces behind it and its possible predictors are still largely ambiguous and debated, which resulted in the formulation of multiple theoretical explanations. We only focus on summarizing the relevant theories of underpricing that we use to derive our research hypothesis.

A majority of the existing literature argues that information asymmetry is the main cause of underpricing, Baron (1982) and Rock (1986) among others. The theories that rely on information asymmetry to explain IPO underpricing assume that one of the stakeholders involved in an IPO process (i.e., issuers, underwriters and investors) obtain superior amount of information compared to their counterparties. Information asymmetry can mainly be identified in three different relations: information asymmetry among the issuer and the underwriter; information asymmetry among the underwriter and investors (or different groups of investors); information asymmetry among the issuer and investors.

Baron (1982) argue that information asymmetry occurs between the underwriter and the issuer. The underwriter is assumed to have superior information regarding the aggregated market demand and deliberately underprice an IPO in order to reduce the distribution efforts. As the underwriter is compensated based on total proceeds, he is hence incentivized to set a lower price to ensure full subscription. IPO underpricing is, in this case, induced by the observed agency problem between the two stakeholders.

Contrarily to Baron (1982), Rock (1986) argues that information asymmetry exists between investors. In the model of Rock (1986), there are two separate groups of investors, namely

informed investors, holding superior information about an issuing firm and uninformed investors. The informed investors will only choose to subscribe to issues when positive initial return is expected and, hence, crowd out the uninformed investors. Consequently, the uninformed investors only receive the remaining issues that are not yielding positive initial returns and are therefore discouraged to subscribe to any issues. Rock (1986) refers to the phenomenon as the “winner’s curse” and it affects the uninformed investors on the market. According to the hypothesis of the winner’s curse, a rational issuer underprices an IPO in order to attract both informed and uninformed investors to participate in an IPO. Ritter (1984) similarly argue that investors need to be compensated for the winner’s curse problem by receiving higher positive initial returns in an IPO with more information asymmetry.

In contrast to the theories of Rock (1986) and Baron (1982), the signaling theory provided by for instance Allen and Faulhaber (1989) argue that an issuer holds the most information about the firm and is deliberately underpricing its shares. According to this theory, IPO underpricing is therefore a way to signal to investors that an issue is good, as it signals that they are able to recoup the losses generated by the initial positive returns. Welch (1989) and Grinblatt and Hwang (1989) similarly argue that underpricing signals to investors that it is a high-quality firm going public. In general, the signaling theory proposes that a firm can convey information to the investors through several types of variables including, for instance, the choice of underwriter and auditor. In fact, it is not exclusively the offer price and offer size that reveals information, but all types of firm- and offer-specific characteristics can provide insights regarding the credibility of a firm to its investors prior to the IPO (Allen and Faulhaber, 1989). Numerous researchers, suggest that firms that signal more information to investors, can mitigate the information asymmetry and therefore generate less IPO underpricing (Ritter, 1984; Beatty and Ritter, 1986; Michaely and Shaw, 1994).

Beatty and Ritter (1986) extend the earlier described winner’s curse theory, to additionally include a so-called “ex-ante uncertainty” about the true value of the issuing firm. If ex-ante information asymmetry is high, they assume that the problem of the winner’s curse becomes even worse. Higher information asymmetry is shown to lower the incentives for investors to participate in an issue and underpricing then becomes even more necessary in order to attract uninformed investors. Beatty and Ritter (1986) went on to highlight how different firm-characteristics, such as offer volume and firm age, are used as proxies to understand the level of information asymmetry prior to an IPO. The modeling of firm- and offer-specific characteristics in order to understand the degree of uncertainty surrounding an IPO, is also consistent with an earlier study conducted by Ritter (1984).

Rock (1986) goes on to argue that both the underwriter and the issuer are assumed to attain considerably more information about the issuing firm compared to any of the other single market participants. Yet, they still lack key information about the aggregated market demand, that is setting the final market price which determines the degree of underpricing. This problem is the most prominent one facing both the underwriter and the issuer: what is the actual aggregated market demand for an issue? The degree of underpricing resulting from information asymmetry surrounding the aggregated market demand is shown to be affected by time series, market volatility, and firm-specific characteristics (Ritter, 1984; Pastor and Veronesi, 2005; Beatty and Ritter, 1986). These three factors are modelled together in the study conducted by Lowry et al. (2010).

As previously discussed, there is large ambiguity between researchers on why IPOs on average are underpriced and Lowry et al. (2010)’s study relies on the idea of information

asymmetry between the underwriter and aggregated market participants (see Rock, 1986; Beatty and Ritter, 1986). The study of Lowry et al. (2010) examines US IPOs on US stock exchanges from 1965 to 2005 and contributes to this field of research by not only estimating average initial returns of IPOs, but to also by examining the volatility of initial returns. Their results show strong correlation between average initial returns and standard deviation of initial returns, indicating that a period of time with high average initial returns, will imply high volatility. Lowry et al. (2010) also argue that their study includes more powerful statistical tests than previous research on the topic to assess the dispersion of IPO underpricing over time. They tested for different firm- and offer-specific characteristics that were assumed to incorporate and signal different degrees of information asymmetry, namely underwriter rank, firm age, number of issued shares, exchange location, if a firm's core business is in a high-tech industry or not, if a firm is venture capital backed or not and the difference between offer price and middle of the range prices in prospectus. Consistent with previous studies they find that initial returns and volatility of initial returns are higher for firms with more information asymmetry. Thanks to their approach of modelling and the comprehensiveness of the factors examined, Lowry et al. (2010)'s study is considered to be a benchmark in the field of IPO underpricing research.

## **2.2 Firm-and offer-specific characteristics**

### **2.2.1 Firm size**

Offer size of an IPO, defined as the product of number of offered shares and offer price, is commonly used as a proxy for firm size. Beatty and Ritter (1986) find that a smaller offering size indicates higher risk and is hence expected to incorporate higher ex-ante uncertainty. Later studies (Miller and Reilly, 1987; Ljungqvist, 1997) also find a negative relationship between offer size and information asymmetry, the smaller the offer size the more information asymmetry. Lowry et al. (2010) use number of shares offered as a proxy for firm size instead of offer size.

### **2.2.2 Firm age**

Numerous studies examine the relationship between firm age and information asymmetry. Ritter (1984) argues that it is more costly to gather information about younger firms with limited amount of historical data and consequently investors expect a higher level of positive initial return for these types of issues. Later research (Beatty and Ritter, 1986; Ljungqvist and Wilhelm, 2003) also find that younger firms have higher levels of information asymmetry. Lowry et al. (2010) find similar results.

### **2.2.3 Industry**

Researchers find that the degree of IPO underpricing differ between industries (Ritter, 1984; Loughran and Ritter, 2004). Hwang et al. (2012) find that high-tech firms are associated with more information asymmetry compared to non-high-tech firms. Lowry et al. (2010) also find a positive relationship between high-tech firms and IPO underpricing.

### **2.2.4 US stock exchange**

Firm characteristics generally vary between different US stock exchanges. Larger and more established firms usually opt to list on the New York Stock Exchange (NYSE), whereas

smaller, younger and high-tech firms usually decide to list on Nasdaq (Loughran, 1993). Loughran (1993) argues that firms deciding to list on the NYSE incorporate less information asymmetry whereas firms on Nasdaq incorporate more information asymmetry. Lowry et al. (2010) find similar results in their study.

### **2.2.5 Venture capital backing**

Existing research is inconsistent as to whether firms with venture capital (VC) financing face more or less underpricing. Megginson and Weiss (1991) and Barry et al. (1990) argue that the VC firm can share information about the issuing firm to the underwriter and hence lower the degree of information asymmetry. Contrarily, Lee and Wahal (2004) and Hasan and Francis (2001) find that VC-backed firms experience more underpricing and argue that firms with VC-backing usually are in more risky industries and pick up this effect. Lowry et al. (2010) find that VC-backed firms experience more underpricing and speculate that it is due to the fact that VC firms are in risky high-tech businesses. Kotnik and Tärning (2020) build on the limitation of Lowry et al. (2010) and develop a model to capture the true effect of VC-backing by constructing a non-high-tech VC variable.

### **2.2.6 Foreign**

Early research on the topic of foreign listings on US stock exchanges, focuses on cross-listings (i.e., the foreign firm is prior to going public in the US already listed on its home market or the foreign firm list on the US market and home market simultaneously), with the likes of Miller (1999), Ule (1937), Foerster and Karolyi (1999) and Karolyi (1998) among others. Later studies focus on IPO underpricing among foreign firms going public for the first time on a US stock exchange, either by issuing ADRs or ordinary shares (Francis et al., 2001; Ejara and Ghosh, 2004; Bruner et al., 2004).

Pagano et al. (2002) and Saudagaran (1998) find that foreign firms issuing ADRs have certain firm- and offer- specific characteristics, for instance being large, well-known and mature. Blass and Yaleh (2000) find that many high-tech firms from Israel and the Netherlands, decide to list on US stock exchanges as these exchanges have extensive analyst coverage. Previous researchers also indicate that the level of underpricing of foreign firms differ depending on if the foreign firm originates from an emerging or a developed country. Ejara and Ghosh (2004) find that foreign firms from emerging countries are less underpriced compared to firms from developed countries. Foreign firms from emerging countries are less integrated with the US and are commonly more politically unstable and are therefore associated with more information asymmetry (Harvey, 1995; Comstock et al., 2003).

Existing research on underpricing of foreign firms going public for the first time on a US stock exchange is contradicting. Firstly, Francis et al. (2001) concludes that, in the US, foreign firms incorporate more information asymmetry than their domestic counterparts, as foreign firms are, for instance exposed to currency conversion risk and political risks. Francis et al. (2001)'s study includes ADRs from 1990 to 1993 and foreign firms going public for the first time on any market or simultaneously on its home market. Secondly, Ejara and Ghosh (2004) conclude that US domestic firms are more likely to be underpriced compared to foreign firms, as foreign firms are larger and more mature, which allows for greater availability of information. Ejara and Ghosh (2004)'s study includes ADRs from 1990 to 2001 going public for the first time. Lastly, Bruner et al. (2004) conclude that US domestic and foreign firms experience equivalent levels of IPO underpricing, and argue that, on

average, the potential uncertainty associated with foreign firms is largely offset by their larger size. Bruner et al. (2004) include both ADRs and ordinary shares issued by a foreign firm going public for the first time on a US stock exchange from 1991 to 1999.

Despite the fact that financial globalization has made it easier for foreign firms to list in the US, Bruner et al. (2004) argue that entry into the US market is not frictionless, but rather selective. Foreign firms that want to perform an IPO in the US, are required to fulfill strict registration and reporting requirements and Bruner et al. (2004) therefore suggest that “only the best come here”, referring to the exclusivity of raising capital in the US. Differences in initial returns have been found depending on whether the firm originates from a developed or an emerging country. Ejara and Ghosh (2004) found that foreign IPOs from developed countries were more underpriced.

## 2.3 Research questions and hypothesis development

The US is an attractive market with a high number of IPOs each year and represents the world’s deepest financial market, which makes it an interesting marketplace to study.

As presented in the literature review, voluminous research has been carried out on the topic of IPO underpricing. The study by Lowry et al. (2010) published in *The Journal of Finance*, investigate IPOs performed from 1965 to 2005 on US stock exchanges and introduce a new powerful model to estimate the degree of IPO underpricing. Lowry et al. (2010)’s study does not include foreign IPOs, which represent a large share of firms going public in the US. By contrast, we include both foreign and US domestic firms with the aim to allow for a more thorough analysis of IPO underpricing in the US. To receive a more recent perspective on the topic, we examine all firms going public in the US from 2005 to 2020, a later time period than Lowry et al. (2010). To ensure comparability with Lowry et. Al (2010), we also examine US domestic and foreign IPOs separately.

We aim to follow the methodology of Lowry et al. (2010) yet our research differs in certain ways. Firstly, we do not include the two explanatory variables, “Underwriter rank” and “Price update” due to lack of information. Secondly, we do not adjust for potential autocorrelation and heteroscedasticity in the residuals due to the fact that our time period of study does not appear to include an IPO bubble. Lowry et al. (2010) distinguish the existence of an IPO bubble period from 1998 to 2000, in which the mean and volatility of initial returns are high. Consequently, Lowry et. al. (2010) adjust for autocorrelation and heteroscedasticity in the residuals in order to mitigate the effect of the IPO bubble in their model. Lastly, we do not include the level of market-wide volatility in the US, which is also used in Lowry et al. (2010) to estimate IPO underpricing. We decide to not include market volatility as it is more difficult to accurately measure since our study also includes foreign firms. Foreign firms are shown to be affected by both their home equity market and the US equity market (Bruner et al., 2004).

We examine whether foreign firms are subject to more or less underpricing, *ceteris paribus*, than its US domestic counterparts. Although, a few researchers study the effect of underpricing on foreign firms, the outcomes from these studies show contradicting results. Additionally, the three studies Francis et al. (2001), Ejara and Ghosh (2004) and Bruner et al. (2004), were conducted during the 1990s and both Francis et al. (2001) and Ejara and Ghosh (2004) only include ADRs in their data sample. We include both foreign firms issuing ADRs

and ordinary shares similar to Bruner et al. (2004) in order to analyze a broader spectrum of foreign firms.

Similar to Lowry et al. (2010), we examine the effect that certain firm-and offer-specific characteristics have on the level of information asymmetry. In the light of the information presented above, our research questions are as follows:

*What firm- and offer-specific characteristics determine underpricing on US stock exchanges? Are foreign firms going public in the US more likely to be underpriced compared to US domestic firms?*

We derive the following hypothesis on the outcome of including foreign firms in our study, on IPO underpricing on US stock exchanges:

*We predict that the following firm-and offer-specific characteristics are associated with more information asymmetry: smaller, younger, in a high-tech industry, on Nasdaq, not VC-backed and foreign. Whereas the following firm-and offer-specific characteristics are associated with less information asymmetry: larger, older, not in a high-tech industry, on NYSE, VC-backed and being a US domestic firm.*

## 3. Data

### 3.1 Data sample construction

We gather data of IPOs from January 2005 to December 2020 on US stock exchanges, from the following databases: Securities Data Company (SDC) Platinum, Capital IQ, and Thomson Reuters Eikon.

As a first step in the sample construction, we collect a total sample of 3889 IPOs from the SDC database. The information retrieved about each IPO include issue date, final offer price, 4 weeks after offer date closing price, nation, primary exchange location in the US, total shares offered in the IPO, founding date, if the primary business of the firm is high-tech or not and if the firm is venture capital backed or not. The data sample from the SDC database is used as the initial source of data and is thereafter cleaned similar to Lowry et al. (2010). In order for our results to not be disproportionately affected by the 252 very small IPO offerings, the dataset is restricted to only include firms with an offer price of 5 US dollars or above. Excluded from the initial sample are real estate-investment trusts (REITs), unit IPOs, other types of securities including CAPS, JDR, Ltd Prtnr and Stp securities and firms not primarily listed on a US stock exchange. To verify that a foreign IPO has not conducted an IPO earlier and is not cross-listed, the foreign firms' IPO characteristics have been studied on Capital IQ and those foreign firms that have performed an IPO earlier are excluded from our dataset. Additionally, in case of missing values for the four weeks after closing price or firm age, data was retrieved from either Thomson Reuters Eikon or Capital IQ. Duplicates and observations with missing crucial data points are omitted from the dataset. Extreme values with an initial return exceeding the 99.5<sup>th</sup> percentile and the 0.5<sup>th</sup> percentile are excluded from the dataset. In table one, the steps of the cleaning process are presented in detail. Our final dataset consists of 1751 US domestic IPOs and 299 foreign IPOs, resulting in a total sample of 2050 IPOs.

Compared to the data collection process of our benchmark study, Lowry et al. (2010), we only use the SDC database to set up our initial dataset and we also include ADRs. We decide to only use the SDC database as it is considered to be the most complete database for IPOs in the recent decades. Additionally, the supplementary databases used by Lowry et al. (2010) only cover a small share of their total sample and are primarily used to include the IPOs prior to 1985. We include ADRs as it is one way for a foreign firm to go public on a US stock exchange.

**Table 1**  
**The cleaning process of our data**

In this table, the steps of the cleaning process of our data, are presented. Firstly, the total number of IPOs are presented and then the removed IPOs are shown as negative values. Lastly, the splits between US domestic and foreign IPOs are shown.

| <b>Cleaning steps of IPO data sample</b> |                |
|------------------------------------------|----------------|
|                                          | Number of IPOs |
| <i>IPOs collected from SDC database</i>  | 3889           |
| Offering price < 5 US dollars            | -252           |
| REITs                                    | -106           |
| Unit IPOs                                | -600           |
| Other security types                     | -72            |
| Not primarily listed in the US           | -159           |
| Historical IPO and cross-listing         | -97            |
| Missing values and duplicates            | -533           |
| Extreme values                           | -20            |
| <i>Total number of IPOs</i>              | 2050           |
| US domestic IPOs                         | 1751           |
| Foreign IPOs                             | 299            |

### 3.2 Construction procedure of our matched sample

In order to estimate the isolated effect that the firm-specific characteristic foreign has on IPO underpricing, we compare the sample of foreign IPOs with similar US domestic IPOs. The constructing of the matched group is similar to the method used by Ejara and Ghosh (2004), in which, issue date, issue size and SIC-code are used to match foreign and US domestic IPOs. We only consider three matching criteria to increase the accuracy of the matching procedure, as more matching variables could result in less accuracy. We match each foreign firm with one US domestic firm based on the following three criteria:

- i. Issue date: The US domestic IPO occur at a similar time period as the foreign IPO. A matching criterion used to ensure that the matched sample is not influenced by any time variances.
- ii. Issue size: The US domestic IPO is of similar size as the foreign IPO. A matching criterion commonly used.
- iii. High-tech or not: The US domestic IPO belongs to the same cluster of industry as the foreign IPO. A broader matching criterion than SIC code is used, to ensure sufficient matchings.

### 3.3 Data sample definitions

Our study examines different sub samples in order to answer our research question. Table 2 gives an overview of the different samples and their definitions.

**Table 2**  
**Data sample definitions**

| <b>Data sample</b> | <b>Sub sample</b>                     | <b>Number of<br/>IPOs</b> | <b>Definition</b>                                                                             |
|--------------------|---------------------------------------|---------------------------|-----------------------------------------------------------------------------------------------|
| Total sample       |                                       | 2050                      | Includes IPOs on US stock exchange from 2005 to 2020, both US domestic IPOs and foreign IPOs. |
|                    | <i>US domestic IPO sample</i>         | 1751                      | Includes only US domestic IPOs.                                                               |
|                    | <i>Foreign IPO sample</i>             | 299                       | Includes only foreign IPOs.                                                                   |
| Matched sample     |                                       | 598                       | Includes the foreign IPO sample and its constructed matched US domestic IPOs.                 |
|                    | <i>Foreign IPO sample</i>             | 299                       | Includes only foreign IPOs.                                                                   |
|                    | <i>Matched US domestic IPO sample</i> | 299                       | Includes the matched US domestic IPOs, constructed in part 3.2.                               |

## 4. Methodology

In the following section, we describe the method used in order to answer our research questions. To begin with, we present our dependent and explanatory variables. Next, we explain our cross-sectional regressions. Lastly, we explain our performed robustness tests and our assessment of heteroscedasticity and multicollinearity.

### 4.1 Variable definitions and descriptive analysis

The dependent variable in our study is the initial return of an IPO, defined as the difference between the offer price and the four-week closing price. The majority of researchers use first day closing price to calculate IPO initial returns (see for example, Rock, 1986; Beatty and Ritter, 1986). However, Ruud (1993) and Hanley et al. (1993) show that after the offer day of an IPO, underwriters commonly engage in different price stabilization activities that influences the market price. In order to receive the actual value of an IPO, the four-week closing price should therefore be used. Consequently, we use the four-week closing price similarly to the methodology of Lowry et al. (2010).

IPO initial returns are calculated either on a monthly basis or a firm-level basis. In line with the method of Lowry et al. (2010), the monthly initial returns are calculated to allow for analysis of the mean and standard deviation of initial returns and the correlation in between the two. Monthly mean of initial returns is defined as the mean of all the IPOs' initial returns in a specific month. Monthly standard deviation of initial returns is defined as the standard deviation of all the IPOs' initial returns in a specific month. Aggregated data, for instance by month, is required to calculate the standard deviation and we can therefore only estimate monthly standard deviation when at least two IPOs, take place in a month. In our sample, there are months with less than two IPOs, and as a result we have fewer monthly standard deviations than monthly mean observations. This outcome could be avoided, for instance by aggregating on years or quartiles yet it would decrease the number of observations and we would not follow the methodology of Lowry et al. (2010). The consequence of aggregating the data by month, is that we have fewer observations in our analysis, from 2050 observations in our total sample to 186 monthly means of IPO initial returns and 175 monthly standard deviations of IPO initial returns. Therefore, we also analysis IPO initial returns on a firm-specific level, to allow for more precise estimates and significant results.

Monthly mean and standard deviation of IPO initial returns are used to present the underlying characteristics of our total sample, presented in the first section of the descriptive statistics. For the total sample's monthly mean and standard deviation of IPO initial returns, we present their six autocorrelation lags, in order to understand the time dependence of each monthly datapoint. In the second part of the descriptive statistics the underlying characteristics of our matched sample are presented on a firm-specific level. To understand the accuracy of our matching procedure, we retrieve the p-values of the mean difference of the foreign IPOs and their matched US domestic IPOs. The mean difference is calculated on the three matching criteria: issue date, offer size and high-tech dummy. We retrieve the p-values for the two continuous variables, issue date and offer size by using a paired t-test and for the binary variable, tech dummy by using a McNemar test. High p-values indicate a successful matching procedure.

Equation (1) shows the calculation for the monthly mean of IPO initial returns.

**Equation (1)**

$$\overline{IPO\ IR_z} = \frac{1}{n} \sum_{zi=1}^{zn} \frac{Four\ week\ closing\ price_{zi} - Offer\ price_{zi}}{Offer\ price_{zi}}$$

Equation (2) shows the calculation for the monthly standard deviation of IPO initial returns.

**Equation (2)**

$$IPO\ IR\ \sigma_z = \sqrt{\frac{\frac{1}{n} \sum_{zi=1}^{zn} (IPO\ IR_{zi} - \overline{IPO\ IR_z})^2}{n - 1}}$$

Equation (3) shows the calculation for the firm-specific IPO initial returns.

**Equation (3)**

$$IPO\ IR_i = \frac{Four\ week\ closing\ price_i - Offer\ price_i}{Offer\ price_i}$$

In the three equations above,  $z$  represents the month,  $n$  represents the number of IPOs in that specific month and  $i$  represents each firm-specific IPO.

Our explanatory variables are used as proxies to estimate the level of information asymmetry incorporated in an IPO. The explanatory variables are firm- and offer-specific characteristics. We summarize all our variables in table 3.

**Table 3**  
**Variable definitions**

| Variable                | Definition                                                                                                                                                                                                                                                                                                                             |
|-------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| IPO initial returns     | Percent difference between offer price and the closing price 4-weeks after offer date.                                                                                                                                                                                                                                                 |
| Log (offer size)        | Logarithm of the product of the number of shares (in millions) offered in an IPO and its offer price. Offer size is a proxy for a firm's size.                                                                                                                                                                                         |
| Log (firm age +1)       | Logarithm of the years between founding date and offer date, plus one.                                                                                                                                                                                                                                                                 |
| VC dummy                | The dummy variable is equal to one if the firm undergoing an IPO receives financing from a venture capitalist and zero otherwise.                                                                                                                                                                                                      |
| NYSE dummy              | The dummy variable is equal to one if the firm lists on the NYSE and to zero if it lists on another exchange.                                                                                                                                                                                                                          |
| Nasdaq dummy            | The dummy variable is equal to one if the firm lists on Nasdaq and to zero if it lists on another exchange.                                                                                                                                                                                                                            |
| Tech dummy              | The dummy variable is equal to one if the firm is classified as high-tech and zero if not. We base high-tech industries on the classification given by the SDC database. Firms in the following industries are most commonly considered as high tech: biotech, electronics, communications, general technology and computer equipment. |
| Foreign dummy           | The dummy variable is equal to one if the firm is foreign and to zero if the firm is US domestic.                                                                                                                                                                                                                                      |
| Developed country dummy | The dummy variable is equal to one if a foreign firm originates from a developed country and to zero if the foreign firm originates from an emerging country. This dummy is only included in table 11.                                                                                                                                 |

## 4.2 Cross-sectional models

### 4.2.1 Cross-sectional regression model for our firm- and offer-specific characteristics

Our cross-sectional model is used to examine the descriptive statistics in more detail and to truly understand the relationship between mean and volatility of IPO initial returns and our firm- and offer-specific characteristics. The model described in this section, follows the methodology of Lowry et al. (2010) and is used to model the total sample of IPOs and its two subsamples, the US domestic IPO sample and the foreign IPO sample.

Firstly, a correlation matrix is constructed to understand the overall relationship between our explanatory variables and the monthly mean and standard deviation of IPO initial returns. Monthly firm- and offer-specific characteristics for the dummy variables are calculated by taking the sum of the dummy variables in a month and to divide it by the total number of IPOs in that specific month. Monthly firm- and offer-specific characteristics for the continuous variables, offer size and firm age, are calculated by taking the average of the logarithms in each month.

Secondly, to in more detail understand the relationships shown in the correlation matrix, an ordinary least square (OLS) regression is modelled on a firm-specific level, by following either equation (4) or (5). Equation (4) is set up for the total sample. Equation (5) is set up for the US domestic IPO sample and the foreign IPO sample. The difference between equation (4) and (5) is that equation (4) includes a foreign dummy variable.

#### Equation (4)

$$IR_i = \beta_0 + \beta_1(\text{Log}(\text{Offer size}_i)) + \beta_2(\text{Log}(\text{Firm age}_i + 1)) + \beta_3VC_i + \beta_4NYSE_i + \beta_5Tech_i + \beta_6Foreign_i + \varepsilon_i$$

#### Equation (5)

$$IR_i = \beta_0 + \beta_1(\text{Log}(\text{Offer size}_i)) + \beta_2(\text{Log}(\text{Firm age}_i + 1)) + \beta_3VC_i + \beta_4NYSE_i + \beta_5Tech_i + \varepsilon_i$$

Thirdly, we test for heterogeneity in our OLS regression. The OLS regression is found to violate the assumption of heterogeneity and therefore maximum likelihood-estimations (MLE) of the coefficients are modelled. However, we still show the results from the OLS regression, in order to be able to understand if the MLE actually generate a better fitted model or not. We compare the two models by calculating the loglikelihood for the OLS and MLE model. The model with the highest log likelihood is considered to be the best fitted model. In the MLE, we estimate the coefficients for both the mean and variance of initial returns, in fact, the two are modelled as a function of our explanatory variables. In our MLE model, the mean of initial return follows the same equation as the OLS regression, see equation (4) and (5). The variance of the error term, shown in equation (6) and (7) are according to Greene (1993, pp. 405-407) supposed to be related to the same explanatory variables which influence the degree of initial returns. In our MLE model, the log of the variance of the regression error is calculated according to equation (6) or (7), depending on if the foreign dummy variable is included or not.

### Equation (6)

$$\text{Log}(\sigma^2(\mathcal{E}_i)) = \gamma_0 + \gamma_1 \text{Log}(\text{Offer size}_i) + \gamma_2 \text{Log}(\text{Firm age}_i + 1) + \gamma_3 \text{VC}_i + \gamma_4 \text{NYSE}_i + \gamma_5 \text{Tech}_i + \gamma_6 \text{Foreign}_i$$

### Equation (7)

$$\text{Log}(\sigma^2(\mathcal{E}_i)) = \gamma_0 + \gamma_1 \text{Log}(\text{Offer size}_i) + \gamma_2 \text{Log}(\text{Firm age}_i + 1) + \gamma_3 \text{VC}_i + \gamma_4 \text{NYSE}_i + \gamma_5 \text{Tech}_i$$

The MLE of the mean and the log of the variance of the regression error, is, essentially the weighted least squares estimation of the equation (4) or (5), with the standard deviation of error terms as weights. Modelling of the MLE is in line with the methodology of Lowry et al. (2010).

In following part of this section, we describe in more detail the construction of the MLE model. In order to follow the Gaussian- noise simple linear regression in the set-up of the MLE model, we make the following assumptions:

- i. The distribution of  $X$  is random.
- ii. If  $X = x$ , then our  $Y = \beta_0 + \beta_1 x + \mathcal{E}_i$ . In this equation  $Y$  is initial returns,  $x$  is one of our explanatory variables and  $\mathcal{E}_i$  is some noise variable. This is a simplified equation, as our model has more explanatory variables and coefficients
- iii.  $\varepsilon \sim N(0, \sigma^2)$
- iv.  $\varepsilon$  is independent across all the observations

Equation (8) shows our log-likelihood function that incorporates both the mean and variance equation. This equation incorporates the foreign dummy; however, this dummy is dropped in the MLE regression for the foreign and the US domestic sample.

### Equation (8)

$$\begin{aligned} L(b_0, b_1, b_2, b_3, b_4, b_5, b_6, \gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6) = \\ \log \prod_{i=1}^n p(y_i | b_0, b_1, b_2, b_3, b_4, b_5, b_6, \gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6) = \sum_{i=1}^n \log p(y_i | b_0, b_1, b_2, b_3, b_4, b_5, b_6, \gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6) \\ = -\frac{n}{2} \log 2\pi - n \log(s) - \frac{1}{2s^2} \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 (\text{Log}(\text{Offer size}_i)) + \beta_2 (\text{Log}(\text{Firm age}_i + 1)) + \beta_3 \text{VC}_i + \beta_4 \text{NYSE}_i + \beta_5 \text{Tech}_i + \beta_6 \text{Foreign}_i)^2) \\ \text{where } s = \gamma_0 + \gamma_1 \text{Log}(\text{Offer size}_i) + \gamma_2 \text{Log}(\text{Firm age}_i + 1) + \gamma_3 \text{VC}_i + \gamma_4 \text{NYSE}_i + \gamma_5 \text{Tech}_i + \gamma_6 \text{Foreign}_i \end{aligned}$$

In the MLE, the log likelihood function is maximized to receive the estimates of coefficients. Common practice is to reject the null hypothesis when p-values are lower than 0.05, yet with a bigger sample we argue for that the null hypothesis can be rejected at 0.1 instead. We reject the null hypothesis when p-values are lower than 0.1 throughout our study.

#### 4.2.2 Cross-sectional model for our matched sample

In the second part of our study, we aim to examine whether foreign IPOs are facing more or less underpricing compared to its US domestic counterparts and we therefore use the constructed matched sample. Our methodology in this section is similar to Bruner et al. (2004). We first set up a simple linear regression of the dependent variable, IPO initial returns and the independent variable, the foreign dummy.

##### Equation (9)

$$IR_i = \beta_0 + \beta_1 \text{Foreign}_i + \varepsilon_i$$

Although, the simple linear regression is assumed to have low explanatory power, it still shows the isolated effect between the two variables. In the next model all the remaining explanatory variables, shown in table 3 are included. This more sophisticated model is assumed to increase the R-squared, as we include more explanatory variables. We thereafter perform an OLS of the matched sample, that follows equation (4). Equation (4) is used to ensure comparability with our cross-sectional regression in the section 6.2.

In this model, there are mainly two hypothesis that are tested for: the null hypothesis,  $H_0$ , and the alternative hypothesis,  $H_1$ . We are primarily interested to test if the foreign variable has a coefficient different from zero or not, in order to understand if the foreign variable has an influence on initial returns or not. The two hypotheses are the following:

$$H_0: \beta_{\text{Foreign}} = 0$$

$$H_1: \beta_{\text{Foreign}} \neq 0$$

In the cross-sectional regression, the p-values will show whether we can reject or accept the null hypothesis. In our model, we reject the null hypothesis when the p-values are below 0.1 and can in that case conclude that the foreign variable has a significant effect on IPO initial returns.

##### 4.2.2.1 Robustness tests

We perform two types of robustness tests to ensure that our findings, from the cross-sectional regression on the matched sample, hold.

In the first robustness test, we set up a random sample of US domestic IPOs. The random sample is supposed to represent a smaller version of the total sample. An OLS regression is performed on this sample in order to evaluate if the foreign dummy is significant or not with a smaller sample. Consequently, we compare the results from the OLS regression of the random and the matched sample. This test is performed in order to ensure that our findings are not affected by differences in sample sizes.

In the second robustness test, we arrange the IPOs in the matched and total sample by date and then divide the two samples into two new sub samples. For the matched sample, the first sub sample includes 284 IPOs from 2005 to 2012 and the second one includes 314 IPOs from 2013 to 2020. For the total sample, the first sub sample includes 798 IPOs from 2005 to 2012 and the second one includes 1252 IPOs from 2013 to 2020. We then perform an OLS on each sub sample to ensure that our findings hold over time.

#### 4.2.2.2 Cross-sectional regression model of foreign firms with the inclusion of a developed country dummy

In order to understand whether the degree of IPO underpricing of foreign firms differ between foreign firms from developed and emerging countries, we perform a cross-sectional OLS regression on the foreign IPO sample and include our development country dummy. Equation (10) shows how this OLS regression is set up.

##### Equation (10)

$$IR_i = \beta_0 + \beta_1(\text{Log}(\text{Offer size}_i)) + \beta_2(\text{Log}(\text{Firm age}_i + 1)) + \beta_3VC_i + \beta_4NYSE_i + \beta_5Tech_i + \beta_6Developedcountry + \varepsilon_i$$

### 4.3 Assessment of multicollinearity and heteroskedasticity

In an OLS, we have two implicit assumptions, for instance absence of multicollinearity and heteroskedasticity.

If multicollinearity is shown in an OLS, there is a risk for biased results (Belsley et al., 1980; Greene, 1993). To test for multicollinearity, we use variance inflation factors (VIF). The VIF refers to the degree of which the variance of a certain explanatory variable is described by the other explanatory variables in the OLS model. According to Kutner et al. (2004), a VIF value above five indicates severe multicollinearity.

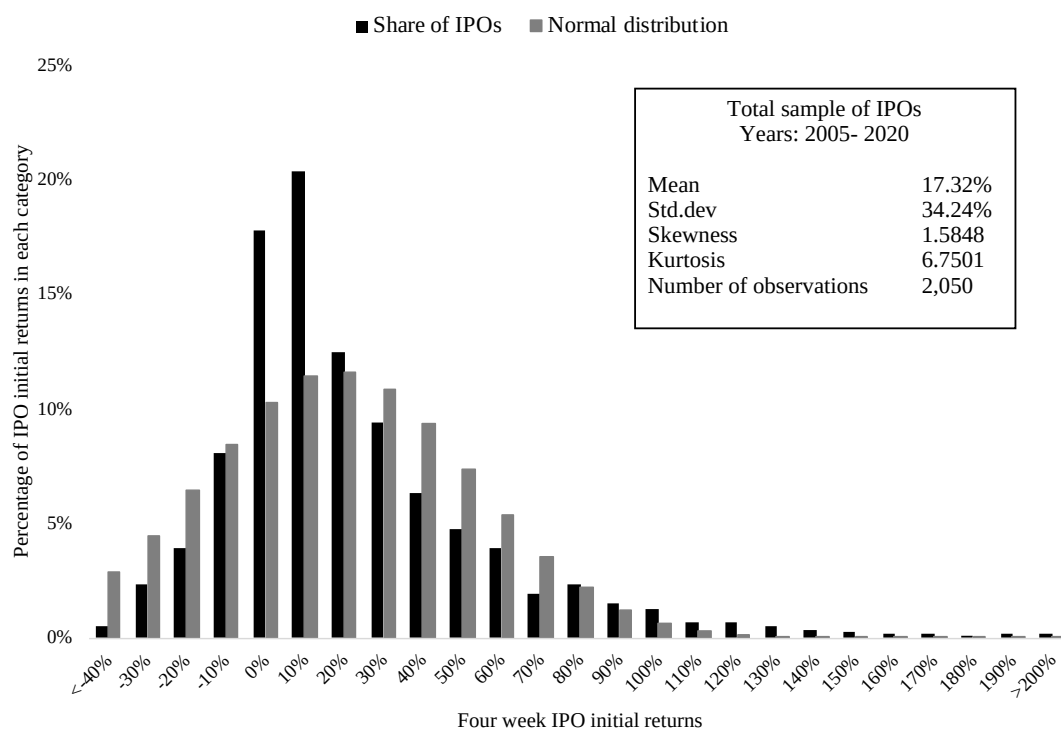
If heteroskedasticity is shown among the residuals in an OLS, there is a risk that the statistical results are not accurate. A Breusch-Pagan test is used to test for heteroskedasticity in an OLS. We adjust to a certain extent in each OLS for heteroskedasticity by using robust standard errors, Whites's (1980) heteroskedasticity-consistent errors.

## 5. Descriptive statistics

In this section, we present the summary statistics of our data. In the first section, descriptive statistics of the total sample and its two sub samples, are shown. In the second section, descriptive statistics of the matched sample, are shown.

### 5.1 Descriptive statistics for US domestic and foreign IPOs in the US

In figure 1, the distribution of IPO initial returns from 2005 to 2020 is shown. The IPO initial returns of our total sample including 2050 IPOs, has a mean of 17.32% and a standard deviation of 34.24%. These estimates are used to construct the normal distribution, also plotted in figure 1. As shown in figure 1 and by the values for skewness (1.5848) and kurtosis (6.7501), the distribution of initial return is positively skewed, and fat tailed. We observe a lower skewness and kurtosis than Lowry et al. (2010) and assume that the explanation to this is that we do not observe an IPO bubble.

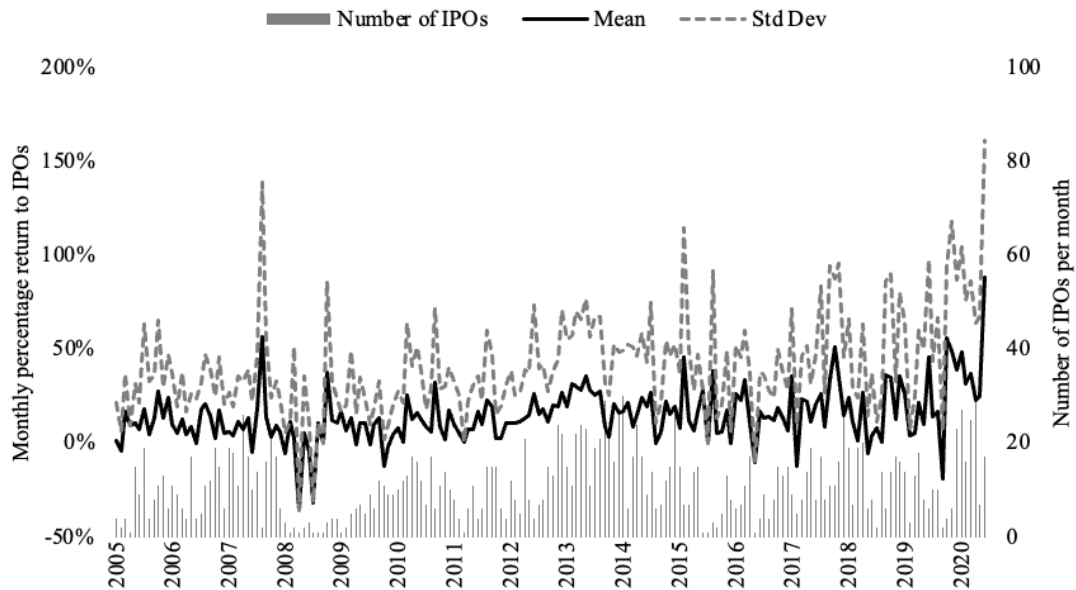


**Figure 1. A frequency distribution of the IPO initial returns of our total sample, from 2005 to 2020.**

In the figure, the distribution of the IPO initial returns for the total sample is plotted. The black bars plot the share of IPOs in each category. The grey bars plot the normal distribution.

In figure 2, the monthly mean of initial returns, cross-sectional standard deviation of initial returns and IPO volume, are shown for the total sample. Our data shows that the number of firms undergoing an IPO each month and that the dispersion of initial returns, follow cycles. We find that months with a high number of IPOs have higher standard deviations and means. Also, to be noted is that our data demonstrates that the mean and standard deviation of IPO initial returns correlate with each other. These findings are also demonstrated in table 4 and

are similar to the findings of Lowry et al. (2010). Figure 2 suggests that our data could be auto-correlated and cross-correlated. We investigate these effects below, in table 4.



**Figure 2. Mean and standard deviation of initial returns and the number of IPOs per month, from 2005 to 2020.**

The total sample of 2050 firms, is used to plot the graph. For every month, the average IPO initial return and IPO standard deviation, are calculated. The mean is represented by the solid black line and the standard deviation is represented by the dotted grey line. The number of IPOs each month is represented by the grey bars.

In table 4, the underlying descriptive statistics for figure 2 and the two subsamples of US domestic IPOs and foreign IPOs are demonstrated. We estimate the mean and standard deviation of initial returns for all IPOs in each specific month. For these monthly statistics, we display mean, median, standard deviation and six autocorrelation lags. The correlation between the monthly mean of initial returns and monthly cross-sectional standard deviation is also shown.

For the total sample, mean of average monthly initial returns is estimated to 14.89% and mean of cross-sectional regression standard deviation is estimated to 28.22%. The correlation between the two time-series is high, a value of 0.7673, which supports the shown positive skewness in figure 1. As assumed with data not including an IPO bubble period, the autocorrelation lags for the prior six months are low and contain two insignificant values.

For the US domestic sample, we find a higher mean of average monthly initial returns of 16% and a lower mean of cross-sectional regression standard deviation of 26.7% compared to the total sample. The data of the US domestic sample is the most similar to the data of Lowry et al. (2010), specifically their time period from 1991 to 2005 with exclusion of the bubble period. We therefore compare the two to understand if mean of average monthly initial returns and mean of cross-sectional regression standard deviation is higher in our more recent time period or not. We find that the statistics are similar yet the correlation between mean of average monthly initial returns and mean of cross-sectional regression standard deviation is higher in our data, 0.7673 compared to 0.5 for the data of Lowry et al. (2010).

For the foreign sample, mean of average monthly initial returns is estimated to 11.15% and mean of cross-sectional regression standard deviation is estimated to 25.97%, lower than both the other samples. The correlation between the two time-series is however strong, a value of 0.6755. Compared to the statistics of the US domestic IPO sample, the monthly estimates for the foreign IPO sample are lower.

Overall, we find a high correlation of the mean of average monthly initial returns and the mean of cross-sectional regression standard deviation, supporting the findings in figure 2. The potential causes of this strong correlation are examined in our cross-sectional regression model. Additionally, we have lower autocorrelation lags compared to Lowry et al. (2010), implying that we do not have as high autocorrelation of the residuals.

**Table 4**  
**Descriptive statistics on monthly mean and volatility of IPO initial returns**

In this table, the descriptive statistics of the average IPO initial returns and cross-sectional standard deviations of IPO initial return by month for the total sample, foreign IPO sample and US domestic IPO sample, are shown. Monthly mean cannot be calculated if not at least one IPO occur in that month and monthly standard deviation can only be calculated if not at least two IPOs occur in a month. There are months with zero or only one observation in our dataset resulting in a lower number of observations on a monthly basis, see the column labeled N with the number of observations. Corr. is the correlation between the monthly mean and standard deviation of IPO initial returns over time, using Pearson correlation coefficient. Autocorrelation for the prior six months are also displayed.

All numbers are also displayed.

|                                     | N   | Mean   | Median | Std.dev | Corr   | Autocorrelation: Lags |        |        |        |        |        |
|-------------------------------------|-----|--------|--------|---------|--------|-----------------------|--------|--------|--------|--------|--------|
|                                     |     |        |        |         |        | 1                     | 2      | 3      | 4      | 5      | 6      |
| <i>Total Sample</i>                 |     |        |        |         |        |                       |        |        |        |        |        |
| Average IPO IR                      | 186 | 0.1489 | 0.1311 | 0.1485  |        | 0.211*                | 0.194* | 0.251* | 0.113  | 0.132  | 0.148* |
| Cross-sectional $\sigma$ of IPO IRs | 175 | 0.2822 | 0.2515 | 0.1379  | 0.7583 | 0.259*                | 0.23*  | 0.277* | 0.109* | 0.139* | 0.167* |
| <i>US domestic IPO sample</i>       |     |        |        |         |        |                       |        |        |        |        |        |
| Average IPO IR                      | 183 | 0.1600 | 0.1394 | 0.1656  |        | 0.155*                | 0.148* | 0.205* | 0.077  | 0.124  | 0.226* |
| Cross-sectional $\sigma$ of IPO IRs | 170 | 0.2670 | 0.2366 | 0.1365  | 0.7673 | 0.301*                | 0.331* | 0.317* | 0.259* | 0.317* | 0.309* |
| <i>Foreign IPO sample</i>           |     |        |        |         |        |                       |        |        |        |        |        |
| Average IPO IR                      | 132 | 0.1115 | 0.0335 | 0.2916  |        | -0.025                | -0.053 | 0.060  | -0.052 | 0.074  | 0.060  |
| Cross-sectional $\sigma$ of IPO IRs | 81  | 0.2597 | 0.2241 | 0.2063  | 0.6745 | 0.174*                | -0.072 | 0.102  | -0.021 | 0.051  | -0.057 |

Signif. codes: 0 '\*\*\*\*' 0.001 '\*\*\*' 0.01 '\*\*' 0.05 '.' 0.1 ' ' 1

## 5.2 Descriptive statistics for the matched sample

The method used for our matching procedure is the propensity score matching with nearest neighbour. We match each foreign firm with a similar US domestic firm. We use different statistical tests depending on whether the variable is continues or binary. In table 5, the differences between issue date, offer size and the tech dummy for the foreign firms and the matched US domestic firms are displayed. The p-value, the used statical test and the mean differences between the foreign firms and US domestic firms in the matched sample are shown. The high p-values indicate that our matching procedure is successful and that the two samples are similar in terms of issue date, offer size and high-tech characteristic.

**Table 5**  
**Level of accuracy of our matching procedure**

Table 5 shows the number of observations, p-values, used statistical test and the mean differences between the foreign firms and the matched US domestic firms. The paired t-test is used to calculate the p-values for the continuous variables, issue date and offer size. The McNemar test is used to calculate the p-value for the binary variable, the tech dummy. In parenthesis, the t-values are showed for the paired t-tests, and the chi-squared is shown for the McNemar's test. No mean difference is retrieved in the McNemar test for a binary variable.

|            | N   | P-values             | Statistical test | Mean difference   |
|------------|-----|----------------------|------------------|-------------------|
| Issue Date | 598 | 0.7332<br>(-0.34115) | Paired t-test    | -51 days          |
| Offer size | 598 | 0.8055<br>(0.24651)  | Paired t-test    | 5 (million) US \$ |
| Tech dummy | 598 | 0.5624<br>(0.33562)  | McNemar's test   | N. A              |

In table 6, we show the statistics of the foreign and US domestic IPOs in the matched sample on a firm-specific level. Additionally, we also show the statistics of foreign firms from developed and emerging countries separately. Table 6 shows the mean of initial returns, median of initial returns, average offer size in million US dollars, percentage of tech firms, percentage of firms listed on the NYSE, percentage of firms that are VC-backed and average firm age.

The mean of initial returns of all the US domestic IPOs in our data sample is calculated to 18.2% on a firm specific- level, while the US domestic matched IPOs has a lower mean of 16.7%. Compared to the US domestic IPOs, the mean and median of initial returns of the foreign IPOs are lower. We also show that foreign firms from developed countries have a lower mean of initial returns than foreign firms from emerging countries.

As for the characteristics of the two sub samples, there is not a large discrepancy for the variables that are used as matching criteria, offer size and tech. Additionally, table 6 shows that US domestic firms are older, have a smaller share of firms listed on the NYSE and are financed by venture capitalists.

**Table 6**  
**Descriptive statistics of the matched sample on a firm-specific level**

Table 6 shows, the number of IPOs, average of initial return, median of initial return, average offer size in million US \$, percentage of tech firms, percentage of firms listed on the NYSE, percentage of firms that are VC-backed and average age for the US domestic and the foreign IPOs in our matched sample. The foreign IPOs are additionally divided into two sub samples including firms from developed countries and firms from emerging countries.

|                            | N   | Mean IR | Median IR | Mean offer size (\$M) | Percent tech | Percent NYSE | Percent VC-backed | Average firm age |
|----------------------------|-----|---------|-----------|-----------------------|--------------|--------------|-------------------|------------------|
| US domestic matched IPOs   | 299 | 16.7%   | 9.4%      | 187                   | 50.8%        | 33.4%        | 42.5%             | 10.6             |
| Foreign IPOs               | 299 | 12.2%   | 2.0%      | 182                   | 53.5%        | 40.8%        | 50.2%             | 8.6              |
| <i>Developed countries</i> | 79  | 10.3%   | 2.1%      | 215                   | 64.5%        | 41.8%        | 45.6%             | 10.4             |
| <i>Emerging countries</i>  | 220 | 12.9%   | 1.2%      | 170                   | 49.5%        | 40.5%        | 51.8%             | 8.0              |

## **6. Results**

### **6.1 The impact of firm- and offer-specific characteristics on IPO initial returns**

In this section, we demonstrate our findings on the effect that certain firm-and offer-specific characteristics have on the level of information asymmetry and consequently IPO underpricing. Firms that are characterized to have a higher degree of information asymmetry, are expected to have both greater mean of initial returns and volatility of initial returns (Ritter, 1984). According to our hypothesis, IPO underpricing is predicted to be higher when less amount of information is available about a specific IPO. The firm- and offer-specific characteristics used as proxies to estimate the level of information asymmetry in IPOs are summarized in table 3. In this section, we follow the methodology of Lowry et al. (2010), yet the coefficients in our cross-sectional regression model might differ, as we do not include all the explanatory variables used by Lowry et al. (2010) and we investigate another time period. To begin with, we examine the relationship between monthly mean of IPO initial returns and monthly cross-sectional standard deviation of IPO initial returns. Secondly, we study in detail the extent to which the firm- and offer-specific characteristics affect IPO initial returns.

#### **6.1.1 Correlation between the average firm-and offer- specific characteristics and IPO underpricing**

In table 7, we present the correlation that average firm- and offer- specific characteristics have with monthly average of initial returns and monthly standard deviation of initial returns. The correlation estimates show both the direction and level that firm- and offer- specific characteristics have on IPO underpricing. The correlation matrix separately displays the correlation for the total sample, the US domestic IPO sample and foreign IPO sample. We only include the foreign dummy variable when examining the total sample. We expect that a month with a high share of firms subject to greater levels of information asymmetry will show higher mean and standard deviation of initial returns and vice versa.

For the total sample, we observe positive correlation between firms that are larger, older, listed on Nasdaq, VC-backed and classified as high-tech and monthly average and standard deviation of initial returns within months. While we observe a negative correlation between firms listed on the NYSE and monthly average and standard deviation of initial returns. Consistent with our predictions, are the findings of the three explanatory variables: tech, NYSE and Nasdaq. While, inconsistent with our predictions are the findings of the three explanatory variables: firm age, offer size and VC. Additionally, foreign firms are shown to have a negative correlation with monthly average and standard deviation of initial returns. This finding is not in accordance with our prediction, as we predicted that foreign firms should be characterized by greater information asymmetry than US domestic firms.

For the sub sample of US domestic IPOs, the results point in the same direction as in the total sample. However, the correlations estimates are smaller in magnitude except for the VC and tech variable. For the sub sample of foreign IPOs the correlation estimates are not significant. Overall, the correlation table, shows the suggestive evidence of the underlying dynamics behind the positive mean and standard deviation of initial returns. In the following section, we investigate these correlations more directly by constructing a cross-sectional regression model.

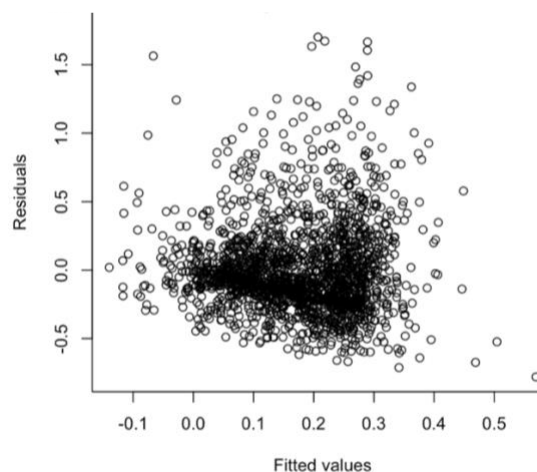
**Table 7**  
**Correlation between average firm-and offer-specific characteristics and monthly average and standard deviation of initial returns**

In this table, the correlations between the monthly mean and standard deviation of IPO initial returns and monthly firm- and offer-specific characteristics are shown, calculated by using Pearson correlation test. In parentheses are the asymptotic p-values. The definitions of the explanatory variables are summarized in table 3. The monthly firm-and offer-specific characteristics for the dummy variables are calculated by taking the sum of the dummy variables and divide it by the number of IPOs that specific month. The monthly firm-and offer-specific characteristics for the continuous variables, offer size and firm age are calculated by taking the average for each month.

|                           | (a)                 |                        | (b)                           |                        | (c)                       |                        |
|---------------------------|---------------------|------------------------|-------------------------------|------------------------|---------------------------|------------------------|
|                           | <i>Total sample</i> |                        | <i>US domestic IPO sample</i> |                        | <i>Foreign IPO sample</i> |                        |
|                           | Average<br>IPO IR   | Std. dev. of<br>IPO IR | Average<br>IPO IR             | Std. dev. of<br>IPO IR | Average<br>IPO IR         | Std. dev.<br>of IPO IR |
| Average log (Offer size)  | 0.29<br>(0.0000)    | 0.15<br>(0.0553)       | 0.14<br>(0.0564)              | 0.14<br>(0.0789)       | 0.13<br>(0.1512)          | -0.14<br>(0.2167)      |
| Average log (Firm age +1) | 0.24<br>(0.0012)    | 0.17<br>(0.0246)       | 0.21<br>(0.0041)              | 0.1<br>(0.2009)        | 0.04<br>(0.6444)          | -0.08<br>(0.4711)      |
| Percent VC dummy          | 0.14<br>(0.0600)    | 0.16<br>(0.0389)       | 0.33<br>(0.0000)              | 0.21<br>(0.067)        | 0.02<br>(0.8109)          | 0.15<br>(0.1803)       |
| Percent NYSE dummy        | -0.14<br>(0.0589)   | -0.13<br>(0.0842)      | -0.24<br>(0.0011)             | -0.21<br>(0.0053)      | 0.02<br>(0.8623)          | -0.07<br>(0.5078)      |
| Percent Nasdaq dummy      | 0.18<br>(0.0169)    | 0.19<br>(0.0113)       | 0.3<br>(0.0000)               | 0.3<br>(0.0000)        | -0.02<br>(0.8280)         | 0.09<br>(0.4329)       |
| Percent tech dummy        | 0.19<br>(0.0103)    | 0.19<br>(0.0123)       | 0.19<br>(0.0122)              | 0.07<br>(0.3789)       | 0.09<br>(0.3284)          | 0.14<br>(0.2161)       |
| Percent foreign dummy     | -0.12<br>(0.0999)   | 0.04<br>(0.5798)       |                               |                        |                           |                        |

### 6.1.2 Cross-sectional analysis of US domestic and foreign firms going public in the US

Prior to running the cross-sectional regression model, we investigate whether the two assumptions of the OLS are met, namely: multicollinearity and heteroskedasticity. To test for multicollinearity, we perform a VIF test, and it shows that two of our explanatory variables have a VIF degree above five, namely the Nasdaq and the NYSE variable. We therefore decide to drop the Nasdaq variable and then our OLS regressions no longer have multicollinearity. In our regression models, we only have the NYSE dummy variable as proxy to estimate the information asymmetry associated with a specific exchange listing. In our data, the majority of the firms that are not listed on the NYSE are, in fact, listed on Nasdaq. To test for heteroskedasticity, we perform the Breusch-Pagan test and plot the residuals against the fitted values to investigate if any pattern can be observed. The Breusch-Pagan test shows that the null hypothesis of the homoscedastic error terms, is rejected at a significance level of 1%. We can therefore conclude that heteroskedasticity is present in our OLS for the total sample and its two sub samples. In figure 3, the residuals of the OLS regression of the total sample are plotted against the fitted values. This figure also indicates the presence of heteroskedasticity. A potential cause to the existence of heteroskedasticity in our OLS, is omitted explanatory variables yet within the research field of IPO underpricing there is not a complete set of variables mapped out to fully explain IPO initial returns.



**Figure 3. Residuals of the OLS on the total sample**

In this figure, the residuals of the total sample from the OLS are plotted against its fitted values. The figure indicates that there is a presence of heteroskedasticity.

The findings in table 7, indicate that the changes of the types of firms undergoing an IPO both affect the level and volatility of monthly initial returns. We examine the results from table 7 more directly in table 8, by modelling the firm- and offer-specific characteristics jointly in both an OLS and a MLE regression model. We expect that the violation of the assumption of no heteroskedasticity in the OLS, will generate a less suitable model compared to the MLE of coefficients, which is heteroskedasticity consistent. In order to understand if the MLE actually generates a better fitted model or not, we continue to demonstrate the results of the OLS. In the MLE, we estimate the coefficients for both the mean and variance of initial returns and the two are modelled as a function of our explanatory variables. We show the results from the OLS and MLE for the total sample and its two sub samples.

To understand if the MLE model describes our data better than the OLS, we compare their log-likelihoods. The log-likelihood is higher in the MLE, for all the three samples, which indicates that the MLE is a superior cross-sectional regression model to explain the underlying dynamics of IPO initial returns. The signs and magnitudes of the coefficients in the OLS and MLE, are similar for the three samples. Overall, the significance of the coefficients is similar for the MLE and the OLS. The total sample has the most significant coefficients, while the US domestic IPO sample has less significant coefficients and the foreign IPO sample has the least significant coefficients. We assume a possible explanation to this finding is that the samples differ in size.

The statistically significant estimates indicate that our firm- and offer-specific characteristics affect both the mean and the variance of initial returns. Lowry et al. (2010) shows that the volatility of initial returns is higher than the mean of initial returns. By contrast, we find that the magnitudes of the coefficients are similar in the MLE for the mean and variance. We expect that this is driven by the fact that we do not have a bubble period in our data.

Consistent with our hypothesis, we find that high-tech firms experience a positive relationship with mean and volatility of initial returns and that firms that decide to list on the NYSE experience a negative relationship with mean and volatility of initial returns. However, we also find that some of our results are contradicting to our hypothesis.

Firstly, we find that firms receiving VC-backing have a higher degree of positive mean and volatility coefficients of initial returns. These findings are similar to Lowry et al. (2010) and they argue that the venture capital variable might pick up a risky-industry effect that is larger than the expected reduction of information asymmetry that VC backing should imply. In our data, we find that the majority of the VC backed firms are also classified as being in a high-tech industry and we therefore also argue that these firms might pick up a risky industry effect.

Secondly, we find that older and larger firms experience positive mean and volatility coefficients of initial returns. These findings are contradicting to our predictions and to Lowry et al. (2010)'s findings. In our study, we follow the IPO theories that argue for that the level of information asymmetry drives the level of IPO underpricing. The findings that older and larger firms have less available information is consequently puzzling. We therefore find it necessary to turn to other theories behind IPO underpricing in order to understand this relationship. A possible explanation could be that older and larger firms deliberately underprice their shares in order to signal high-quality to the investors, in line with the signalling theory proposed by Allen and Faulhaber (1989). Older and larger firms may be more confident about their ability to recoup the losses of IPO underpricing compared to younger firms. Another possible explanation could be that more investors want to participate in an IPO of an older and more established firm and thereby bid up the price more than expected by the underwriter.

Thirdly, we find a significant negative coefficient of the foreign dummy variable, which indicates that foreign firms are less volatile and have lower level of initial returns than US domestic firms. Contrarily, to our prediction that foreign firms would experience a higher level and volatility of initial returns than US domestic IPOs. We suggest that the foreign firms may pick up the effect of being larger and to list on the NYSE more than the effect of being foreign, in line with the argumentation of Francis et al. (2001). In the next section, we aim to investigate this suggestion further by comparing foreign firms with its US domestic counterparts.

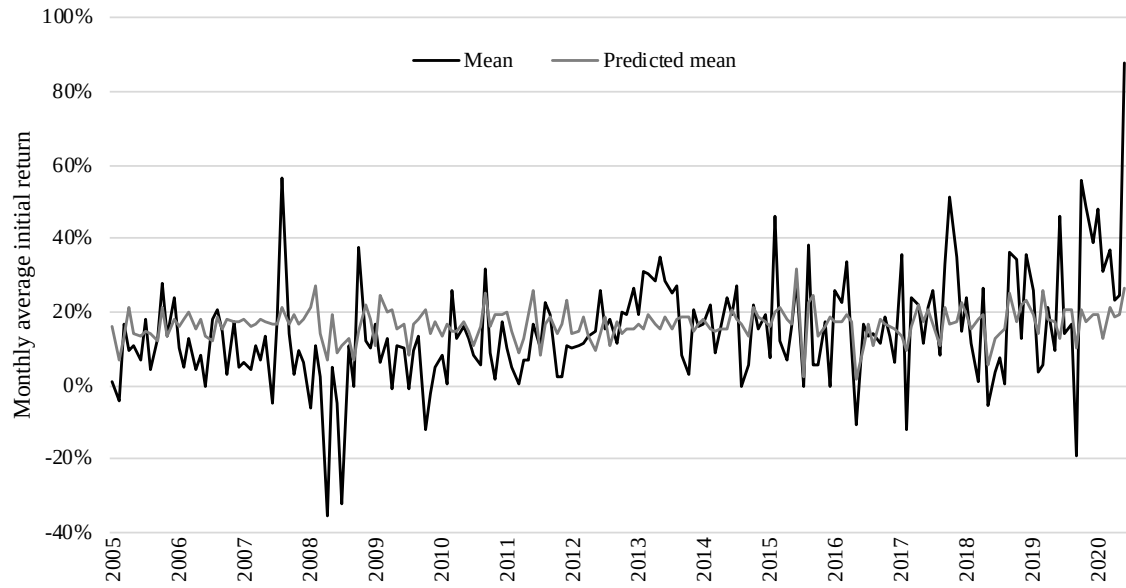
**Table 8**  
**The relationship of mean and variance of IPO initial returns and**  
**IPO firm- and offer-specific characteristics**

For the total sample and its two sub samples, an OLS and MLE regression is set up. The firm-and offer-specific characteristics used in the model are explained in table 3. In the parenthesis in the OLS regression columns, the t-statistics of the values are shown, calculated by using White's (1980) heteroskedasticity- consistent standard errors. The  $R^2$  is the adjusted R-squared. The MLE columns show the maximum likelihood estimates. In the parenthesis in the MLE regression columns, the z-statistics are shown. The log-likelihood estimates show the improvement of using a MLE model.

|                   | (a)                     |                         |                         | (b)                     |                         |                         | (c)                     |                         |                       |
|-------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-----------------------|
|                   | Total sample            |                         |                         | US domestic IPO sample  |                         |                         | Foreign IPO sample      |                         |                       |
|                   | OLS                     | MLE                     |                         | OLS                     | MLE                     |                         | OLS                     | MLE                     |                       |
|                   |                         | Mean                    | Variance                |                         | Mean                    | Variance                |                         | Mean                    | Variance              |
| Intercept         | -0.9935<br>(-6.6688)*** | -0.7757<br>(-6.5727)*** | -0.1189<br>(-1.6344)    | -1.0543<br>(-6.5339)*** | -0.7475<br>(-5.9553)*** | -0.2310<br>(-3.067)**   | -0.8158<br>(-2.0144)*** | -1.0368<br>(-3.3502)*** | 0.4459<br>(2.1883)*   |
| Log (Offer size)  | 0.0573<br>(7.0873)***   | 0.0458<br>(7.0847)***   | 0.0194<br>(4.7136)***   | 0.0608<br>(6.9122)***   | 0.0446<br>(6.4680)***   | 0.0262<br>(6.0983)***   | 0.0445<br>(2.0694)***   | 0.0563<br>(3.4047)***   | -0.0158<br>(-1.4326)  |
| Log (Firm age +1) | 0.0264<br>(4.6909)***   | 0.0252<br>(4.5780)***   | 0.0100<br>(2.3049)*     | 0.0249<br>(4.2228)***   | 0.0228<br>(3.9305)***   | 0.0079<br>(1.6981).     | 0.0354<br>(1.9516)***   | 0.0458<br>(2.598)**     | 0.0577<br>(3.7548)*** |
| VC dummy          | 0.1179<br>(6.2137)***   | 0.1222<br>(6.8619)***   | 0.0913<br>(7.9402)***   | 0.1315<br>(6.3928)***   | 0.1326<br>(6.8619)***   | 0.0957<br>(7.6763)***   | 0.0463<br>(0.9810)*     | 0.0633<br>(1.4076)      | 0.0941<br>(3.2181)**  |
| NYSE dummy        | -0.0312<br>(-1.7464).   | -0.0323<br>(-2.0862)*   | -0.0533<br>(-4.9489)*** | -0.0450<br>(-2.3443)*   | -0.0369<br>(-2.2121)*   | -0.0652<br>(-5.6393)*** | 0.0376<br>(0.7973).     | -0.0250<br>(-0.6739)    | -0.0160<br>(-0.5401)  |
| Tech dummy        | 0.0397<br>(2.1977)*     | 0.0329<br>(1.9547) .    | 0.0624<br>(5.5015)***   | 0.0368<br>(1.8813) .    | 0.0225<br>(1.2384)      | 0.0479<br>(3.9884)***   | 0.0297<br>(0.6316)      | 0.0356<br>(0.7975)      | 0.1338<br>(0.0000)*** |
| Foreign dummy     | -0.0587<br>(-2.5474)**  | -0.0554<br>(-2.6132) ** | 0.0515<br>(3.2998)***   |                         |                         |                         |                         |                         |                       |
| $R^2$             | 0.07805                 |                         |                         | 0.08768                 |                         |                         | 0.02137                 |                         |                       |
| Log-likelihood    | -624.4083               | -516.1001               |                         | -487.7743               | -400.2525               |                         | -126.7076               | -103.8853               |                       |
| Sample Size       |                         | 2050                    |                         |                         | 1751                    |                         |                         | 299                     |                       |

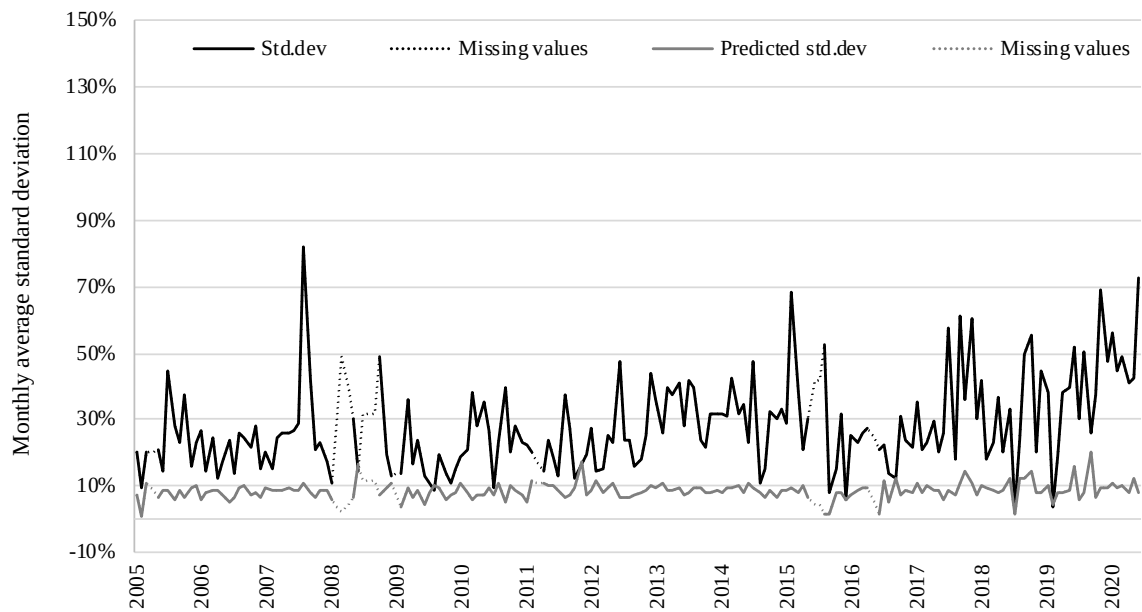
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Similar to Lowry et al. (2010), we plot the mean and standard deviation of initial returns on a monthly basis in figure 4 and 5, in order to understand the accuracy of our predicted values in the MLE model. We use the predicted values from MLE in column (a) which is for the total sample. Figure 4 suggests that our predicted values of the mean of initial returns are relatively similar to the actual values. Yet, the predicted standard deviations of initial returns are less accurate. Compared to Lowry et al. (2010) that have a peak of standard deviation of initial returns at merely 200 %, our data on volatility does not reach above 90%.



**Figure 4. The actual and predicted mean of monthly initial returns of IPOs, from 2005 to 2020.**

The black line represents the actual monthly mean of IPO initial returns. The grey line represents the predicted monthly mean of initial returns, from the MLE regression in table 5. The values are taken from the MLE in column (a) with the total sample, including the dummy variable.



**Figure 5. The actual and predicted standard deviation of monthly initial returns of IPOs, from 2005 to 2020.**

The black line represents the actual monthly standard deviation of IPO initial returns. The grey line represents the predicted monthly standard deviation of initial returns, from the MLE regression in table 5. The values are taken from the MLE in column (a) with the total sample, including the dummy variable.

## 6.2 The degree of information asymmetry of foreign IPOs

Our findings from cross-sectional regression in table 8, for the total sample, indicate a statistically significant negative relationship between foreign firms and IPO initial returns. We aim to investigate this relationship further and to examine whether this relationship holds when comparing foreign firms with our matched US domestic firms. Previous researchers (Saudagaran, 1988; Francis et al., 2001; Blass and Yalah, 2000) have shown that foreign firms going public typically have different institutional characteristics compared to US domestic firms. We predict that the negative relationship between foreign firms and IPO initial returns will not hold in our cross-sectional regression with foreign firms and its US domestic counterparts.

### 6.2.1 Cross-sectional regression of our matched sample

To begin with, we run a simple regression in order to understand the overall relationship between the firm-characteristic of being foreign and IPO initial returns. We perform a simple regression on both the total and matched sample, these estimates are shown in table 9. To be noted, is that the foreign dummy is significant for the total sample, yet non-significant for the matched sample. The non-significant coefficient of the foreign variable in the matched sample, demonstrate that foreign firms do not experience more or less underpricing compared to its US domestic counterparts. The simple regression model has a low R-square for both the matched and the total sample, indicating that the model has a low explanatory power. We will therefore set up a cross-sectional regression model controlling for other potential factors.

Prior to setting up the cross-sectional regression model, we control for heteroskedasticity in the matched sample. In the Breusch-Pagan test, we fail to reject the null hypothesis and we can therefore assume that heteroskedasticity in the matched sample is absent. Therefore, we do not set up an MLE model in this section and instead perform an OLS regression. However, our total sample contains heteroskedasticity and to control for a certain extent for heteroskedasticity, we use White's (1980) heteroskedasticity-consistent standard errors.

**Table 9**

#### **A simple OLS regression between the foreign variable and IPO underpricing**

Table 9 shows OLS regressions on the total and the matched sample. In the parenthesis, the t-statistics of the estimates are shown, calculated by using White's (1980) heteroskedasticity-consistent standard errors. The  $R^2$  is the adjusted R-squared.

|                                                               | Total sample           | Matched sample        |
|---------------------------------------------------------------|------------------------|-----------------------|
| Intercept                                                     | 0.1819<br>(22.6985)*** | 0.1666<br>(8.8445)*** |
| Foreign dummy                                                 | -0.0598<br>(-2.5780)** | -0.0446<br>(-1.5472)  |
| R-squared                                                     | 0.0033                 | 0.0023                |
| Log-likelihood                                                | 1419.321               | -224.1085             |
| Sample size                                                   | 2050                   | 598                   |
| Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 |                        |                       |

In table 10, we show the OLS cross-sectional regression of the total and matched sample. The first column shows the estimates of the OLS regression for the total sample, from table 8, which is used to compare the findings of the matched sample. The second column shows the OLS regression of the matched sample that includes 299 foreign firms and 299 US domestic matched firms. Compared to the simple regression, the cross-sectional OLS regression with more explanatory variables has a higher R-squared, indicating a better model and more solid results can therefore be drawn.

In the OLS regression, for the matched sample, the coefficient of the foreign dummy is negative, but not significant. The non-significant coefficient of the foreign dummy variable indicates that foreign and US domestic firms experience equivalent degrees of IPO underpricing. For the OLS regression of the matched sample, the sign of the coefficients is similar to those in the total sample with the exception of the NYSE and tech dummy, yet not significant.

**Table 10**  
**OLS regression to test for the significance of the foreign dummy variable**

Table 10 shows OLS regressions on the total sample and the matched sample. In the parenthesis, the t-statistics of the estimates are shown, calculated by using White's (1980) heteroskedasticity-consistent standard errors. The  $R^2$  is the adjusted R-squared.

|                                                               | Total sample            | Matched sample         |
|---------------------------------------------------------------|-------------------------|------------------------|
| Intercept                                                     | -0.9922<br>(-6.6604)*** | -0.9388<br>(-3.1167)** |
| Log (Offer size)                                              | 0.0573<br>(7.0808)***   | 0.0550<br>(3.3931)***  |
| Log (Firm age +1)                                             | 0.0264<br>(4.6842)***   | 0.0275<br>(2.5022)*    |
| VC dummy                                                      | 0.1179<br>(6.2139)***   | 0.0795<br>(2.2653)*    |
| NYSE dummy                                                    | -0.0312<br>(-1.7448).   | 0.0038<br>(0.1144)     |
| Tech Dummy                                                    | 0.0397<br>(2.1949)*     | -0.0035<br>(-0.1025)   |
| Foreign Dummy                                                 | -0.0587<br>(-2.5791)**  | -0.0436<br>(-1.5603)   |
| R-squared                                                     | 0.07813                 | 0.03911                |
| Log-likelihood                                                | -624.321                | -210.3482              |
| Sample size                                                   | 2050                    | 598                    |
| Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 |                         |                        |

## 6.2.2 Robustness tests

We perform two different robustness tests to ensure that our finding of equivalent IPO initial returns for foreign and domestic firms hold (results are shown in appendix).

Our first robustness test examines whether the sample size in the matched sample has an effect on the insignificance of the foreign dummy variable. A random sample of US domestic firms are therefore constructed, that represents a smaller version of the total sample. In the

OLS regression of the random sample we find that the foreign dummy is significant, which shows that our results are not sensitive to the sample size.

In our second robustness test, we examine if our findings hold over time by dividing our total and matched sample into two time periods, 2005 to 2012 and 2013 to 2020. We perform an OLS regression on each sample's time period. We find that the foreign dummy is not significant in the time period from 2005 to 2012 for neither the matched nor the total sample, which indicates that foreign and domestic firms experience equivalent levels of IPO underpricing. However, we find that the foreign dummy is statistically significant in the time period 2013 to 2020 for both the matched and the total sample, indicating that foreign firms experience less IPO underpricing than US domestic firms. In the second time period, the explanatory power of the OLS regressions, for the matched and total sample, is higher than in the first time period.

These results indicate that our findings are not consistent over time and an overall conclusion on the effect of the foreign variable can therefore not be drawn. We conclude that in the first time period IPO underpricing can be expected to be equivalent for foreign and US domestic firms. Whereas in the second time period, foreign firms are less underpriced than US domestic firms. One possible explanation to this finding is that information asymmetry across borders continues to diminish as a result of financial globalization.

## 6.2.2 Cross-sectional regression to account for the developed country dummy

In table 11, we show the cross-sectional regression of the foreign sample with the inclusion of a developed country dummy variable. We aim to examine whether a difference in IPO underpricing exists between foreign firms originating from emerging and developed countries. Our cross-sectional OLS regression shows that foreign firms from developed countries experience less underpricing yet we cannot draw any conclusion as the coefficient is non-significant.

**Table 11**  
**Regression model on foreign firms including the developed country dummy**

Table 11 shows OLS regression on the foreign sample with the inclusion of the developed country dummy. In the parenthesis, the t-statistics of the estimates are shown, calculated by using White's (1980) heteroskedasticity-consistent standard errors. The  $R^2$  is the adjusted R-squared.

|                                                               | Foreign IPO Sample    |
|---------------------------------------------------------------|-----------------------|
| Intercept                                                     | -0.8862<br>(-2.1890)* |
| Log (Offer size)                                              | 0.0489<br>(2.2740)*   |
| Log (Firm age +1)                                             | 0.0346<br>(1.9143) .  |
| VC dummy                                                      | 0.0410<br>(0.8665)    |
| NYSE dummy                                                    | 0.0351<br>(0.7453)    |
| Tech dummy                                                    | 0.0379<br>(0.7603)    |
| Developed country dummy                                       | -0.0479<br>(-1.0813)  |
| R-squared                                                     | 0.02099               |
| Log-likelihood                                                | -126.2554             |
| Sample size                                                   | 299                   |
| Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 |                       |

## 7. Conclusions

Despite the growing tendency for firms to turn to foreign markets in order to raise capital, little research has been carried out to ascertain whether firms going public abroad are more likely to be underpriced compared to their domestic counterparts. Such findings represents a determining factor for firms evaluating whether to go public in their domestic market or abroad, for instance on the ever most attractive US stock exchanges.

The purpose of this paper is therefore to build upon existing literature in the field of IPOs, by thoroughly examining the discrepancies of IPO underpricing between US domestic and foreign IPOs. While leveraging the methodology outlined from Lowry et al. (2010), we expand past research mainly by: analyzing a more recent period, namely from 2005 to 2020; bridging the gap between US-domestic IPOs and foreign IPOs in the US by comparing the two simultaneously; assessing both mean and volatility of initial returns for foreign firms, compared to previous studies assessing only mean initial returns.

Previous research in this field has shown inconsistent results when assessing the degree of IPO underpricing for foreign firms. Amongst the various studies, our results are in line with findings from both Ejara and Ghosh (2004) and Bruner et al. (2004).

In fact, our total sample of 2050 IPOs shows a strong relationship between the mean and standard deviation of IPO initial returns. In both our correlation matrix and MLE model, we find that all our explanatory variables have a significant impact on IPO underpricing and the volatility of initial returns. Our findings from the total sample show that larger offerings, older firms, firms with VC-backing, firms in a tech industry have positive mean and volatility coefficients of initial returns. Whereas firms on the NYSE and foreign firms are found to have negative mean and volatility coefficients of initial returns.

Contrarily to our original hypothesis, we find that the foreign variable is insignificant in the matched sample, indicating that foreign and US domestic firms experience equivalent degrees of IPO underpricing. Similar to previous researchers (Bruner et al., 2004), we expect that our findings are a result of the foreign variable being outweighed by other firm-and offer-characteristics that contribute to less information asymmetry.

We then perform two types of robustness tests to control if our findings hold. The first test indicates that our results are not sensitive to the sample size. However, the second test indicates that our results are not consistent in time. In the first time period, 2005 to 2012, the foreign variable is insignificant for both the total and matched sample, whereas in the second time period, 2013 to 2020, we find that the foreign variable is significant for both the total and matched sample. This result indicates that foreign firms have become relatively less underpriced compared to US domestic firms during the more recent time period.

Firms evaluating whether to go public in their domestic market or on one of the attractive star-spangled exchanges, should not fear to experience higher IPO underpricing than its US domestic counterparts.

## 7.1 Limitations and further research

Our study provides valuable insight into how specific firm- and offer-specific characteristics effect initial returns and volatility of initial returns, as well as advancing the research field of underpricing for foreign firms. However, it is also subject to various limitations. In this section, we present the main limitations of our work and suggestions for further research.

Firstly, a large extent of factors can impact IPO initial returns and volatility of initial returns. This study mainly relies on the theories of information asymmetry to explain IPO underpricing, as in Lowry et. Al. (2010). However, our findings highlight how larger and more mature firms experience more underpricing, a result which seems to be in contrast with the traditional theory of information asymmetry. Such contradiction suggests that other driving forces that have not been assessed throughout this study might help explain further the phenomenon of IPO underpricing.

Our cross-sectional regression model might not accurately fit all potential variables explaining IPO underpricing. As a result of this, the explanatory power of our models never exceeds an adjusted R-square of 10%. This indicates that our model can at most explain 10% of the factors that contribute to underpricing. Since there are many other aspects that influence underpricing, one should be cautious of drawing too strong conclusions from our results. Lowry et al. (2010) have adjusted R-square values ranging from around 3% to 24%, also indicating that there are important factors that their model does not explain.

Additionally, the results from this study seems to be different depending on the period examined for foreign IPO underpricing. Indeed, we observe how foreign firms become relatively less underpriced compared to US domestic firms as time passes, which calls for additional research to explain the underlying factors contributing to this phenomenon. Why are foreign firms becoming relatively less underpricing compared to US domestic firms? Lastly, we have not looked into the effect that market volatility has on initial return, something that Lowry et al. (2010) accounts for in their study. For foreign firms, market volatility's impact is more difficult to measure as they are impacted by both their home's equity market and the US equity market. This, in turn, calls for future research, to look into how market volatility can affect underpricing of foreign firms.

In conclusion, to date, relatively little research has been conducted on the implications of underpricing of foreign IPOs and initial conclusions are contradictory. In order to fully understand how foreign IPOs and their domestic counterparts vary in regard to initial returns, we call for further research to include and assess more possible driving factors, to consider the evolution of foreign underpricing across time and to measure how market volatility affects underpricing.

## References

- Allen, F., & Faulhaber, G. (1989). Signaling by underpricing in the IPO market. *Journal of Financial Economics*, 23, pp. 303-323.
- Baron, D. P. (1982). A Model of the Demand for Investment Banking Advising and Distribution Services for New Issues. *The Journal of Finance*, 37, pp. 955-976.
- Barry, C., Muscarella, C., Peavy III, J., & Vetsuypens, M. (1990). The role of venture capital in the creation of public companies: Evidence from the going-public process. *Journal of Financial Economics*, 27(2), pp. 447-471.
- Beatty, R. P., & Ritter, J. (1986). Investment Banking, Reputation, and the Under-Pricing of Initial Public Offerings. *Journal of Financial Economics*, 15, pp. 213-232.
- Belsley, D. A., Kuh, E., & Welsch, R. E. (1980). Regression diagnostics: Identifying influential data and sources of collinearity. New York, NY: Wiley.
- Blass, A., & Yafeh, Y. (2000). Vagabond shoes longing to stray: Why foreign firms list in the United States. *Journal of Banking and Finance*, 25, pp. 555-572.
- Box, G., & Jenkins, G. (1984). Time series Analysis: Forecasting and control, 2<sup>nd</sup> ed. San Francisco: Holden Day, 1984.
- Bruner, R., Chaplinsky, S., & Ramchand, L. (2004). U.S.-bound IPOs: issue costs and market selectivity. *Financial Management*, 33, pp. 39-60.
- Caglio, C., Weiss Hanley, K., & Marietta-Westberg, J. (2016). Going Public Abroad. *Journal of corporate finance*, 41, pp. 103-122.
- Comstock, A., Kish, R.J., & Vasconcellos, G.M. (2003). The post-privatization financial performance of former state-owned enterprises. *Journal of International Financial Markets, Institutions and Money*, 13(1), pp. 19-37.
- Doidge, C., Karolyi, G.A., & Stulz, R. (2013). The U.S. left behind? Financial globalization and the rise of IPOs outside the U.S. *Journal of Financial Economics*, 110, pp. 546-573.
- Dong, M., Michel, J.-S., & Pandes, A. J. (2011). Underwriter Quality and Long-Run IPO Performance. *Financial Management*, 40(1), pp. 219-251.
- Ejara, D. D., & Ghosh, C. (2004). Underpricing and aftermarket performance of American depositary receipts (ADR) IPOs. *Journal of Banking and Finance*, 28, pp. 3151-3186.
- Errunza, V., & Miller D.P. (2000). Market Segmentation and the Cost of Capital in International Markets. *Journal of Financial and Quantitative Analysis* 35, pp. 577-600.

- Foerster, S., & Karolyi GA. (1999). The Effects of Market Segmentation and Investor Recognition on Asset Prices: Evidence of Foreign Stock Listings in the US. *Journal of Finance* 54, pp. 981-1014.
- Francis, B., Hasan, I., & Li, F. (2001). Underpricing of foreign and domestic IPOs in the US market: Empirical evidence. *Financial Markets, Institutions & Instruments*, 10, pp. 1–18.
- Greene, William H. (1993). *Econometric Analysis*, Second edition, Prentice Hall, New York
- Grinblatt, M., & Hwang, C.Y. (1989). Signalling and the Pricing of Unseasoned New Issues. *Journal of Finance*, 44, pp. 393-420.
- Hanley, K.W., Kumar, A., & Seguin, P. (1993). Price stabilization in the market for new issues. *Journal of Financial Economics* 34, pp.177-197
- Harvey, C.R., 1995. Predictable risk and returns in emerging markets. *Review of Financial Studies*, 773–816.
- Henderson, B., Jegadeesh, N., & Weisbach, M. S. (2006). World markets for raising new capital. *Journal of Financial Economics*, 82, pp.63–101.
- Hwang, C.Y., & Clarysse, B. (2012). Endorsing Legitimacy To Avoid Ipo Underpricing When Markets For Technology Fail, *Academy of Management Proceedings*, Vol 2012 (1), pp. 17168
- Ibbotson, R.G. (1975). Price performance of common stock new issues. *The Journal of Financial Economics*, 2(3), pp. 235-272.
- Judge, G., Hill, C., Griffiths, W., & Lee, T. (1985) *The Theory and Practice of Econometrics*. New York: John Wiley and Sons
- Karolyi, A.G. (1998). What Happens to Stocks that List Shares Abroad? A Survey of Evidence and Its Managerial Implications, *NYU Salomon Brothers Center Monograph*, 7, pp. 1-60.
- Kotnik, A., & Tärning, J. (2020). The Role of Venture Capital Funding on IPO Underpricing: A Study on U.S. IPOs Between 1985 and 2020., *Stockholm School of Economics, Bachelor Thesis*
- Kutner, M., Nachtsheim, C., & Neter, J. (2004). *Applied linear regression models* (4th ed.). New York, NY: McGraw-Hill/Irwin
- Lee, P. M., & Wahal, S. (2004). Grandstanding, certification and the underpricing of venture capital backed IPOs. *Journal of Financial Economics*, 73(2), pp. 375-407.
- Ljung, G. M., & Box, G. E. (1978). On a measure of lack of fit in time series models. *Biometrika*, 65(2), pp. 297-303.
- Ljungqvist, A. P. (1997). Pricing Initial Public Offerings: Further Evidence from Germany. *European Economic Review*, 41(7), pp. 1309-1320.

Ljungqvist, A. P. & Wilhelm, W. J. (2003). IPO Pricing in the Dot-Com Bubble, *Journal of Finance*, 58, pp.723-752.

Loughran, T. (1993) NYSE vs NASDAQ Returns - Market Microstructure or the Poor Performance of Initial Public Offerings? *Journal of Financial Economics*, 33, pp. 241- 260.

Loughran, T., Ritter, J. R. & Rydqvist, K. (1994). Initial Public Offering: International Insights, *Pacific-Basin Finance Journal*, 2, pp. 165-199.

Loughran, T. & Ritter, J. R. (2002). Why Don't Issuers Get Upset About Leaving Money on the Table in IPOs? *Review of Financial Studies*,15 (2), pp. 413-443.

Loughran, T., & Ritter, J. R. (2004). Why has IPO underpricing changed over time?. *Financial Management*, 33 (3), pp. 5-37.

Lowry, M., Officer, M. S., & Schwert, G.W. (2010). The variability of IPO initial returns. *The Journal of Finance*, 65, pp. 425-465.

Meggison, W., & Weiss, K. (1991). Venture capitalist certification in initial public offerings. *Journal of Finance*, 46, pp. 879-903.

McDonald, J. G., & Fisher, A. K. (1972). New Issue Stock Price Behavior. *Journal of Finance*, 27, pp.165-177.

Miller, D.P. (1999). The Market Reaction to International Cross-Listing: Evidence from Depositary Receipts. *Journal of Financial Economics*, 51, pp.103-124.

Miller, R. E., & Reilly, F. (1987). An Examination of Mispricing, Returns, and Uncertainty for Initial Public Offerings. *Financial Management*,16, pp. 33-38.

Michaely, R., & Shaw, W. H. (1994). The Pricing of Initial Public Offerings: Tests of Adverse Selection and Signalling Theories. *Review of Financial Studies*,7(2), pp. 279-319.

Nelson, D.B. (1991). Conditional heteroskedasticity in asset returns: A new approach, *Econometrica*, 59, 347-370.

Pagano, M., Röell, A. A., & Zechner, J. (2002). The geography of equity listing: Why do companies list abroad?. *Journal of Finance*, 57, pp. 2651–2694.

Pastor, L., & Veronesi, P. (2005). Rational IPO waves. *Journal of Finance*,60 (4), pp.1713-1757.

Reilly, F. K. & Hatfield, K. (1969). Investor Experience with New Stock Issues. *Financial Analysts Journal*, 25(5), pp. 73-80.

Ritter, J. (1984). The “Hot Issue” Market of 1980. *Journal of Business*, 57 (2), pp. 215- 240.

Ritter, J. (2021). Initial Public Offerings: Foreign Companies Going Public in the U.S., 1980-2020. University of Florida, Available Online: <https://site.warrington.ufl.edu/ritter/ipo-data/> [Accessed 10 May 2021]

Rock, K. (1986). Why New Issues are Underpriced. *Journal of Financial Economics*, 15, pp. 177–212.

Ruud, J., (1993). Underwriter price support and the IPO underpricing puzzle. *Journal of Financial Economics*, 34, pp. 135-151.

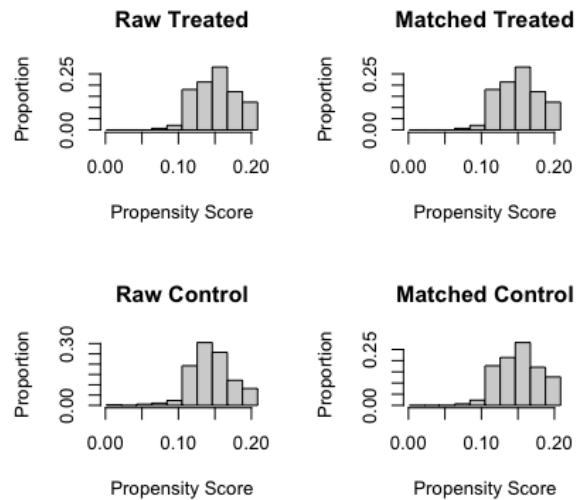
Saudagaran, S. M. (1988). An empirical study of selected factors influencing the decision to list on foreign stock exchanges. *Journal of International Business Studies*, 19, pp. 101–127.

Ule, G. M. (1937). Price Movements of Newly Listed Common Stocks. *The Journal of business of the University of Chicago*, 10.4, pp. 346–369.

Welch, I. (1992). Sequential Sales, Learning, and Cascades. *Journal of Finance*, 47 (2), pp. 695-732.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, *Econometrica*, 48, pp. 817-838.

## Appendix



### A. Figure of the accuracy of the matching procedure

The figures above show the Propensity Score distribution. The raw treated consist of the 299 foreign IPOs and raw control consist the 1751 domestic IPOs. Matched treated consist of the same foreign IPO sample as the raw treated and the matched control consist of the matched US domestic IPOs, consisting of 299 IPOs.

### B. Number of IPOs by country for the foreign IPO sample

In the table below the foreign listings have been separated into two subgroups, developed markets and emerging markets. Presented is number of IPOs performed in each country.

| Country                        | N         | Country                       | N          |
|--------------------------------|-----------|-------------------------------|------------|
| <i>Developed Markets</i>       |           | <i>Emerging Markets</i>       |            |
| Australia                      | 1         | Argentina                     | 3          |
| Austria                        | 1         | Bermuda                       | 11         |
| Belgium                        | 1         | Brazil                        | 3          |
| British Virgin                 | 2         | Cayman Islands                | 1          |
| Canada                         | 8         | China                         | 140        |
| Denmark                        | 2         | Cyprus                        | 1          |
| France                         | 3         | Greece                        | 11         |
| Germany                        | 5         | Hong Kong                     | 10         |
| Ireland-Rep                    | 8         | India                         | 2          |
| Italy                          | 1         | Indonesia                     | 1          |
| Jersey                         | 2         | Israel                        | 31         |
| Luxembourg                     | 6         | Jordan                        | 1          |
| Monaco                         | 2         | Malaysia                      | 1          |
| Netherlands                    | 12        | Panama                        | 1          |
| Singapore                      | 2         | Russian Fed                   | 1          |
| South Korea                    | 4         | Taiwan                        | 2          |
| Switzerland                    | 6         | <i>Total Emerging markets</i> | <i>220</i> |
| United Kingdom                 | 12        |                               |            |
| Utd Arab Em                    | 1         |                               |            |
| <i>Total Developed markets</i> | <i>79</i> |                               |            |

### C. Variance inflation factors (VIF)

|                            | Variance inflation factor (VIF) |                   |          |            |              |            |               |
|----------------------------|---------------------------------|-------------------|----------|------------|--------------|------------|---------------|
|                            | Log (Offer size)                | Log (Firm age +1) | VC dummy | NYSE dummy | Nasdaq dummy | Tech Dummy | Foreign dummy |
| OLS total sample           | 1.279127                        | 1.052421          | 1.437292 | 5.667038   | 5.445444     | 1.459951   | 1.020177      |
| OLS US domestic IPO sample | 1.298180                        | 1.051040          | 1.513162 | 5.104878   | 4.927370     | 1.539833   |               |
| OLS foreign IPO sample     | 1.185438                        | 1.051214          | 1.162069 | 15.768903  | 15.422899    | 1.164124   |               |

### D. Variance inflation factors (VIF) without the Nasdaq variable

|                            | Variance inflation factor (VIF) |                   |          |            |            |               |
|----------------------------|---------------------------------|-------------------|----------|------------|------------|---------------|
|                            | Log (Offer size)                | Log (Firm age +1) | VC dummy | NYSE dummy | Tech Dummy | Foreign dummy |
| OLS total sample           | 1.256274                        | 1.048414          | 1.405468 | 1.314002   | 1.445995   | 1.017693      |
| OLS US domestic IPO sample | 1.272905                        | 1.045998          | 1.477075 | 1.522291   | 1.339995   |               |
| OLS foreign IPO sample     | 1.177701                        | 1.051213          | 1.145043 | 1.164016   | 1.173399   |               |

## E. Robustness tests for our finding of equivalent IPO underpricing for foreign and US domestic IPOs

Table E shows the results of our robustness tests. Column (a) and (e) shows the results from the OLS regression in table 10. Column (b) shows the OLS regression of our random sample. Column (c) shows the OLS regression for the matched sample in the time period 2005-2012 whereas column (d) shows for the time period 2013-2020. Column (f) shows the OLS regression for the total sample in the time period 2005-2012 whereas column (g) shows for the time period 2013-2020. In the parentheses, the t-statistics of the values are shown, calculated by using White's standard errors. Adjusted R-squared and log-likelihood is shown.

|                   | (a)<br>Matched sample  | (b)<br>Random<br>sample | (c)<br>Matched<br>sample<br>time period<br>2005-2012 | (d)<br>Matched sample<br>time period 2013-<br>2020 | (e)<br>Total<br>sample  | (f)<br>Total sample<br>time period<br>2005-2012 | (g)<br>Total sample<br>time period<br>2013-2020 |
|-------------------|------------------------|-------------------------|------------------------------------------------------|----------------------------------------------------|-------------------------|-------------------------------------------------|-------------------------------------------------|
| Intercept         | -0.9388<br>(-3.1162)** | -0.8004<br>(-3.1547)**  | -0.5675<br>(-1.6734) .                               | -1.0118<br>(-2.4029)*                              | -0.9922<br>(-6.6604)*** | -0.5060<br>(-2.7537)**                          | -1.1405<br>(-5.9932)***                         |
| Log (Offer size)  | 0.0550<br>(3.3923)***  | 0.0477<br>(3.5230)***   | 0.0317<br>(1.7153) .                                 | 0.0619<br>(2.7448)**                               | 0.0573<br>(7.0808)***   | 0.0267<br>(2.6828)**                            | 0.0679<br>(6.5673)***                           |
| Log (Firm age +1) | 0.0275<br>(2.5038)*    | 0.0190<br>(1.6484) .    | 0.0236<br>(2.0158)*                                  | 0.0284<br>(1.5722)                                 | 0.0264<br>(4.6842)***   | 0.0379<br>(5.7620)***                           | 0.0188<br>(2.3248)*                             |
| VC dummy          | 0.0795<br>(2.2657)*    | 0.0631<br>(1.8541) .    | 0.0793<br>(1.7765) .                                 | 0.0647<br>(1.244)                                  | 0.1179<br>(6.2139)***   | 0.1136<br>(4.6035)***                           | 0.1196<br>(4.6472)***                           |
| NYSE dummy        | 0.00389<br>(0.1152)    | -0.0043<br>(-0.1338)    | 0.01562<br>(0.3531)                                  | 0.0063<br>(0.1217)                                 | -0.0312<br>(-1.7448).   | 0.0227<br>(0.9804)                              | -0.0524<br>(-2.0832)*                           |
| Tech Dummy        | -0.0035<br>(-0.1018)   | 0.0444<br>(1.3310)      | -0.0175<br>(-0.3865)                                 | 0.0156<br>(0.3114)                                 | 0.0397<br>(2.1949)*     | -0.0212<br>(-0.8636)                            | 0.0630<br>(2.5662)*                             |
| Foreign Dummy     | -0.0436<br>(-1.5603)   | -0.0466<br>(-1.6859) .  | -0.0008<br>(-0.0249)                                 | -0.0784<br>(-1.8037) .                             | -0.0587<br>(-2.5791)**  | -0.0143<br>(-0.4819)                            | -0.0745<br>(-2.2236)*                           |
| R-squared         | 0.03911                | 0.03493                 | 0.0115                                               | 0.04374                                            | 0.07813                 | 0.07345                                         | 0.08326                                         |
| Log-likelihood    | -210.3482              | -200.0335               | 46.5239                                              | -144.2222                                          | -624.321                | -2.4833                                         | -513.58                                         |
| Sample Size       | 598                    | 598                     | 284                                                  | 314                                                | 2050                    | 798                                             | 1252                                            |

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1