Comparing Apples to Peers: Studying the Importance of Industry Affiliation for Private Company Discounts in Europe

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May 16, 2022

Abstract: Private company transactions have been found to be, on average, valued lower than comparable public transactions, giving rise to what is often in the literature called a Private Company Discount (PCD). Building on previous literature, this study extends our understanding of how the occurrence of a PCD might differ between different industries, and what firm characteristics that could explain such cross-sectional heterogeneity. Using a thorough matching procedure, building comparable portfolios of European public transactions, this study finds an average PCD of 33%, ranging between 25-65%, depending on industry. Some explanatory factors are found to be significant for all industries, such as profitability. Interestingly, others, such as financial sponsors being the acquirer, seem to matter only for the service industry. Through industry granularity, this study thus deepens our understanding of what matters to the occurrence of a private company discount – and not.

JEL classification: G20; G24; G32; G34

Keywords: Private company discount; Private company transactions; M&A

Acknowledgements: We would like to thank Dong Yan, Assistant Professor of Finance at the Stockholm School of Economics (SSE) and a Research Fellow at the Swedish House of Finance (SHoF), for the valuable guidance and support during the research process.

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I Introduction

During 2021, an all-time record for global Mergers and Acquisitions (M&A) was set, reaching a total value of $5.9 trillion, spanning across 63,000 deals (Refinitiv Eikon, 2022). While highly central to the financial industry, M&A is also a substantial research field within academia. One of many relevant areas of study, both for practitioners as well as researchers, regards the similarities and differences between private and public companies.

In several aspects, private companies are distinctive to public companies. Firstly, not being publicly traded on the stock exchange, private companies are generally not required to disclose financial information to the public. Further, private companies tend to have less constraining accounting standards than public firms (Damodaran, 2006). As a result, external investors in private companies are not able to make sound investments purely based on readily available information. To solve this issue of asymmetric information, the bidder usually conducts thorough due diligence processes before investing in private companies, resulting in high transaction costs. Secondly, private companies generally do not have access to the liquidity of public capital markets, resulting in an increased cost of capital (Berk & DeMarzo, 2019). As both transparency and liquidity are of value to investors, private companies are on average valued lower than comparable public firms, giving rise to what is often in the literature called a Private Company Discount (PCD).

Previous research on the existence of a private company discount have been conducted using a variety of methods, in this study categorized as (I) the restricted stock approach, (II) the pre-IPO approach and (III) the comparable acquisition method. As the literature has developed, the comparable acquisition method has become increasingly dominant. However, previous literature still suffers from a couple of flaws, two in particular. Firstly, little has been said about the importance of considering industry classifications when studying the occurrence of a PCD, and how the private company discount might vary across industries. Secondly, the literature is lacking consideration with regards to potential cross-sectional heterogeneity in PCD: different firm characteristics might be valued differently in different industries. This paper extends previous research by making a comprehensive regression analysis, generating a significantly higher explanatory power than previous studies, as well as shedding additional light on the importance of taking industry classification into consideration when discussing the occurrence of a private company discount. Furthermore, important contributions are also made to understand how different explanatory variables carry different weights in different industries.

This study builds on previous literature, using the acquisition method to compare private and public transactions. Rather than matching private and public transactions on a 1-on-1 basis, private transactions are matched against a portfolio of comparable public transactions through an extensive process focusing on company size, industry classification (4-digit SIC code) and transaction year, using a large data set compromising of 13,850 European transactions. The findings add substantial depth to both how the PCD varies across industries – and why. While the average PCD is calculated to 33%, it is found to vary across industries, spanning between 25% (Manufacturing) and 65% (Wholesale). While some variables, such as profitability and asset turnover, seem to be universally important in determining the PCD across industries, the cross-sectional analysis also shed light on some characteristics that seem to matter only in certain industries. For example, financial sponsors being the purchasing entity seem to carry significant weight in the service industry, including software and other computer-related companies.

The paper is outlined as follows: Section II gives an overview of previous research on the occurrence of a private company discount, including methodological considerations and existing research gaps; Section III contains this paper's hypotheses and their motivations;

Section IV describes the data set utilized in this paper; Section V outline the methodology applied when matching reference portfolios and the considerations that have been made as well as the technique for calculating the PCD; Section VI presents the private company discount prevalent in said data set; Section VII describes the regression model applied to study the explanatory variables that drive the discount; Section VIII presents the results from the regression analysis; Section IV discuss the results; and Section X conclude on this papers results and suggestions for future research.

II Literature review

As a rule of thumb, practitioners often assume a private company discount of around 20-30% relative to comparable public companies (Damodaran, 2005). However, from an academic perspective, estimating such a discount empirically is not as straightforward given the absence of observable prices for private companies. The current body of literature concerning PCD is mainly comprised of three distinct approaches used to try and estimate the PCD: (I) the restricted stock approach, (II) the pre-IPO approach and (III) the comparable acquisition method.

a. The restricted stock approach

The approach to estimate the private company discount that was initially used is commonly described as the restricted stock approach. This method focuses on public companies' issuances of restricted stock, i.e. the stocks that public companies issue to through private placements which are restricted from being resold in the open market for a specific time-period (Damadoran, 2006). The method aims to estimate the discount by studying the price of a restricted stock and the price difference compared to its freely tradeable public counterpart, which normally is considered equivalent except for the restriction.

According to US Securities and Exchange Commission (SEC) regulation, securities that are privately placed with a few institutional investors do not need to be registered with the SEC. However, according to Rule 144 of the SEC Securities Act, shareholders of restricted stock are not allowed to resell the stock in the open market before a one-year holding period has passed. To compensate investors for this illiquidity, companies that issue restricted shares normally do so at a price discount compared to the publicly tradeable stock (Koeplin et al., 2000). As for previous studies, Pratt & Niculita (2008) gives a comprehensive overview of 12 previous empirical studies, covering restricted stock transactions between 1960 and 1998, estimating an average price discount for restricted stock between 20% (Johnson, 1999) and 45% (Pittock & Stryker, 1983).

Estimating the PCD using the restricted stock approach has received two main critiques. Firstly, the discount that is captured in the comparison can have other roots than those usually interlinked with a PCD. Rather than being compensation for say illiquidity, the restricted stock discount may be given as a compensation to private placement investors who have been providing advisory services to the issuing company (Koeplin et al., 2000). Hertzel & Smith (1993) try to isolate this potential difference from the provision of advisory services by comparing unregistered private placements having marketability restrictions to registered placements, finding a 13.5% difference between restricted and registered stock. As this entails comparing companies with different characteristics, Bajaj et al. (2001) controls for company differences and consequently finds a more limited discount of 7.2%.

Secondly, some have argued that marketability restriction is an unreliable proxy for illiquidity. For example, Dodel (2009) points out that restricted stock becomes marketable after a specific holding period, whereas private companies may be restricted indefinitely. Furthermore, selection bias might be at play as companies making private placements tend to be relatively smaller, riskier, and less well-performing (Hertzel & Smith, 1993). Partly because of this, empirical studies using the restricted stock approach tend to have unfavorably small sample sizes and considerable standard errors (Damodaran, 2005).

b. The pre-IPO method

Instead of using the restricted stock approach, the illiquidity discount can be quantified through comparing the price at which a stock is privately traded just prior to an IPO (pre-IPO price) to the price of the same stock at the time the stock is initially offered to the public through an IPO (IPO price), a method often described as the pre-IPO method (Damodaran, 2005). Using this method, Emory (1997) finds a mean price discount of 46% studying transactions taking place up to five months before the IPO; Willamette Management Associates (2005) estimate the mean discount to range from 18-56% using a three-year period before the IPO (Pratt & Niculita, 2008).

The Pre-IPO approach has also been criticized for having a self-selection bias a weakness, as IPO studies by definition exclude troubled firms that fail to go public, as compared to the successful ones that do (Hitchner, 2011). Furthermore, the discount may once again be a result of compensation for a provided service rather than the securities' illiquidity (Dodel, 2009). For example, management compensation might be a part of these structures, as pre-IPO transactions often include options issued to management rather than shares issued for cash (Pratt et al., 2000).

c. The acquisition method

The comparable acquisition approach has been the most prominent approach to study PCD in recent years. In essence, this approach compares valuation metrics of private transactions with comparable public transactions. Koeplin et al. (2000) studied the illiquidity discount by comparing valuation multiples derived from private acquisitions with comparable public acquisitions throughout the period of 1984-1998. The illiquidity PCD is measured in accordance with Equation 1.

$$PCD_i = 1 - \left(\frac{Private\ Company\ Multiple_i}{Public\ Company\ Multiple_i}\right) \tag{1}$$

The authors suggested that comparability can be drawn between private and public acquisitions when the targets share the same industry classification, the transactions take place within the same calendar year, and the targets share the same country of incorporation. In accordance with the abovementioned, the authors used a sample of 84 US- and 108 foreign transactions to significantly prove average Enterprise value/EBIT and Enterprise value/EBITDA PCDs for US (foreign) firms of 28.3% (6.0%) and 18.1% (23.5%), respectively. That said, the authors point out that the private firms in their sample are substantially smaller (in terms of revenue) and have different growth rates than their public peers. As such, it is unclear whether the difference in multiples is solely a result of illiquidity of private firms, or a combination of illiquidity, size differences, and growth projections. Furthermore, Kooli et al. (2003) criticized the one-by-one matching technique of Koeplin et al. (2000) stating that choosing a single public comparable transaction is a noisy procedure to match risk characteristics. Hence, instead of matching private and public acquisitions on a one-by-one basis, Kooli et al. (2003) constructed various reference portfolios of public acquisitions on the basis of size, transaction year, and industry (2-digit SIC code). Each private acquisition was then compared to its relevant reference portfolio. As such, the authors calculated the illiquidity PCD in accordance with Equation 2.

$$PCD_i = 1 - \left(\frac{Private\ Company\ Multiple_i}{Median\ Public\ Company\ Multiple_i}\right) \tag{2}$$

Adding to Kooli et al. (2003)'s technique of matching private transactions with reference portfolios of public transactions on the basis of size, industry (2-digit SIC) and transaction year, Officer (2007) also included firm specific- and market liquidity conditions to the variables affecting the PCD. The author showed with 364 observations that the PCD increases in accordance with parent company illiquidity. That is, all else equal, subsidiaries whose parent company is financially healthy trade at a lower discount compared to subsidiaries whose parent company is in greater need of liquidity. Furthermore, the author showcases a positive correlation between general debt market liquidity and PCD; when debt markets – measured as the four-quarter moving average of the spread of commercial and industrial loan rates over the federal funds rate in line with Harford (2005) – are readily available (i.e., interest rates are high) the PCD increases. Officer (2007) argues that the latter is a result of liquidity from the proceeds being more valuable in times when the cost of capital is high.

Paglia & Harjoto (2010) criticized previous research using the acquisition method, arguing that the widely used 2-digit SIC code is insufficient to distinguish and fully explain PCD variations across industries. The authors further criticized the small sample sizes of previous studies – e.g., Koeplin et al. (2000) and Kooli et al. (2003) – arguing that smaller sample sizes may lead to inaccurate transaction matching. In accordance with their criticism, Paglia & Harjoto (2010) improved the industry classification, using 6-digit North American Industry Classification System (NAICS) codes in its matching procedure. Furthermore, in order to increase its sample size, the authors compared multiples of private acquisitions with a reference portfolio of comparable firms' trading multiples. This method generated a sample of 675 match pairs of US transactions between 1993 and 2008. After controlling for size, profitability, industry, buyer status, and transaction timing (the authors lag the trading data of public firms by one year to account for the fact that private transaction multiples are based on LFY financials), the authors find PCDs upward of 80%.

Scheibel & Klein (2013) took a different approach to the comparable acquisition method. By analyzing the buyer's status (i.e., public vs private acquirers), all else equal, the authors argued that one can capture the transaction costs associated with the listing procedure that private firms inevitably will incur. As such, they argue that publicly listed acquirers ought to be able to acquire private firms at a lower discount compared to private acquirers. Scheibel & Klein (2013) thus added buyer status to the factors affecting PCD (in addition to transaction timing, industry (undefined), profitability and size). With its 2 sets of samples – 1042 (613) transactions in which the acquirer had private (public) status throughout the period 1999-2009

– the authors showcase a larger discount for private acquirers, implying the effect acquirer status has on PCD. Furthermore, the authors find a median PCD range for Enterprise value/EBITDA of 16.0%-21.5%.

Like Scheibel & Klein (2013), Covrig & McConaughy (2015) also studied PCD differences across acquirer status. After controlling for targets' industry (1-digit SIC), size, age, estimated growth rate, profitability and timing of the transaction, the authors suggests that public acquirers on average pay 27.0% and 32.6% Enterprise value/Revenue and Enterprise value/EBITDA, respectively, less than private acquirers. The authors argue that, in addition to avoiding listing costs of private firms, other explanations justifying a lower PCD for public acquirers are access to public capital market, and thereby lower costs of capital, as well as greater scope for top-line synergies.

d. Research gaps and motivation of study

As described, several approaches have been used to examine and estimate the PCD, resulting in a wide array of studies. It is evident from past research that the restricted stock approach and the pre-IPO approach entails inherent flaws and/or biases that are difficult to properly adjust for (Koeplin et al., 2000; Dodel, 2009; Hitchner, 2011), which presumably is why most recent studies in the field have focused on the acquisition method. While earlier studies using the acquisition method (e.g., Koeplin et al. 2000; Kooli et al. 2003) focused on determining the PCD, more recent studies have been explanatory in nature, seeking to identify the reasoning behind the PCD itself as well as the variance across different factors (e.g., Paglia & Harjoto, 2010; Scheibel & Klein, 2013). Previous studies have been limited in several ways, however.

Firstly, from a methodological point of view, most studies mention industry categorization as essential to properly match private and public firms, yet most use 2-digit SIC codes as a proxy for the private-public matching (Kooli et al. 2003; Officer, 2007; Covrig & McConaughy, 2015). One could argue that the disparities between the verticals under each 2-digit SIC code is too great to sufficiently address industry comparability. For instance, within the 2-digit SIC code 73 lies the 4-digit SIC codes 7372 (prepackaged software) and 7353 (heavy construction equipment rental and leasing) which arguably are characterized by highly different underlying growth drivers and risk profiles. Paglia & Harjoto (2010), who carried out their study by solely including American firms, is currently the only study in which private and public transactions are matched on a >4-digit level. However, the authors use trading multiples rather than acquisition multiples, thereby not addressing the issue of controlling interest premia. As such, with regards to the matching procedure of private and public transactions, there is room for improvement in terms of the industry factor. Hence, this study seeks to use a comprehensive matching procedure on a large data set and match transactions based on the 4-digit SIC level, thus improving comparability of matched transactions.

Secondly, industry granularity likely matters not only for matching transactions that are actually comparable, but also for a correct understanding of how PCDs might differ across different industries, having presumably very different characteristics affecting the PCD. While some studies take no notice of this, a few present PCDs split up on a 1-digit industry classification, which is, as previously discussed, a highly heterogenous classification. Therefore, this study seeks to study PCDs on a more granular industry classification level which could carry important implications in understanding cross-sectional variances.

Thirdly, little is known about cross-sectional heterogeneity across industries. For instance, while much has been said about what variables might explain a general occurrence of a PCD, little has been said about whether certain explanatory factors are more important in certain industry verticals. As such, this study seeks to conduct cross-sectional regression analyses on

1-digit as well as 2-digit industry levels, potentially revealing important findings on this matter. Furthermore, while previous studies have found that the target's size, profitability, growth rate, industry membership, as well as non-target specific factors such as acquirer status and general market conditions plays an imperative role in determining the discount for a given company, most previous studies fail to address the various factors affecting the PCD in a comprehensive manner. That is, rather than incorporating significant factors from previous research, most studies tend to analyze new factors without incorporating said known variables. For instance, Covrig & McConaughy's (2015) model tests for acquirer status, sales, type of corporation, gross margin, and age of target, but does not account for market liquidity which is deemed imperative to evaluate a proper PCD according to Officer (2007). Hence, although previous studies have presented significant findings and thus claimed certain factors to affect the PCD, most studies rest on very low coefficients of determination (R^2) values (e.g., Kooli et al., 2003; Covrig & McConaughy, 2015) or do not present an R^2 (e.g., Scheibel & Klein, 2013) which implies substantial unexplained variability in the dependent variables. A more comprehensive regression model could potentially yield significantly higher explanatory power than previous studies', therefore this study seek to include previously shown variables of importance as well as potentially new ones, such as asset turnover and whether the acquirer is a financial sponsor.

III Hypotheses

Summarizing and scrutinizing previous empirical research on PCD, a coherent picture emerges supporting the existence of a private company discount on acquisition multiples relative to comparable public firms. As mentioned, public companies are inherently different to private companies. Two main aspects set them apart, impacting the acquirer's willingness to pay for private companies relative to public. Firstly, private companies are less liquid. Whereas owners of public firms can trade their ownership stakes in public securities markets, which are both liquid and transparent, owners of private firms face higher transaction costs to access liquidity. Liquidity can be realized, naturally, either through a public listing, which will entail high fees and a risk of IPO underprizing, or through a private divestment, which generally are less competitive than public processes (Logue, 1973; Ibbotson, 1975; Block & Stanley, 1980). Secondly, information asymmetries are generally more prevalent in private companies. As compared to public companies, private companies are generally not required to disclose financial information publicly. Limited transparency and information asymmetries, and consequentially the transaction costs associated with the levelling of information symmetry, further underpin the price acquirers are willing to pay. This is summarized in the first hypothesis.

H1: *Transaction multiples from acquisitions of private firms are on average lower than those of comparable public firms*

Although several studies have found support for a PCD, there is a gap in the literature regarding whether the difference in transaction multiples (the PCD) is more pronounced in some firm characteristics that could explain potential variations in the discount. The additional hypotheses thus seek to further the understanding of the occurrence of private company discounts by controlling for different factors of potential importance. As different industries, and verticals within different industries, can have vastly different characteristics, it is reasonable to assume that the PCD would vary as well. In terms of liquidity, one could argue that the PCD should be lower in industries in which companies are more prone to hold liquid assets (Block, 2007). Consider the difference between commercial banks and companies in heavy machinery manufacturing. The commercial bank is relatively liquid regardless of whether it is publicly traded or privately held given that a large part of its balance sheet is made up of assets that are easily converted into cash. Contrast this to the liquidity dynamic between privately held- and publicly traded heavy machinery manufacturers. Although the company's publicly traded stock is liquid, its assets are not, thus justifying a higher PCD relative to the commercial bank. The abovementioned rationale is comprised in the following hypothesis.

H2: *The PCD varies across industries.*

Another factor of potential influence is revenue growth. Having a historically high revenue growth is generally an attractive characteristic and something that may lead buyers to pay relatively more (Capron & Shen, 2007). Previous studies have shown the PCD to be smaller when the target has a higher historical growth (Kooli et al., 2003). This may partly be a result of increased asymmetric information in the case of a private acquisitions, where the acquirer of a private firm needs to rely more on historical growth rates as a proxy for its future growth potential. The above rationale is summarized in the third hypothesis.

H3: *The discount for private firms is negatively correlated with historical revenue growth.*

Previous research has concluded that the size of the private target plays an important role in determining the PCD (e.g., Kooli et al., 2003). As the PCD is partly a result of lack of transparency of target information, it is reasonable to assume that larger firms trade at a lower PCD. The aforementioned reasoning rest on the assumption that larger targets are disclosing more relevant information to potential investors as larger firms face more constrained accounting standards. Further arguments that may justify a lower PCD for larger targets are lower risk profiles and proven business concepts. The aforementioned rationale is comprised in the following hypothesis.

H4: *The discount for private firms is negatively correlated with the size of the private firm.*

Furthermore, Block (2007) and Paglia & Harjoto (2010) states that the PCD is negatively correlated with profitability, arguing that private companies suffer more of a liquidity discount than larger public companies. As private firms generally face higher cost of debt and equity capital compared to public firms, it is reasonable to assume that private target's ability to generate cash internally is more important than for their public peers both prior to- and in the event of financial distress. Hence, it is reasonable to assume that the PCD decreases as the target's ability to generate cash increases. The aforementioned reasoning is comprised in the following hypothesis.

H5: *The discount for private firms is negatively correlated with the target's profitability.*

As discussed in the literature review and previous hypotheses, illiquidity has often been described as a significant explanatory variable to the occurrence of a private company discount. To realize liquidity, owners of private firms are on average willing to sell their ownership stakes at a discount relative to comparable public peers, as the acquirers are being compensated for the illiquidity. However, the types of consideration matter, as a cash consideration is a more liquid form of payment compared to a consideration of stock. Consequently, it is assumed that the PCD will be larger in cash deals compared to stock deals, as sellers in stock deals are less willing to give a discount given a degree of continued illiquidity. Furthermore, from the perspective of asymmetric information, one could argue that a stock deal ought to generate a lower PCD. As risk is shared between the buyer and the seller in an equity deal structure, and thereby reduces problems related to moral hazard, higher valuations and thus lower PCDs may be justified. The aforementioned reasoning is comprised in the following hypothesis.

H6: *The private company discount is higher in transactions where the consideration is paid in cash.*

Based on the conclusions of Scheibel & Klein (2013) and Covrig & McConaughy (2015) that public acquirers tend to pay less discount than their private peers due to e.g., the avoidance of transaction costs associated with the 'inevitable' listing procedure of the target, greater potential for synergy extraction, and generally lower costs of capital given their access to public capital markets, a higher PCD is expected when the acquirer is private.

H7: *The private company discount is lower when the acquirer is publicly listed*

Building on the characteristics of the acquirer, this study also seeks to analyze the behavior of the PCD across financial and strategic acquirers. Compared to strategic players, Financial acquirers tend to have shorter holding periods and finance their acquisitions with a higher portion of debt. The increased leverage paired with the shorter holding periods of Financial acquirers implies a higher internal rate of return which thus could motivate higher valuations and thus lower PCDs. The aforesaid logic relies on the general conditions of debt markets. When the cost of debt capital is high the logic may not hold. Furthermore, Financial acquirers are more likely to make platform investments where the potential for synergy extraction is lower compared to strategic acquirers that tend to acquire companies with cross-selling and/or cost synergy potential. Hence, although agnostic regarding the sign of the relationship, it is expected that the PCD depends on the type of acquirer.

H8: *The private company discount varies between financial and strategic acquirers.*

General macroeconomic factors would likely also be important for a PCD. Importantly, understanding illiquidity in relation to a PCD is not only a matter of how illiquid the asset is, but also at what time it is illiquid (Acharya & Pedersen, 2005). For an asset to be illiquid when the market itself is illiquid, which usually is the case during down markets and economic recessions, should be more negative, and resulting in a higher discount, than if the asset is illiquid when the market is liquid (Damodaran, 2005). This is partly due to the fact that private companies being riskier, uncertainty being discounted at a higher rate when the firm is private (Sahin et al., 2011) and private companies being more dependent on external financing (Shourideh & Zetlin-Jones, 2012), and partly because stronger equity markets would positively influence the possibility for owners of private companies to obtaining liquidity through an IPO (Officer, 2007). These factors and their effect on a PCD are summarized in the following hypothesis.

H9: *Increasing cost of realizing liquidity increases the private company discount.*

Previous PCD-studies have generally focused on US companies. Adding to the literature by looking at a wide European sample, this study seeks to analyze differences across countries. Given information asymmetries' and financing opportunities' effect on the PCD, it naturally follows that capital market efficiency should impact the PCD. All else equal, a more efficient capital market should entail better financing opportunities for private companies, who arguably are more dependent on debt (bank) financing relative to their public peers, thus justifying lower a PCD. Since countries have varying capital market efficiencies, the PCD ought also to vary across countries. Furthermore, previous studies have also found differences with aspect to time (Kooli et al. 2003; Paglia & Harjoto, 2010). For example, Kooli et al. (2003) found that the median discount decreases during periods when M&A activity is higher and, similarly, increases during downturns. Based on the aforementioned logic, it is expected that the PCD varies across both countries and years.

H10: *The private company discount varies across countries and years.*

According to Ernst & Young (2019), some of the most reported drivers of integration costs are shutdown of assets in the pursuit of cost synergy extraction. One could speculate that, as a result of the nature of information sharing in public versus private entities, there exists more hidden transaction costs in private firms than in public firms. Hence, if hidden transaction costs are accounted for in the valuation model, the private company ought to be valued at a lower multiple, ceteris paribus. One could further argue that the more vital a certain asset is to the generation of income, the less likely it is to be shut down post transaction. As such, one could hypothesize that there is smaller potential for cost-cutting initiatives in targets where the asset turnover is high. The aforementioned logic is comprised in the following hypothesis.

H11: *The private company discount is negatively correlated with the target's asset efficiency*

IV Data

a. Sample selection process

The transaction data in this study is solely collected from Refinitv Eikon. Data is collected for completed private and public investments throughout the period 1998-2022 in which the target resides within the European Economic Area (EEA) including United Kingdom and Switzerland. The rationale for the geographic distinction is to ensure general comparability, mainly related to ensuring comparability of accounting treatments and thus reported metrics. For instance, the International Financial Reporting Standards (IFRS) do not allow companies to use the last in, first out (LIFO) method in the treatment of inventory, whereas the Generally

Accepted Accounting Principles (GAAP) does indeed allow it (IFRS, n.d.). The implication of the different treatments may have subsequent effects on the target's balance sheet, thus creating biases in the data set related to the calculation of e.g., asset turnover.

All EU- and EEA-based listed companies are required to prepare their consolidated financial statements in accordance with IFRS under regulation (EC) No 1606/2002 (European Commission, 2021). Although Switzerland is not part of the EEA, and thus not obligated to follow IFRS, compliance with IFRS ensures compliance with the Swiss Foundation for Accounting and Reporting's account standards (ARR/FER or Swiss GAAP) and as such many Swiss companies tend to follow IFRS (IAS Plus, n.d.). Similarly, although the United Kingdom left the EU in January 2020 and after the transition period ending in December 2020 are no longer obliged to follow EU laws and directives, and thus EU-adopted IFRS, all companies with securities trading on regulated markets need to prepare accounts in accordance with the UK-adopted IFRS standards which is considered nearly identical to the EU-adopted standards (IFRS, 2021). Furthermore, to avoid biases related to controlling interest premia, minority investments are excluded in accordance with e.g., Koeplin et al. (2000) to better isolate the PCD. Transactions in which the target belong to the 1-digit SIC-code 6, excluding 2-digit SIC code 65 (real estate) are further excluded. The aforementioned exclusion rests on the rationale that the accounting treatment of financial firms is different from that of other firms, making transaction multiples incomparable (Damodaran, 2005). Financial firms usually record income below EBIT as financial income, and as such sales multiples, used to measure the PCD in this study, may become distorted.

Transactions with negative EBITDA are excluded to improve comparability in terms of financial performance across public and private targets, diminishing the number of targets under financial distress. In line with previous studies (e.g., Paglia & Harjoto, 2010) transactions in which the target's LFY sales are below EUR 10m are excluded under the rationale that private firms with >EUR 10m in sales are more prone to report in accordance with IFRS, more eligible for a public listing and in turn access to public capital which allows for less noise and better isolation of the PCD. The abovementioned screening yields an initial sample of 13,850 transactions of which 7,887 (5,963) are public (private) transactions.

b. IQR and outliers

The transaction data in the sample are based on LFY financials. In many of the transactions, there exists substantial time between the LFY reporting period and the transaction date. This creates a situation in which a reported multiple may become severely inflated/deflated depending on the target's growth development between the LFY reporting date and the transaction date. For instance, targets may have experienced abnormally low sales because of externalities such as the Covid-19 pandemic that leads to a lower than normal topline that particular year. As enterprise values are usually based on the target's current trading and projected cash flows, the target's multiple may be severely inflated given that the sales decrease in LFY is in fact an irregularity. As such, although arbitrary from a generalizability perspective, it is deemed imperative to truncate the data as outliers resulting from the abovementioned LFY-dilemma is not suitable as comparable transactions as they do not depict the true multiple of the company[1]. Outliers as defined in Equation 3 and negative PCDs exceeding 100% are therefore truncated in accordance with Officer (2007) and Paglia & Harjoto (2010).

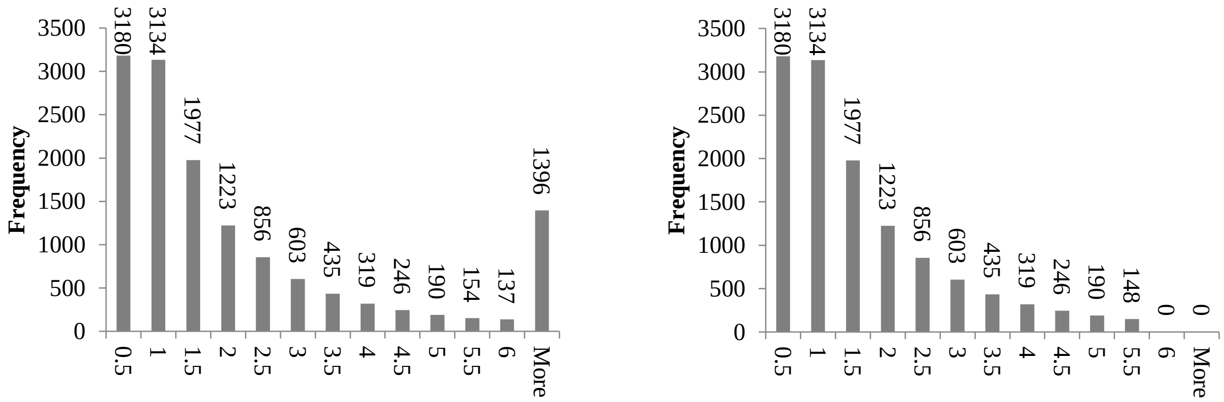
[1] Because of this, there exist extreme outliers in the sample, with multiples upwards of 2000x. Previous studies have used both transformation- and truncation techniques to limit the effect of outliers in its data. For instance, Officer (2007) and Paglia & Harjoto (2010) exclude transactions based on PCD outliers (i.e., outliers based on the PCD itself and not transaction multiples in the raw data) whereas Covrig & McConaughy (2015) winsorized outliers in the raw transaction multiples. Winsorizing outliers would only reduce their effect on the PCD.

$$Multiple_i = \begin{cases} Outlier\ \forall\ Multiple_i \in (-\infty, Q1 - IQR * 1.5) \cup (Q3 + IQR * 1.5, \infty) \\ Not\ outlier\ \forall\ Multiple_i \in [Q1 - IQR * 1.5, Q3 + IQR * 1.5] \end{cases} \tag{3}$$

Where:

$$Q1 = First\ sample\ quartile$$
$$Q3 = Third\ sample\ quartile$$
$$IQR = Inner\ quartile\ range = Q3 - Q1$$

Figure 1*: Enterprise value/Revenue frequency pre- and post-truncation*



c. Descriptive statistics

Table 1*: Descriptive statistics*

Table 1 reports descriptive statistics on the data set pre-truncation. The table present the total number of transactions including Enterprise values, Revenue, two-year historical growth rate, EBITDA and EBITDA-margin for private and public transactions, respectively. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Private Targets	**Public Targets**	**T-test (Z-test)**
Enterprise value (€ million)	186.8	734.8	-10.84***
	(32.3)	(74.7)	-12.05***
	[5419]	[6892]	
Revenue (€ million)	529.4	2216.6	-11.60***
	(59.1)	(205.4)	-12.54***
	[5419]	[6892]	
Revenue growth (%, 2Y)	92.9	45.1	1.08
	(7.2)	(5.7)	0.90
	[3340]	[5613]	
EBITDA (€ million)	70.4	399.3	-10.36***
	(7.52)	(30.0)	-13.12***
	[3321]	[5523]	
EBITDA-margin (%)	15.7	15.5	-0.27
	(10.7)	(11.7)	0.29
	[3361]	[5412]	

V Methodology

a. Acquisition method and matching company technique

This study builds on the acquisition method used by e.g., Koeplin et al. (2000), Kooli et al. (2003) and Officer (2007). Furthermore, the matching procedure of public and private companies follows the rationale of Kooli et al. (2003). That is, rather than matching private and public transactions on a 1-on-1 basis, private transactions are matched against a portfolio of comparable public transactions to reduce noise associated with company specific risks. The matching procedure of private and public transactions takes a multi-step approach. Firstly, portfolios of public transactions are created based on (a) size, (b) industry classification, and (c) transaction year in line with e.g., Kooli et al. (2003). Median metrics are then extracted from each portfolio in accordance with Equation 4, including firm specific metrics such as relevant multiples, revenue, EBITDA-margin, historical growth rate, assets, and asset turnover.

$$Median(M)_{b,e,g} = \begin{cases} M\left[\frac{n}{2}\right] & if\ n\ is\ even \\ \dfrac{\left(M\left[\frac{n-1}{2}\right] + M\left[\frac{n+1}{2}\right]\right)}{2} & if\ n\ is\ odd \end{cases} \tag{4}$$

Where:

$$M = Ordered\ list\ of\ multiple\ values\ in\ the\ given\ data\ set$$
$$n = Number\ of\ values\ in\ the\ given\ data\ set$$

The rationale for using median metrics, as opposed to mean, is partly due to previous studies' tendency of using median metrics, thus enabling this study's findings to be more accurate in terms of comparison, and partly due to conservative reasons, as mean metrics are more biased upwards given the positive skewness of the data (see Figure 1), thus reducing the risk of overestimating the PCD. Secondly, private transactions are then matched against the above reference portfolio based on the same (b) size categorization, (e) industry classification, and

(g) transaction year. However, to increase the total number of matches and reduce noise related to individual transactions, private transactions are matched against public reference portfolios within a 2-year range of the private transaction. Thirdly, the reference portfolios' metrics are then weighted in accordance with the number of transactions included in each portfolio and subsequently summed to arrive at the final public comparable metric (see Equation 5).

$$W.Avg\left[Median(M)_{b,e,g\pm2}\right]_i = \frac{\sum_{i=1}^{n} w_i \left[Median(M)_{b,e,g\pm2}\right]_i}{\sum_{i=1}^{n} w_i} \tag{5}$$

Where:

$$W.Avg = Weighted\ average$$
$$n = Number\ of\ median\ multiples\ to\ be\ averaged$$
$$w_i = Weights\ based\ on\ the\ number\ of\ transactions\ included\ in\ each\ portfolio$$

As such, the PCD is calculated in accordance with Equation 6[2].

$$PCD_i = 1 - \left(\frac{Private\ Company\ Multiple_i}{W.Avg\left[Median(M)_{b,e,g\pm2}\right]_i}\right) \tag{6}$$

b. Statistical significance

While previous research on the occurrence of a private company discount generally has applied an unpaired t-test to test significance, thus testing for a discount on an aggregate sample level rather than testing significance levels for each individual observation, Newbold et al. (2019) argue in favor of using a dependent t-test for matched pairs of observations, decreasing the variance when the matched pairs are positively correlated. However, it should be noted that such a methodology postulates not only insignificant outliers regarding the difference between the matched pairs, but also that the difference between the matched pairs is normally

[2] Please refer to Appendix a for a theoretical example of the matching procedure and subsequent PCD calculation

distributed. When the data indicates the presence of outliers, a Wilcoxon signed rank test is conducted in addition to the dependent t-test to check the robustness of the results. Being a non-parametric test, outliers are less of a concern as the sample does not have to be normally distributed (Newbold, 1995).

VI Analyzing the occurrence of a private company discount

a. Estimates of private company discounts within industries (1-digit)

Table 2 presents the median Enterprise value/Revenue multiples for private companies and reference portfolios of public companies, respectively, as well as the implied discount. Not considering industry specifics, private companies are sold at a 33% discount compared to public companies, a result that is significant on a 1% level. Examining different industries, using the broadest SIC-classification, most matched transactions are, as one would expect, found in the *Manufacturing* (30% of total observations) and *Services* (34%) industries, which both display a somewhat lower discount than the sample median (25% and 32%, respectively). The highest discount is found within the *Wholesale* as well as *Construction* industries (65% and 49%, respectively). While these industries have less matched pairs, the results are still significant at a 1% level. No industry displays a discount below 21% (*Agriculture, Forestry, Fishing and Mining*). For an analysis of the different drivers behind the PCD in different industries, see the regression analysis in Section VIII.

***Table 2**: PCD across 1-digit industries*

Table 2 reports the calculated PCD for each 1-digit industry, respectively. The 1-digit SIC code are basic industry categories based on two-digit SIC codes. The table present the total amount of matched pairs per industry, as well as how the data set is distributed across the different industries. The median transactions are also reported for private and public transactions, respectively, followed by the median discount for all matched and calculated PCD per industry. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Industry	**SIC Code**	**Matched pairs**	**Frequency (%)**	**EV/Sales (private)**	**EV/Sales (public)**	**Discount incl. t-test**
Agriculture, Forestry, Fishing and Mining	0-14	26	1%	0.8	1.4	21%**
Construction	15-17	84	4%	0.3	0.8	49%***
Manufacturing	20-39	701	30%	0.8	1.2	25%***
Transportation & Public Utilities	40-49	416	18%	1.0	1.6	29%***
Wholesale	50-51	73	3%	0.3	0.9	65%***
Retail Trade	52-59	155	7%	0.6	1.2	40%***
Real Estate	65	74	3%	1.3	2.4	42%***
Services	70-89	789	34%	0.9	1.3	32%***
Total		**2318**	**100%**	**0.8**	**1.3**	**33%*** **

b. Estimates of private company discounts within industries (2-digit)

When deepening the analysis to include industry classifications on a more granular level, namely on a 2-digit SIC code level, interesting patterns starts to emerge. To be able to analyze potential differences within different subsegments of the data, the *Manufacturing* industry (SIC code 20-39) and *Services* industry (SIC code 70-89) is selected in more detail due to them being the largest industry segments in terms of observations. Furthermore, *Manufacturing* and *Services* are assumed to be quite different in terms of characteristics, being more tangible in nature (*Manufacturing*) or more intangible (*Services*). This is likely also prevalent in terms of *Asset turnover*, *Cash conversion* etc., making the two subsegments suitable to compare in terms what drives the private company discount in different industries. At a more granular level, both the *Manufacturing* and the *Services* industry display significant differences. While *Manufacturing* as a whole has been purchased at a 25% discount, some subsegments such as *Printing and publishing* had a mere 3% discount, while *Metal industries* on average had a 45% discount for private company transactions.

Table 3*: PCD across 2-digit industries*

Table 3 reports the calculated PCD for two 1-digit industries (Manufacturing and Services), but on a 2-digit level, as compared to table 2. The 2-digit SIC are reported in the parenthesis after the 2-digit industry name. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Observations refer to the total amount of matched pairs per 2-digit industry classification.

Manufacturing	**Discount**	**Observations**
Food Products (20)	26%***	105
Tobacco Products (21)	5%	1
Textile Mill Products (22)	0%	8
Apparel Products (23)	-33%	5
Lumber/Wood Prod. (24)	5%	5
Furnituure, fixtures (25)	11%	1
Paper Products (26)	33%**	29
Printing, publishing (27)	3%**	42
Chemical Products (28)	11%***	81
Petroleum Refining (29)	87%	3
Rubber & Plastics (30)	7%	30
Leather Products (31)	-13%	1
Stone, Concrete etc. (32)	23%***	21
Metal Industries (33)	45%**	13
Fabricated Metal (34)	13%**	28
Ind./Computer Eq. (35)	29%***	57
Electro equipment (36)	42%***	64
Transportation Equi. (37)	43%***	62
Measuring Equi. (38)	12%**	58
Mis.Manufacturing (39)	66%***	8

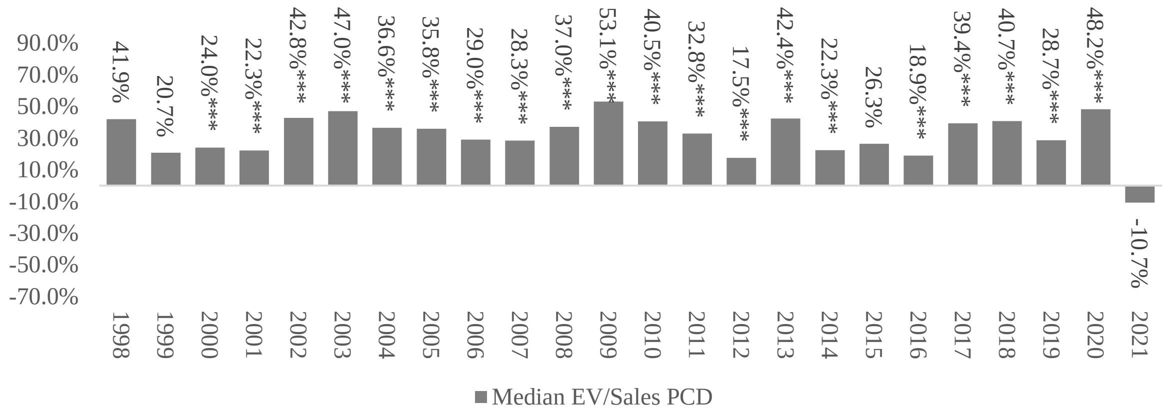
Services	**Discount**	**Observations**
Hotels etc. (70)	30%	39
Personal Services (72)	-16%	1
Business Services (73)	36%***	482
Automotive Services (75)	85%	1
Motion Pictures (78)	24%**	19
Recreation Services (79)	41%**	46
Health Services (80)	32%***	17
Educational Services (82)	69%	3
Social Services (83)	-	0
Eng., acc., services (87)	14%***	181

c. Private company discounts across time and countries

Figure 2 presents the median Enterprise value/Revenue PCD across the sample period. As one would expect, the PCD varies across different time periods. The lowest statistically significant PCD is found in *2012* (17%). Interestingly, the highest PCDs are found in *2009* (53%) and *2020* (48%), years characterized with high uncertainty from the the aftermath of the financial crisis of 2008 and COVID-19 pandemic, respectively. PCDs tend to increase after substantial market downturns. For instance, the PCD rose by 21-, 16-, 25-, and 19- percentage points following the dot com crisis, the financial crisis of 2008, the European debt crisis as well as the Covid-19 pandemic, respectively.

***Figure 2**: PCD throughout the sample period*

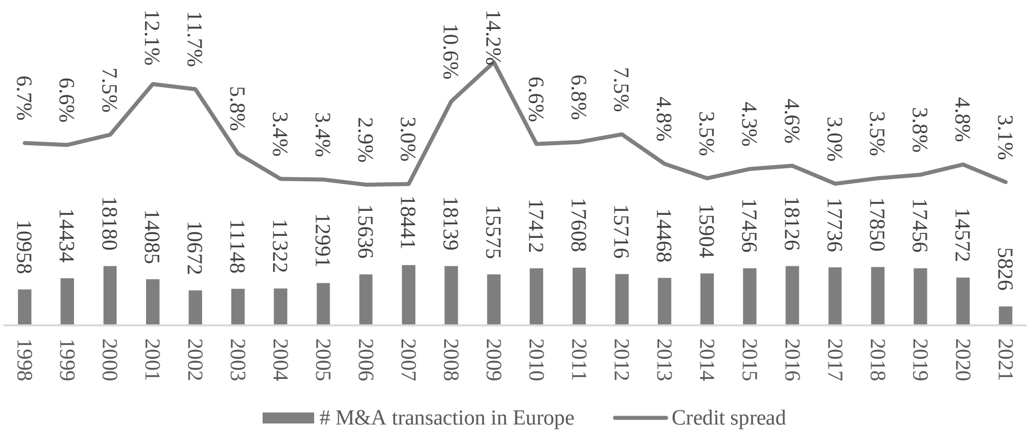
Figure 2 reports the calculated PCD across the years included in the sample period. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.



A potential explanation for the tendency is that *Credit spreads* tend to increase following recessions which impact valuations of private firms to a higher degree than public firms (see Figure 3). As a result of private equity firms' leveraged buyouts, private acquisitions are, arguably, usually financed with a higher portion of debt than public acquisitions. Hence, from a cost of capital perspective, as the cost of debt increases it naturally follows that valuation levels of private firms decrease to a greater extent than public firms. The aformentioned reasoning is in line with the findings presented in Section VI.

***Figure 3**: M&A activity and credit spreads throughout the sample period*

Figure 3 reports the total number of European M&A transactions as well as credit spreads throughout the sample period. M&A activity is retrieved per 2022-04-10 from the Institute for Mergers, Acquisitions & Alliances.



In terms of cross-country differences, there is no major difference across statistically significant PCDs. The largest PCD is found in *Switzerland* (38.3%) whereas the lowest PCD is found in *Norway* (29.6%). Please refer to Appendix b for an overview of cross-country differences.

VII Cross-sectional regression analysis

Hitherto, analysis of the data gives support for not only the occurrence of a private company discount (H1) but also a varying level of discounts within different industries (H2). To analyze what variables, explain the size of the private company discount as well as the variation across the data, and thus to test the additional hypotheses (H3-H11), a cross-sectional regression analysis is conducted. Model (1) is a linear model defined as:

$$\begin{gathered} PCD_i = \alpha + \beta_1 Growth + \beta_2 Profitability + \beta_3 \log Size + \\ \beta_4 \log Assets + \beta_5 Asset\ turnover + \beta_6\ Deal\ structure + \\ \beta_7\ Acquirer\ status + \beta_8\ Financial\ acquirer + \beta_9\ Credit\ spread \end{gathered} \tag{1}$$

As a dependent variable, the regression model uses the private company discount, first across the whole data set and later across different industries. As explanatory variables, the regression model uses private company characteristics, such as private company *Growth*, private company *Size*, private company *Profitability, Assets* and *Asset turnover*. Private company *Growth* is a dummy variable, defined as 1 if the private company's compounded annual growth rate for the last two consecutive years is higher than that of the matched portfolio's weighted average median (see Equation 4-6 in Section IV) compounded annual growth rate, i.e. if the private company has, in terms of percentage, outgrown its reference portfolio. Similarly, private company *Profitability* is defined as 1 if the private company's EBITDA-margin is higher than the weighted average median for the reference portfolio. Private company *Size* refers to the revenue of the private company, which already is matched based on revenue in relation to the reference portfolio, and the data is log transformed to deal with potential skewness. Similarly, *Assets* is a log transformed variable describing the private company's total asset base (book value). *Asset turnover* is calculated as the private company's total revenue divided by the Assets and is a measure of capital efficiency. *Asset turnover* is a dummy variable, defined as 1 if the private company's asset turnover is higher than the weighted average for the matched reference portfolio.

Furthermore, deal-specific characteristics are also included, such as *Deal structure*, *Acquirer status* and whether the buyer is a *Financial acquirer*. The regression model also includes a variable to estimate the influence of liquidity on private company discounts. *Deal structure* is a dummy variable, defined as 1 if the deal was an all-cash deal. Similarly, *Acquirer status* is defined as 1 if the acquirer was public and *Financial acquirer* is defined as 1 if the acquirer was a *Financial acquirer*. Finally, the *Credit spread* variable is based on ICE BofA Euro High Yield Index, an index with calculated spreads between euro dominated bonds and treasuries, retrieved from St. Louis Fed.

VIII Results of cross-sectional regression

The results from the multivariate regression model, incorporating company-specific as well as deal-specific characteristics, are presented in Table 4. On a general level, before testing on an industry-specific level, all the explanatory variables display statistical significance, rendering a coefficient of determination (R^2) of 25.7% which is a substantial improvement from previous studies. As for company-specific characteristics, high-*Growth* and high-*Profitability* companies generate lower private company discounts, significant on a 1% level. Similarly, larger companies in terms of *Assets* generate lower private company discounts. In terms of revenue *Size* however, larger companies seem to render higher discounts. Moreover, companies with higher *Asset turnover* are also favored by investors, lowering the discount compared to comparable public companies. As for deal-specific characteristics, all-cash deals generate lower discounts. So do transactions with acquirers being public or a *Financial acquirer*, albeit these deal-specific characteristics seem to be of less importance than company-specific characteristics in terms of the size of the discount. Finally, higher *Credit spreads* generate significantly higher private company discounts.

Deepening the granularity of the analysis, the regression is subsequently made for different industries, using what corresponds to the broadest SIC-classification (1-digit), also displayed in Table 4. As the data set is, as expected, unevenly distributed within different industries, some of the smaller industries, such as *Agriculture, Forestry and Fishing* as well as *Wholesale* and *Real Estate*, have too few observations for the results to be robust. More specifically, there is a real risk of overfitting the regression model when the observations are too few given a certain set of explanatory variables. According to the “one in ten rule”, regression analyses would thus preferably have 10 observations per variable (Draper & Smith, 1998). For a more detailed discussion on this issue, see Section IX. That said, larger industry subsets of the data, such as *Manufacturing, Transport & Public Utilities* and *Services*, display interesting patterns. *Profitability* is for these three industry verticals significant on a 1% level, lowering the discount. Similarly, a higher *Asset turnover* will for all these three industries generate lower private company discounts. Interestingly, however, some industry differences seem to occur. *Manufacturing* is the only larger industry where *Deal structure* is showing significant results. *Acquirer status* and *Financial acquirer* on the other hand, is highly significant for the *Services* industry, rendering lower discounts. These aspects are discussed in more detail in Section IX.

***Table 4**: Regression analysis on 1-digit SIC level*

Table 4 reports the results from the OLS regression analysis, using the PCD for either all industries (column 2) or each 1-digit industry classification (column 3-10) as the dependent variable. Growth is a dummy variable, defined as 1 if the private company's compounded annual growth rate for the last two consecutive year is higher than that of the matched portfolio's average compounded annual growth rate, i.e. if the private company has, in terms of percentage, outgrown its reference portfolio. Profitability is defined as 1 if the private company's EBITDA-margin is higher than the average for the reference portfolio. Size refers to the revenue of the private company, which already is matched based on revenue in relation to the reference portfolio, and the data is log transformed to deal with potential skewness. Similarly, assets is a log transformed variable describing the private company's total asset base (book value). Asset turnover is calculated as the private company's total revenue divided by the total assets and is a measure of capital efficiency. Asset turnover is a dummy variable, defined as 1 if the private company's asset turnover is higher than the average for the matched reference portfolio. Deal structure is a dummy variable, defined as 1 if the deal was an all-cash deal. Similarly, acquirer status is defined as 1 if the acquirer was public and financial acquirer is defined as 1 if the acquirer was a financial buyer. Finally, the credit spread variable is based on ICE BofA Euro High Yield Index, an index with calculated spreads between euro dominated bonds and treasuries, retrieved from St. Louis Fed. The numbers presented in the top row refers the coefficients from the OLS regression. T-statistics are presented in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Industry	**All industries**	**Agriculture, Forestry etc.**	**Construc-tion**	**Manufa-cturing**	**Transport & Public Utilities**	**Wholesale**	**Retail Trade**	**Real Estate**	**Services**
SIC	**1-89**	**1-14**	**15-17**	**20-39**	**40-49**	**50-51**	**52-59**	**65**	**70-89**
Intercept	0.26***	0.20	0.76***	0.55***	0.53***	0.75*	0.59**	1.59***	0.46***
	(4.26)	(0.24)	(4.32)	(4.45)	(3.74)	(1.79)	(2.39)	(4.44)	(3.29)
Growth	-0.11***	-0.16	-0.18	-0.09	0.03	-0.22	-0.25**	-0.52***	-0.09
	(-3.79)	(-0.45)	(-1.54)	(-1.59)	(0.44)	(-1.22)	(-2.27)	(-3.19)	(-1.50)
Profitability	-0.23***	0.30	-0.27**	-0.16***	-0.29***	0.03	-0.40***	-0.57***	-0.28***
	(-7.11)	(0.56)	(-2.51)	(-2.81)	(-3.88)	(0.11)	(-3.17)	(-3.45)	(-4.42)
Log size	0.19***	0.31*	0.06*	0.01	-0.02	-0.04	0.05	0.05	0.02
	(7.93)	(2.32)	(1.70)	(0.28)	(-0.77)	(-0.92)	(1.44)	(0.93)	(0.79)
Log assets	-0.18***	-0.15	-0.03	-0.01	-0.03	0.06	-0.01	-0.14**	-0.17
	(-7.86)	(-1.12)	(-0.82)	(-0.86)	(-1.31)	(1.18)	(-0.33)	(-2.29)	(-0.86)
Asset turnover	-0.14***	-1.07*	-0.45***	-0.34***	-0.37***	-0.06***	-0.35***	-0.59***	-0.18***
	(-3.66)	(-2.11)	(-3.95)	(-5.63)	(-5.20)	(-2.92)	(-3.14)	(-3.82)	(-2.89)
Deal Structure	-0.07**	-0.39	-0.23**	-0.11*	0.07	-0.07	-0.18*	-0.16	-0.07
	(-2.27)	(-1.00)	(-2.39)	(-1.95)	(1.00)	(-0.46)	(-1.74)	(-1.08)	(-1.14)
Acquirer Status	-0.09***	-0.71	-0.17*	-0.06	0.06	-0.37**	0.09	0.10	-0.18***
	(-2.71)	(-1.72)	(-1.70)	(-1.00)	(0.71)	(-2.56)	(0.70)	(0.53)	(-2.72)
Financial Acquirer	-0.07*	0.14	-0.32**	-0.05	0.11	(omi-	0.06	-0.21	-0.17**
	(-1.87)	(0.17)	(-2.61)	(-0.72)	(1.43)	ted)	(0.50)	(-0.96)	(-2.52)
Credit spread	1.47***	-0.94	3.36**	0.47	2.13*	3.37	-1.20	-1.59	1.95*
	(2.98)	(-0.24)	(2.15)	(0.54)	(1.96)	(1.01)	(-0.70)	(-0.55)	(1.84)
Observations	960	15	42	281	171	31	74	31	315
Adjusted R^2	24.6%	55.3%	58.6%	15.6%	29.4%	43.4%	31.1%	59.4%	13.7%

Considering the number of observations in every industry, the data allows for some additional regression analysis, extending the granularity to a 2-digit SIC code. Following the guidelines of Draper & Smith (1998), an additional regression analysis is conducted on a 2-digit level, considering two subsegments within the *Services* industry with the most observations, namely *Business services* (SIC code 73) and *Engineering*, *Accounting*, *Research*, *Management and Related Services* (SIC code 87), the latter being around the lower bound in terms of observations (94). The results are presented in Table 5. Interestingly, while higher *Profitability* renders lower private company discounts for both subsegments, this variable being significant on a 1% level in both cases, *Business Services* shows highly significant results for both *Acquirer status* as well as *Financial acquirer*, resulting in lower private company discounts, whereas *Engineering, Accounting, Research, Management and Related Services* do not. Potential explanations for this are further discussed in Section IX.

__Table 5__: Regression analysis on 2-digit SIC level

Table 5 reports the results from the OLS regression analysis, using the PCD for two 2-digit industries as the dependent variable (Business Services, SIC code 73, and Engineering, Accounting, Research, Management and Related Services, SIC code 87). Growth is a dummy variable, defined as 1 if the private company's compounded annual growth rate for the last two consecutive year is higher than that of the matched portfolio's average compounded annual growth rate, i.e. if the private company has, in terms of percentage, outgrown its reference portfolio. Profitability is defined as 1 if the private company's EBITDA-margin is higher than the average for the reference portfolio. Size refers to the revenue of the private company, which already is matched based on revenue in relation to the reference portfolio, and the data is log transformed to deal with potential skewness. Similarly, assets is a log transformed variable describing the private company's total asset base (book value). Asset turnover is calculated as the private company's total revenue divided by the total assets and is a measure of capital efficiency. Asset turnover is a dummy variable, defined as 1 if the private company's asset turnover is higher than the average for the matched reference portfolio. Deal structure is a dummy variable, defined as 1 if the deal was an all-cash deal. Similarly, acquirer status is defined as 1 if the acquirer was public and financial acquirer is defined as 1 if the acquirer was a financial buyer. Finally, the credit spread variable is based on ICE BofA Euro High Yield Index, an index with calculated spreads between euro dominated bonds and treasuries, retrieved from St. Louis Fed. The numbers presented in the top row refers the coefficients from the OLS regression. T-statistics are presented in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Industry	**Business Services**	**Eng., Acc. Services etc.**
SIC	**73**	**87**
Intercept	0.47**	0.47
	(2.61)	(1.50)
Growth	-0.09	-0.03
	(-1.09)	(-0.24)
Profitability	-0.23***	-0.38***
	(-2.68)	(-3.08)
Log size	0.01	-0.03
	(0.20)	(-0.56)
Log assets	0.02	-0.00
	(0.91)	(-0.04)
Asset turnover	-0.174**	-0.108
	(-1.99)	(-0.86)

Industry	**Business Services**	**Eng., Acc. Services etc.**
SIC	**73**	**87**
Deal Structure	-0.10	0.09
	(-1.24)	(0.73)
Acquirer Status	-0.28***	-0.10
	(-3.17)	(-0.75)
Financial Acquirer	-0.28***	-0.02
	(-2.95)	(-0.11)
Credit spread	2.15	-1.82
	(1.61)	(-0.82)
Observations	169	94
Adjusted R^2	13.4%	7.9%

Based on the discussion in Section IV, outliers are not expected to affect the results of the regressions in any significant way. This is confirmed by using the robust regression method offered by Stata, limiting the weight of data points that vary significant from the data set, the results being presented in Table 7 and Table 8, Appendix c. While some of the industry subsegments already suffer from limited number of observations, the ones that doesn't – *Manufacturing*, *Transport & Public Utilities* and *Services* (including the two 2-digit segments) as well as the combined set of all industries – are largely unaffected by running a robust regression, except for minor adjustments such as *Deal structure* becoming slightly more significant in explaining the private company discount in the *Manufacturing industry*.

Similarly, to control for heteroscedasticity, an additional round of regressions is made applying robust standard errors. Once again, the results are consistent with the original results presented in Table 4 and Table 5, Minor adjustments include *Credit spread* showing slightly higher significance for explaining the private company discount in *Transport & Public Utilities* and *Services*, including *Business Services*. OLS regressions with robust standard errors are presented in Table 8 and Table 9, Appendix c.

IX Analysis and discussion of the regression results

a. Comparison with previous research and the study's hypotheses

Analyzing the regression results in Section VI-VIII, it is evident that most hypotheses can be confirmed from a comprehensive, non-industry specific perspective. However, although the regression results are significant for all variables in the model, some variables showed different relationships to the PCD from what was expected.

In chronological order, the results indicate a negative relationship between historical Gr*owth* rate and PCD, consistent with hypothesis H3 and the findings of Kooli et al. (2003). Also significant to the PCD is the target's *Size* (H4). Hypothesis H4 is built on the findings of Kooli et al. (2013) and Paglia & Harjoto (2010) as well as the rationale that larger firms are generally disclosing more information than smaller firms. The increased transparency of larger firms together with their, relatively speaking, proven business concepts and thus lower risk profiles suggest that larger firms ought to trade at a lower discount compared to smaller firms. The size of the target is measured in terms of two different variables, total *Size* (revenue) and *Assets*. When measured in terms of *Assets*, hypothesis H4 is confirmed, strengthening the conclusions of Kooli et al. (2003). However, when measured in terms of revenue (*Size*), the findings suggest the opposite relationship, implying that there are other revenue-related factors influencing the PCD. Potential explanations to the observed positive relationship between revenue and the PCD might entail larger potential for revenue synergies, e.g., accelerated topline as a result of cross-selling and leveraging the acquirer's customer base, in firms characterized with lower revenue which arguably justifies higher valuation levels and thus lower PCDs. Furthermore, given the revenue *Size* distinction in this study (targets whose sales do not exceed EUR 10m are truncated due to comparability concerns) the abovementioned rationale may therefore not be applicable to this study's specific sample. One could argue that businesses exceeding EUR 10m in sales already have established proof of business concept, and that the disparity between information sharing in firms exceeding EUR 10m is marginal. Instead, one could speculate that there exists a breaking point around EUR 10m in revenue after which the target's increased cost of integration outweighs the marginal benefits of increased transparency.

Furthermore, the results show a significant negative relationship between the target's *Profitability* and the observed PCD, consistent with hypothesis H5. The findings are in line with those of Block (2007) and Paglia & Harjoto (2010) implying that, given private firms' limited access to public capital markets, the target's ability to generate cash internally is of greater importance in private versus public acquisitions. Moreover, the results show a significant relationship between the *Deal structure* and the PCD, confirming that the PCD is influenced by the type of consideration offered. Hypothesis H6 stipulates those deals paid in cash to experience higher PCDs, resting on the rationale that cash deals offer increased liquidity and less risk sharing between the transaction parties (Shleifer & Vishny, 2003; Officer, 2007). The relationship between cash considerations and PCD was different from what was expected. According to the results, transactions in which the acquisition is paid in cash generate a lower discount than other forms of payment. It is important to consider that the sample data includes flaws with respect to *Deal structure*. There exist many data points defined as 0 for which the deal structure is unknown. As such, given the possibility of error, it is highly suggested to interpret the finding with caution.

Moreover, according to the results, transactions in which the acquirer is public (*Acquirer status*) tend to experience lower PCDs. The finding is consistent with hypothesis H7 and the findings of Scheibel & Klein (2013) and Covrig & McConaughty (2015), implying that public acquirers' access to public markets and thus lower cost of capital, justify higher valuation levels and lower PCDs. That said, the significance of *Acquirer type* seems to be more pronounced in certain industry verticals (see Table 5). Another interesting aspect to consider is the idea that a private target acquired by a public firm essentially goes through a listing procedure without the otherwise timely and costly IPO process which further justifies a lower PCD. Building on the characteristics of the acquirer, the results also show a significant relationship between *Financial acquirer* and the PCD, confirming hypothesis H8 that the PCD varies across financial and strategic buyers. Although initially agnostic about the sign of the relationship, it can be confirmed that *Financial acquirers* tend to acquire firms at lower PCDs. The relationship implies that the marginal benefits of *Financial acquirers*, e.g., shorter holding periods enabling the use of LBO strategies, outweigh the marginal benefits of strategic acquirers, e.g., the presumed greater scope for synergy extraction. It is important to note that, due to size limitations in the data, no cross-analysis has been made on the relationship over time and acquirers' access to cheap debt financing. If the reasoning behind the lower PCDs for *Financial acquirers* is related to the abovementioned, one would expect the sign to vary in line with credit spreads and the general availability of debt financing.

On the note of *Credit spreads*, the results showcase a significant positive relationship between *Credit spreads* and PCD, confirming hypothesis H9 that PCDs increases in times when the cost of realizing liquidity is high, further strengthening the findings of Officer (2007). Interestingly, through the confirmation of hypothesis H9 a highly relevant discussion point emerges related to the variation of PCDs across time. As mentioned in Section VI, there exists sufficient evidence of PCD variation across years, confirming hypothesis H10. Kooli et al. (2003) argued that the variation of PCD across years seemed to be a result of varying degrees of general M&A activity, whereas Paglia & Harjoto (2010) argued that the variation is in large a result of varying market conditions across time. The findings in this study support the logic brought forward by Paglia & Harjoto (2010) as the results suggest that PCDs tend to increase in the aftermath of recessions and increased credit spreads (see Section VI).

Lastly, the findings suggest a negative relationship between *Asset turnover* and PCD, confirming hypothesis H11 that firms with high-efficiency assets are acquired at lower PCDs.

b. The importance of industry differences

As for how the PCD varies across industries, several interesting conclusions can be made. Firstly, this study confirms not only that the discount varies across industries, but also that different factors drive the discount's size. As discussed in Section VI, on a 1-digit SIC code level, the discount ranges between 21% (*Agriculture, Forestry, Fishing and Mining*) and 65% (*Wholesale*), the average private company discount being 33%. The dispersion is even wider on a 2-digit level, as the *Manufacturing* industry displays very different but significant PCDs, ranging from 3% (*Printing*, SIC code 27) to 66% (*Miscellaneous Manufacturing Industries*, SIC code 39). Similarly, the *Services* industry displays significant PCDs ranging from 14% (*Engineering, Accounting, Research, Management and Related Services,* SIC code 87) to 41% (*Recreation Services,* SIC code 79). It is therefore highly unsatisfactory to consider only a general PCD, which most of the previous studies have done. Indeed, different industries, having very different characteristics, seem to be discounted very differently by practitioners.

Furthermore, as previously discussed, when regressing over the whole data set, not considering industry affiliation, all explanatory variables show significance. Interestingly, the regression analysis in Section VII-VIII also shed light on how different variables seem to matter, explaining the different discounts across different industries. As is always the case for regression analysis, there is a genuine risk of overfitting the model when deepening the analysis to a more granular level, potentially using more variables than can be justified by the decreasing number of observations. As discussed by Draper & Smith (1998) and Vittinghoff & McCulloch (2007), there are different rules of thumb spanning between 5-10 observations per independent variable. Using the more conservative alternative favored by Draper and Smith (1998), suggesting 10 observations per independent variable, puts constraints on what industries the data allow for more granular analysis. However, compared to previous studies (e.g., Paglia & Harjoto, 2010), this study is still exhaustive enough to be able to analyze a comprehensive set of explanatory variables across several industry verticals.

As presented in Section VII, considering a 1-digit SIC code industry classification, three industries, namely *Manufacturing* (281 observations), *Transport & Public Utilities* (171 observations) and *Services* (315 observations) are industry segments where the data allow for more granular analysis given the comprehensive set of explanatory variables. For the other five, the results should be interpreted with caution, as the suspiciously high R^2 also suggests. However, for these three, interesting differences appear. Some variables, such as *Profitability* and *Asset turnover*, seem to be universally important in determining the PCD across industries. Interestingly, the regression analysis indicates that *Asset turnover* has a larger impact in lowering the PCD for *Manufacturing and Transport & Public Utilities* than for *Services*. This could potentially be a result of these industries being more tangible in nature than *Services*, assuming that the two former industries have less liquid assets, thus mirroring the suggestion made by Block (2007).

Other variables – such as *Deal structure* and *Acquirer type* differ, once again illuminating how unsatisfactory a universally applied PCD is. *Manufacturing* is the only larger industry where *Deal structure* is showing significant results. Importantly, matched transactions within the *Service* industry display a highly significant impact of the buyer being either a public company or a *Financial acquirer*, an effect that isn't significant for any other industry. This is an interesting result. Advancing the analysis, two of the 2-digit subsegments, *Business services* (SIC code 73) and *Engineering, Accounting, Research, Management and Related Services* (SIC code 87), have enough observations for an additional regression analysis, the latter being around the lower bound in terms of observations (94), as presented in Table 3. Interestingly, at this level, significant impact of the buyer being either a public company or a *Financial acquirer* is prevalent for *Business Services* (SIC code 73) but not for *Engineering, Accounting, Research, Management and Related Services* (SIC code 87). This can likely be explained by the growing fraction of private equity investments going to technology industries (Döskeland & Strömberg, 2018) such as *Business Services* (including subsegments such as information services, computer services and software). Indeed, as indicated by Block (2007), different industries have different characteristics, also when it comes to suitability for applying buy-and-build strategies or taking on additional leverage. As such, the three different types of "engineering" that Kaplan and Strömberg (2009) describe as the way private equity increase value of their portfolios are likely applied differently and with different ease, depending on industry. Whereas this study gives support for a lowered PCD within *Business Services*, driven by *Financial acquirers*, the same can't be supported for *Engineering, Accounting, Research, Management and Related Services*. Once again, general assumptions about private company discounts are highly insufficient, if not misleading.

c. Explanatory power

Importantly, while previous studies have used regression models with notably low explanatory power (e.g., Kooli et al., 2003; Covrig & McConaughy, 2015), implying substantial unexplained variability in the dependent variables, this study has, by incorporating a wide set of explanatory variables carrying statistical significance, been able to present a considerably higher adjusted R^2. In practice, building a suitable regression model will be trade-off between adding explanatory variables, potentially increasing the model's explanatory power in terms of R^2, at the expense of the number of industry verticals with enough observations, the number being negatively correlated with the number of explanatory variables. Compared to previous studies, this study has been able to do both, given the rich data set and significant amount of time dedicated to the matching procedure, being done at a 4-digit SIC code level. Thus, explanatory power has increased, still being able to extend previous research in terms of the importance of considering industry segments when studying private company discounts, as there is substantial variance across industries.

X Conclusion

This study provides significant evidence for an average PCD of 33%, ranging from 25% to 66% depending on industry classifications. Further, the purpose of this study was to build on and address previous research's limitations. In doing so, it makes three important contributions. Firstly, this study is the first of its kind to analyze PCD differences across the 2-digit SIC level, illuminating the inadequacy of a universal PCD and generalizing PCDs across the 1-digit SIC level. Moreover, by exhibiting that certain variables' effect on the PCD is not constant across industry verticals, it provides guidance to valuation practitioners in their pursuit of extracting proper valuation discounts. Secondly, by building a comprehensive model of variables previously identified in the academic literature, as well as adding variables previously not accounted for, this study showcases significantly higher explanatory power than what has previously been the standard. Thirdly, by finding significant relationships between *Asset turnover* and *Financial acquirer* and the PCD, this study expand the list of previously known variables affecting the PCD.

That said, although this study's data set is significantly larger than previous studies' and being sufficient for a cross-industry analysis on the 2-digit SIC level, the main limitation in this study is yet the lack of observations. Only three verticals include observations exceeding 100 transactions, thereby satisfying the 10-to-1 ratio of dependent variables to total observations (Draper & Smith, 1998). As such, there is still room for exploration in the space of industry heterogeneity from a 2-digit SIC perspective. Furthermore, given what is argued in the initial sections of this study, one could argue that 2-digit SIC codes are yet insufficient to fully understand the phenomena.

Given the abovementioned, future research in the space of industry heterogeneity and PCD ought to focus on deepening the understanding of PCD variations across unexplored 2-digit

SIC industries as well as improving granularity to the 4-digit SIC level, taking into account the tradeoff between number of total observations and the quality of those observations.

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XII Appendices

a. Example of matching procedure and PCD calculation

Example of sample data

Public transaction ID	Size category (b)	4-digit SIC (e)	Transaction year (g)	Matching index (b,e,g)
Public transaction 1	1	41	2010	1, 41, 2010
Public transaction 2	0	50	2015	0, 50, 2015
Public transaction 3	1	12	2010	1, 12, 2010
Public transaction 4	1	41	2010	1, 41, 2010
Public transaction 5	1	41	2010	1, 41, 2010
Public transaction 6	0	41	2019	0, 41, 2019
Public transaction 7	1	41	2010	1, 41, 2010
Public transaction 8	1	41	2011	1, 41, 2011
Public transaction 9	0	41	2019	0, 41, 2019
Public transaction 10	1	41	2011	1, 41, 2011

Step 1: Creating reference portfolio with index 1,41,2010

Transaction ID	Matching index	Relevant multiple
Public transaction 1	1, 41, 2010	2.2x
Public transaction 4	1, 41, 2010	2.6x
Public transaction 5	1, 41, 2010	1.8x
Public transaction 7	1, 41, 2010	1.9x
Median		**2.1x**

Step 2: Creating reference portfolios within two year range of private transaction (in this case index 1,41,2011)

Transaction ID	Portfolio index	Relevant multiple
Public transaction 8	1, 41, 2011	2.2x
Public transaction 10	1, 41, 2011	2.6x
Median		**2.4x**

Step 3: Construction of matching reference portfolio for private transaction with index 1,41,2010

Portfolio index	# of transactions	Weight	Weighted multiple
1, 41, 2010	4	67%	1.4x
1, 41, 2011	2	33%	0.8x
Sum	**6**	**100%**	**2.2x**

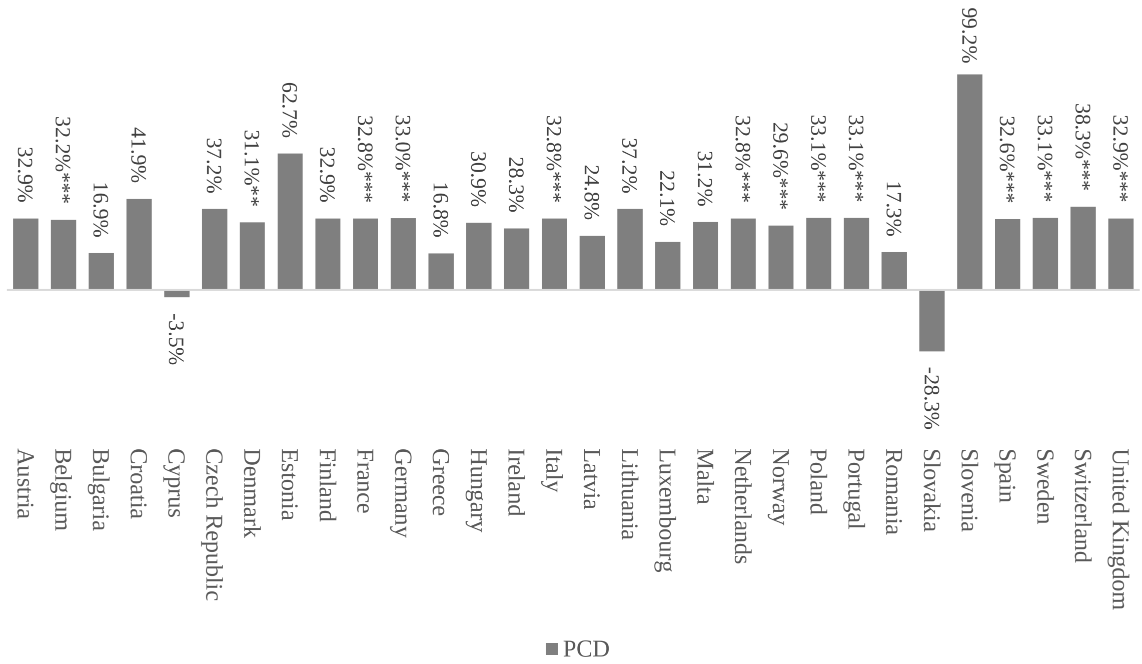
Step 4: PCD calculation

Transaction	Index (indices)	Relevant multiple
Private company transaction	1, 41, 2010	1.9x
Public reference portfolio	(1, 41, 2008-2012)	2.2x
PCD = (1-private multiple/public multiple)		**12%**

b. PCD across countries

***Figure 4**: PCD across countries*

Table 6 reports the PCD across countries. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.



c. Robust regression analysis

Table 6: *Robust regression analysis on 1-digit SIC level*

Table 6 reports the results from the robust regression analysis offered by Stata, using the PCD for either all industries (column 2) or each 1-digit industry classification (column 3-10) as the dependent variable. Growth is a dummy variable, defined as 1 if the private company's compounded annual growth rate for the last two consecutive year is higher than that of the matched portfolio's average compounded annual growth rate, i.e. if the private company has, in terms of percentage, outgrown its reference portfolio. Profitability is defined as 1 if the private company's EBITDA-margin is higher than the average for the reference portfolio. Size refers to the revenue of the private company, which already is matched based on revenue in relation to the reference portfolio, and the data is log transformed to deal with potential skewness. Similarly, assets is a log transformed variable describing the private company's total asset base (book value). Asset turnover is calculated as the private company's total revenue divided by the total assets and is a measure of capital efficiency. Asset turnover is a dummy variable, defined as 1 if the private company's asset turnover is higher than the average for the matched reference portfolio. Deal structure is a dummy variable, defined as 1 if the deal was an all-cash deal. Similarly, acquirer status is defined as 1 if the acquirer was public and financial acquirer is defined as 1 if the acquirer was a financial buyer. Finally, the credit spread variable is based on ICE BofA Euro High Yield Index, an index with calculated spreads between euro dominated bonds and treasuries, retrieved from St. Louis Fed. The numbers presented in the top row refers the coefficients from the robust regression. T-statistics are presented in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Industry	**All industries**	**Agriculture, Forestry etc.**	**Construc-tion**	**Manufa-cturing**	**Transport& Public Utilities**	**Wholesale**	**Retail Trade**	**Real Estate**	**Services**
SIC	**1-89**	**1-14**	**15-17**	**20-39**	**40-49**	**50-51**	**52-59**	**65**	**70-89**
Intercept	0.28***	0.59**	0.78***	0.57***	0.60***	0.51*	0.62***	1.58***	0.51***
	(4.58)	(3.56)	(3.97)	(4.45)	(4.20)	(1.64)	(3.40)	(3.92)	(3.43)
Growth	-0.11***	-0.20**	-0.17	-0.08	0.01	0.02	-0.26***	-0.49**	-0.09
	(-3.68)	(-2.91)	(-1.35)	(-1.49)	(0.14)	(0.11)	(-3.24)	(-2.68)	(-1.37)
Profitability	-0.26***	0.27*	-0.27**	-0.19***	-0.30***	-0.68***	-0.59***	-0.57***	-0.32***
	(-7.93)	(2.54)	(-2.30)	(-3.20)	(-4.02)	(-3.71)	(-6.40)	(-3.06)	(-4.78)
Log size	0.21***	0.38***	0.05	0.01	-0.02	-0.03	0.02	0.06	0.01
	(8.58)	(14.30)	(1.40)	(0.29)	(-0.81)	(-0.93)	(0.56)	(0.93)	(0.56)
Log assets	-0.20***	-0.26***	-0.03	-0.01	-0.03	0.06	0.06*	-0.15**	-0.02
	(-8.57)	(-9.71)	(-0.72)	(-0.65)	(-1.50)	(0.85)	(1.85)	(-2.11)	(-0.77)
Asset turnover	-0.15***	-1.15***	-0.45***	-0.35***	-0.40***	-0.08	-0.26***	0.60***	-0.18***
	(-3.89)	(-11.61)	(-3.64)	(-5.68)	(-5.43)	(-0.55)	(-3.17)	(-3.49)	(-2.64)
Deal Structure	-0.07**	-0.30**	-0.22**	-0.12**	0.08	-0.13	-0.16**	-0.16	-0.07
	(-2.32)	(-3.99)	(-2.05)	(-2.02)	(1.14)	(-1.17)	(-2.09)	(-0.96)	(-1.20)
Acquirer Status	-0.08***	-0.64***	-0.16	-0.04	0.05	-0.21*	0.08	0.10	-0.18***
	(-2.37)	(-7.89)	(-1.43)	(-0.69)	(0.64)	(-1.99)	(0.89)	(0.45)	(-2.64)
Financial Acquirer	-0.06*	0.08	-0.28**	-0.05	0.13	(omi-	-0.10	-0.18	-0.19**
	(-1.78)	(0.48)	(-2.15)	(-0.70)	(1.62)	ted)	(-1.17)	(-0.74)	(-2.59)
Credit spread	1.55***	-0.91	3.37**	0.38	2.00*	-0.50	-2.38	-1.40	2.21*
	(3.12)	(-1.20)	(1.98)	(0.42)	(1.81)	(-0.20)	(-1.90)	(-0.42)	(1.97)
Observations	960	15	42	281	171	31	74	31	315

Table 7: *Robust regression analysis on 2-digit SIC level*

Table 7 reports the results from the robust regression analysis offered by Stata, using the PCD for two 2-digit industries as the dependent variable (Business Services, SIC code 73, and Engineering, Accounting, Research, Management and Related Services, SIC code 87). Growth is a dummy variable, defined as 1 if the private company's compounded annual growth rate for the last two consecutive year is higher than that of the matched portfolio's average compounded annual growth rate, i.e. if the private company has, in terms of percentage, outgrown its reference portfolio. Profitability is defined as 1 if the private company's EBITDA-margin is higher than the average for the reference portfolio. Size refers to the revenue of the private company, which already is matched based on revenue in relation to the reference portfolio, and the data is log transformed to deal with potential skewness. Similarly, assets is a log transformed variable describing the private company's total asset base (book value). Asset turnover is calculated as the private company's total revenue divided by the total assets and is a measure of capital efficiency. Asset turnover is a dummy variable, defined as 1 if the private company's asset turnover is higher than the average for the matched reference portfolio. Deal structure is a dummy variable, defined as 1 if the deal was an all-cash deal. Similarly, acquirer status is defined as 1 if the acquirer was public and financial acquirer is defined as 1 if the acquirer was a financial buyer. Finally, the credit spread variable is based on ICE BofA Euro High Yield Index, an index with calculated spreads between euro dominated bonds and treasuries, retrieved from St. Louis Fed. The numbers presented in the top row refers the coefficients from the robust regression. T-statistics are presented in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Industry	**Business Services**	**Eng., Acc. Services etc.**
SIC	**73**	**87**
Intercept	0.51***	0.48
	(2.78)	(1.40)
Growth	-0.12	0.00
	(-1.41)	(-0.03)
Profitability	-0.27***	-0.42***
	(-3.11)	(-3.11)
Log size	-0.02	-0.02
	(-0.42)	(-0.38)
Log assets	0.04	-0.01
	(1.41)	(-0.24)
Asset turnover	-0.15*	-0.14
	(-1.66)	(-0.98)

Industry	**Business Services**	**Eng., Acc. Services etc.**
SIC	**73**	**87**
Deal Structure	-0.06	0.09
	(-0.78)	(0.68)
Acquirer Status	-0.25***	-0.10
	(-2.78)	(-0.70)
Financial Acquirer	-0.28***	-0.01
	(-2.86)	(-0.04)
Credit spread	2.06	-1.26
	(1.48)	(-0.51)
Observations	169	94

d. OLS regression with robust standard errors

Table 8*: OLS regression on 1-digit SIC level (robust standard errors)*

Table 8 reports the results from the OLS regression analysis with robust standard errors, using the PCD for either all industries (column 2) or each 1-digit industry classification (column 3-10) as the dependent variable. Growth is a dummy variable, defined as 1 if the private company's compounded annual growth rate for the last two consecutive year is higher than that of the matched portfolio's average compounded annual growth rate, i.e. if the private company has, in terms of percentage, outgrown its reference portfolio. Profitability is defined as 1 if the private company's EBITDA-margin is higher than the average for the reference portfolio. Size refers to the revenue of the private company, which already is matched based on revenue in relation to the reference portfolio, and the data is log transformed to deal with potential skewness. Similarly, assets is a log transformed variable describing the private company's total asset base (book value). Asset turnover is calculated as the private company's total revenue divided by the total assets and is a measure of capital efficiency. Asset turnover is a dummy variable, defined as 1 if the private company's asset turnover is higher than the average for the matched reference portfolio. Deal structure is a dummy variable, defined as 1 if the deal was an all-cash deal. Similarly, acquirer status is defined as 1 if the acquirer was public and financial acquirer is defined as 1 if the acquirer was a financial buyer. Finally, the credit spread variable is based on ICE BofA Euro High Yield Index, an index with calculated spreads between euro dominated bonds and treasuries, retrieved from St. Louis Fed. The numbers presented in the top row refers the coefficients from the regression. T-statistics are presented in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Industry	**All industries**	**Agriculture, Forestry etc.**	**Construc-tion**	**Manufa-cturing**	**Transport& Public Utilities**	**Wholesale**	**Retail Trade**	**Real Estate**	**Services**
SIC	**1-89**	**1-14**	**15-17**	**20-39**	**40-49**	**50-51**	**52-59**	**65**	**70-89**
Intercept	0.26***	0.20	0.78***	0.55***	0.53***	0.75*	0.59***	1.59***	0.46***
	(4.67)	(0.22)	(4.98)	(4.95)	(3.49)	(2.03)	(2.79)	(5.06)	(3.65)
Growth	-0.11***	-0.16	-0.18*	-0.09	0.03	-0.22	-0.25**	-0.52**	-0.09
	(-3.85)	(-0.37)	(-1.76)	(-1.59)	(0.44)	(-1.38)	(-2.08)	(-2.96)	(-1.54)
Profitability	-0.23***	0.30	-0.27**	-0.16***	-0.29***	0.03	-0.40***	-0.57***	-0.28***
	(-6.80)	(1.08)	(-2.58)	(-2.76)	(-3.77)	(0.07)	(-3.58)	(-3.81)	(-4.21)
Log size	0.19***	0.31**	0.06*	0.01	-0.02	-0.04	0.05	0.05	0.02
	(8.73)	(3.63)	(1.70)	(0.29)	(-0.86)	(-0.94)	(1.54)	(1.02)	(0.78)
Log assets	-0.18***	-0.15	-0.03	-0.01	-0.03	0.06	-0.01	-0.14**	-0.02
	(-8.75)	(-1.43)	(-0.86)	(-0.83)	(-1.40)	(1.15)	(-0.32)	(-2.39)	(-0.85)
Asset turnover	-0.14***	-1.07**	-0.45***	-0.33***	-0.37***	-0.57*	-0.35***	-0.59***	-0.18***
	(-3.68)	(-2.75)	(-4.66)	(-5.32)	(-5.44)	(-1.80)	(-3.18)	(-4.02)	(-2.83)
Deal Structure	-0.07**	-0.39*	-0.23**	-0.11*	0.07	-0.07	-0.18*	-0.16	-0.07
	(-2.32)	(-2.18)	(-2.58)	(-1.93)	(1.01)	(-0.59)	(-1.81)	(-1.06)	(-1.19)
Acquirer Status	-0.09***	-0.71	-0.17	-0.06	0.06	-0.37**	0.09	0.10	-0.18***
	(-2.71)	(-1.55)	(-1.55)	(-0.97)	(0.70)	(-2.22)	(0.61)	(0.56)	(-2.70)
Financial Acquirer	-0.07*	0.14	-0.32**	-0.05	0.11	(omi-	0.06	-0.21	-0.17**
	(-1.85)	(0.16)	(-2.34)	(-0.74)	(1.42)	ted)	(0.59)	(-0.93)	(-2.53)
Credit spread	1.47***	-0.94	3.36**	0.47	2.13**	3.37	-1.20	-1.59	1.95**
	(3.20)	(-0.19)	(2.45)	(0.56)	(2.20)	(1.10)	(-0.65)	(-0.45)	(2.12)
R^2	25.3%	84.0%	67.7%	18.3%	33.1%	58.5%	39.6%	71.6%	16.2%
Observations	960	15	42	281	171	31	74	31	315

***Table 9**: OLS regression on 2-digit SIC level (robust standard errors)*

Table 9 reports the results from the OLS regression analysis with robust standard errors, using the PCD for two 2-digit industries as the dependent variable (Business Services, SIC code 73, and Engineering, Accounting, Research, Management and Related Services, SIC code 87). Growth is a dummy variable, defined as 1 if the private company's compounded annual growth rate for the last two consecutive year is higher than that of the matched portfolio's average compounded annual growth rate, i.e. if the private company has, in terms of percentage, outgrown its reference portfolio. Profitability is defined as 1 if the private company's EBITDA-margin is higher than the average for the reference portfolio. Size refers to the revenue of the private company, which already is matched based on revenue in relation to the reference portfolio, and the data is log transformed to deal with potential skewness. Similarly, assets is a log transformed variable describing the private company's total asset base (book value). Asset turnover is calculated as the private company's total revenue divided by the total assets and is a measure of capital efficiency. Asset turnover is a dummy variable, defined as 1 if the private company's asset turnover is higher than the average for the matched reference portfolio. Deal structure is a dummy variable, defined as 1 if the deal was an all-cash deal. Similarly, acquirer status is defined as 1 if the acquirer was public and financial acquirer is defined as 1 if the acquirer was a financial buyer. Finally, the credit spread variable is based on ICE BofA Euro High Yield Index, an index with calculated spreads between euro dominated bonds and treasuries, retrieved from St. Louis Fed. The numbers presented in the top row refers the coefficients from the regression. T-statistics are presented in the parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Industry	**Business Services**	**Eng., Acc. Services etc.**
SIC	**73**	**87**
Intercept	0.47***	0.47
	(3.04)	(1.66)
Growth	-0.09	-0.03
	(-1.13)	(-0.26)
Profitability	-0.23**	-0.38***
	(-2.53)	(-3.30)
Log size	0.01	-0.03
	(0.19)	(-0.64)
Log assets	0.02	-0.00
	(0.92)	(-0.04)
Asset turnover	-0.17**	-0.11
	(-1.98)	(-0.94)

Industry	**Business Services**	**Eng., Acc. Services etc.**
SIC	**73**	**87**
Deal Structure	-0.10	0.09
	(-1.29)	(0.75)
Acquirer Status	-0.28***	-0.09
	(-3.36)	(-0.74)
Financial Acquirer	-0.28***	-0.02
	(-3.04)	(-0.11)
Credit spread	2.15**	-1.83
	(2.35)	(-0.80)
Observations	169	94