Market Risk in Private Equities

The Prominent Role of Systematic Risk Factors

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About the Authors

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Executive Summary

This paper investigates market risk in private equities, with a focus on asset-level risk rather than the fund-level risks typically associated with private equity investments. While liquidity and cash flow risks—arising from the structure of private equity funds—are well recognised, this study shifts attention to the underlying market risk borne by investors in the equity of private companies. Specifically, it examines how variable is operating performance and how it relates to insolvency risk across a large sample of private companies and past private equity transactions.

To this end, the study makes extensive use of the PECCS® taxonomy and privateMetrics® to classify companies along PECCS pillars and analyse key risk factors. Key observations include:

1. Operating Performance Volatility and Insolvency Risk in Private Equities

- **Revenue**, **profit**, and **growth** volatilities exhibit **systematic differences** across PECCS pillars, classes, and risk factors.
- **Insolvency risk** can be partly explained by PECCS pillars and exposure to key risk factors, such as growth, profit, leverage, size, and maturity.
- Private equities firm level risk is comparable to that observed for **listed equities**.

2. Evidence from Private Equities Transactions

- **Systematic differences** in average pricing of transactions over 2005-2024 (e.g., P/EBITDA,
  P/S) across the 5 PECCS pillars and risk factors.
- Derived **discount rates** (expected returns) from transactions discriminates across PECCS pillars and risk factors.
- Private equities transactions incorporate **systematic risk** in pricing and can thus be proxied by a well calibrated model.

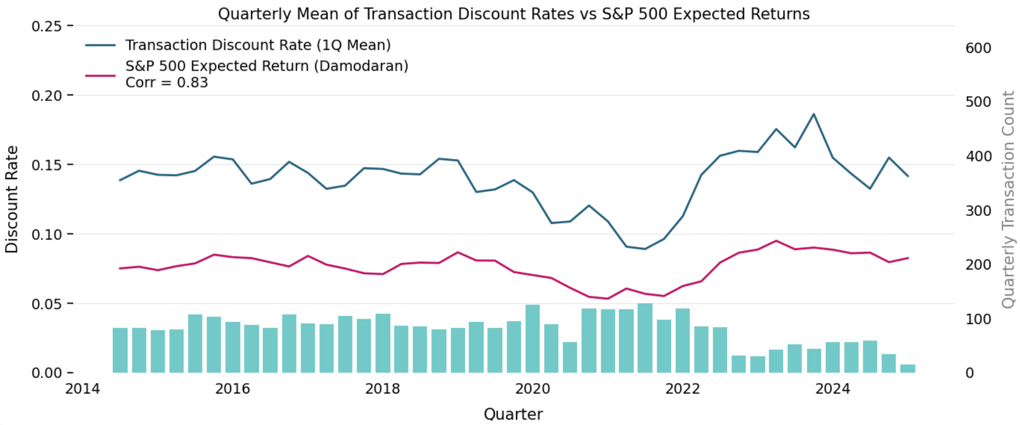
3. Systematic and Idiosyncratic Risks in Private Equities

- **Factor model** using the **systematic risk factors** can explain some of the variation in observed transaction prices.
- **Implied discount rates** for the transactions are estimated as 14% on average (with an interquartile range from 11% to 16%), roughly 6% points over public equity expected returns over time (see Figure E1).
- By expressing the uncertainty around implied discount rates, a **bid-ask spread** can be estimated around the systematically explained prices that varies with asset characteristics and overall private market conditions.
- A **significant share** of the pricing dynamics of transactions are explainable with the combination of the **systematic risk factors** implied price and the **bid-ask spread**.
- Unexplained residual pricing is idiosyncratic, random, and almost normally distributed.

The study confirms both (1) the existence of considerable operating performance and pricing variability in private equities and (2) the systematic variation of that volatility—along with observed insolvency risk—across PECCS segments and key risk factors in both firm-level data and completed transactions. These findings suggest that private equities can be priced by incorporating systematic risk factors and the structural dimensions defined by the PECCS taxonomy. This has important implications for asset-level valuation and for benchmarking private asset funds at the portfolio level.

Executive Summary

FIGURE E1: TIME TRENDS IN ESTIMATED DISCOUNT RATES FOR TRANSACTIONS AND PUBLIC MARKETS, 2013-2024



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1. Introduction

In this paper, we propose an empirical analysis of the market risk of private equities i.e., the risk of investing in private equity at the asset-level. To avoid confusion with the term "private equity" which has become synonymous with investing in private equity funds, we talk of private equities to refer to the market for investing in the underlying equity stakes of private companies.

Market risk is not the only source of risk for an investor or limited partner (LP) into a private market fund managed, and often co-invested, by a general partner (GP). LPs also face liquidity risk since their capital is locked up for multiple years, and cash flow risk because the inflows and outflows from private funds are uncertain and not easily predicted.

We show in this paper that market risk is the least well understood or documented by existing academic research on private equity investment, which solely focuses on fund-level data and thus conflates market risk with liquidity and cash flow risk.

Unlike liquidity and cash flow risks, which are created by the fund structure itself, market risk should be understood first and in isolation before investing private asset funds. Indeed, the rationale to invest in such funds is to seek exposure to private market risk. GPs and LPs also share market risk directly as frequent co-investors in private assets. Identifying and documenting market risk in private equities is pivotal to understand the private equities asset class and compare it with others, especially public equities. It is also the starting point to assess GP performance and their ability to add value when compared to the private market itself.

Private market risk is simply the potential for financial loss or gain due to fluctuations in private equities market prices. Such losses or gains can be expected to have a significant impact on the performance of investments made by private equity fund managers.

Simply put, there is a market for the equity stakes of private companies in which various investors are both buyers and sellers. As in any other market, the price of these stakes fluctuates with supply and demand. Changes in supply may be driven by economic or technological trends in the economy e.g., there are more data centre companies today than there were ten years ago. Likewise, the level of demand for investing in private companies is the reflection of the number of buyers and their risk appetite at one point in time. The past decades have seen an increase in the number of private equity investors (both GPs and LPs) and significant variance of their risk appetite or the level of expected returns from private equities, as we document in this paper.

This is why understanding market risk is crucial for investors as it helps them assess the volatility and potential returns of their investments in private equity funds.

In what follows, we first review the literature on risk in private equity investments and find that there is a gap in existing research which focuses almost entirely on risk at the fund level. There are two main strands in the finance literature on private equity funds: (1) documenting the risk-adjusted returns of investment funds, especially in relation to public equities and (2) developing risk management techniques to understand and address the cash flow and illiquidity risks created by fund structures. Most papers on private equity investment also lament the "stale'" or "smooth" net asset values reported by GPs, which makes any direct measurement of risk at the fund or asset-level technically impossible or fundamentally flawed.

We have shown elsewhere how an asset pricing model can be calibrated using private equity transaction data to capture private market dynamics (see, Selvam and Whittaker (2024)). In this context, we introduced the PrivatE Company Classification Standard or PECCS®, a five-pillar taxonomy designed to capture different types of private equities, as well as a parsimonious list of risk factors that could be used to calibrate a pricing model, namely, the size, profits, leverage, growth and age of the firm, as well as country risk. This technology is known as privateMetrics® and used to shadow price thousands of assets monthly and build market indices such as the private2000 index.

In this paper, we use raw financial data for a large sample of over 1 million firms in 150+ countries, as well as observable transaction data for 10k private equity "exits", to document the risks of private equities. We investigate the level of variability in operational performance of private equities, whether these risks tend to be priced and what proportion of market prices can be explained by systematic risk factors. We also use privateMetrics modelled data to further validate and cross-check our findings.

To analyse risk in private equities, we follow these steps:
1) First, we look at *reported financial data* to assess the importance of micro-economic risks in private equities and whether there exist systematic risk differences between private firms, in other words, whether certain factors or classes of private companies are useful discriminants between different levels of risk found in private equities. For this purpose, we consider two types of risk metrics:

a) Risk as the variance of company level operational performance: we look at the volatility for profits, revenue and revenue growth in private companies over time i.e., volatility in firm characteristics and find systematic differences across private market segments and key risk factors. We also find that the level of volatility in operational performance in private equities is comparable to that of public equities.

b) Risk as extreme outcomes leading to insolvency: we review the likelihood of insolvency events in private companies and examine insolvency rates and the probability of insolvency by PECCS market segment and risk factor exposure level. We also compare insolvency risk with listed equities and with privateMetrics return volatility. Likewise, we find that insolvency risk is partly dependent on PECCS market segments and on the level of exposure to key risk factors.

c) We conclude that differences in risk levels in private equities can be systematically explained (and therefore proxied) by market segments and key risk factors (identified in the PECCS (2023)). These differences can be very large with a range of three to four times the volatility or the chances of insolvency between different segments or risk factor exposure buckets.

2) Next, having established the existence of systematic differences in risk in private equities, we consider whether these risks are priced using observable *transaction price data* and examining whether market prices can also be systematically explained. We consider two types of pricing metrics:

a) Transaction price multiples: we look at EV-to-Ebitda and Price-to-Revenue ratios of thousands of transactions over the past decade and find that average transaction price multiples can be systematically explained by the same differences of market segments and risk factor exposures that were found to describe the level of risks in private equities in the first step.

b) Expected returns: we compute an implied expected return for the same set of transactions and find that implied expected returns as observed in individual market transactions can also be systematically explained by PECCS segments and risk factors exposures.

c) We conclude that the systematic risks found in the previous analysis are indeed priced, which confirms both their systematic nature and the importance of taking market risk into account when investing in private equities since risk pricing is found to correlate with the economic cycle.

3) Finally, having determined the existence of systematic risks and their impact on market prices i.e., the existence of private market mechanisms, we investigate what proportion of private market prices can be explained by systematic factors as opposed to idiosyncratic ones. We consider two perspectives:

a) The proportion of price variance explained by systematic risk factors and market segments: we use regression analysis to determine what proportion of a private equity transaction price is determined by systematic risk factors and segments. We find that systematic risk factors can explain as much as **30%** of the variation in private equities market prices.

b) Role of the bid-ask spread: we propose that the bid ask spread is an important component of market risk i.e., a reflection of supply and demand given the illiquidity of private equities. We measure the bid-ask spread in private transactions by computing a discount rate for each transaction and allowing that to vary based on "good deal bounds" – where a good deal can refer to an investment that is excessively attractive to the buyer or seller relative to other investment choices in the current market, thus inducing them to trade. Combined with the systematic risk implied valuation, the bid-ask spread can explain over **66%** of the variation in private equities market prices.

We conclude with a discussion on the existence of private market mechanisms determined by market forces, with a focus on asset pricing and private fund investment benchmarking purposes.

2. Literature Review: A Gap in Existing Research

Private equity investments are characterised by unique risks due to their illiquidity and unavailability through an exchange. As mentioned in the introduction, these risks can be categorised into three groups:

1) **Liquidity Risk**: Investors often face long holding periods, typically ranging from 10 to 12 years, during which capital is locked in, making it difficult to liquidate investments (Markarian and Breuer, 2023).

2) **Cash Flow Risk**: The unpredictable nature of cash flows from private equity investments can complicate financial planning and risk assessment (Buchner, 2017)).

3) **Market Risk**: Private equity investments are subject to fluctuations in market conditions, which can affect valuations and exit opportunities.

The first two types of risks are inherent to the fund structure used to access the private equity asset class and have led to the development of research on the risk management strategies available to LPs.

For instance, recent research in risk management and private equity focuses on modelling fund dynamics, such as capital drawdowns and distributions, to evaluate liquidity risks and funding needs across different economic states. It also addresses the valuation challenges posed by the illiquidity of private equity to better predict investor cash flow risks. See for example "Portfolio and Risk Management for Private Equity Fund Investments" (OUP, 2024).

Likewise, Jorion (2024) propose a risk management framework for private equity fund investors, focusing on market, liquidity, and cash flow risks. Market risk, typically measured through value-at-risk (VaR) approaches, is uniquely challenging due to infrequent valuations and potential for major cash flow disruptions. To address liquidity risks, because stakes in PE funds are often difficult to sell, their paper develops a liquidity-adjusted VaR (LVaR) model (see also Buchner (2017)). It also introduces a cash flow-at-risk (CFaR) measure to manage cash flow volatility as funds move through their investment life cycles. Implementing staged funding may also help manage moral hazard and align interests between investors and fund managers (Wang and Chen, 2023).

While these strategies can help manage risks and focus on more directly observable cash flow and liquidity risks, market risk is largely hidden by way of the inherent opacity and self-reporting nature of private equity investments (Markarian and Breuer, 2023)).

Thus, when it comes to the market risks of private equity investments, there is limited academic research that goes at the asset-level beyond the self-reported metrics. In effect, the vast majority of the research in finance conflates market, liquidity and cash flow risks because it focuses on risks at the fund level.

For example, Groh and Gottschalg (2005) look at the risk-adjusted performance in private equity funds using mimicking strategies to model volatility and returns. This study estimates betas for private equity fund investments, to provide a comparison with public market equities. Their findings indicate that while PE funds may offer high returns, these come with significant risk, partly due to long investment periods and limited liquidity. The study underscores the need for sensitivity analysis and the importance of understanding liquidity impacts.

Likewise, Markarian and Breuer (2023) show that private equity investments face significant risks due to their quasi-private nature, lack of transparency, and self-reported performance metrics. They show that the COVID-19 pandemic highlighted these risks, leading to under-performance as markets reacted negatively to the inherent riskiness of private equity.

Gupta and Nieuwerburgh (2021) also identify systematic risk in private equity investments through a portfolio cash-flow replicating approach. They find negative risk-adjusted profits for the average fund in most categories, indicating significant risk and performance variation among different private equity funds.

Jegadeesh et al. (2015) also show that private equity investments exhibit greater systematic risk than indices based on self-reported net asset values and that unlisted private equity funds have market betas close to one and positive betas on the size (SMB) factor, indicating significant market sensitivity.

This analysis is consistent with earlier papers such as Gottschalg et al. (2004). In Gottschalg et al. (2004), the authors investigate the performance of private equity by estimating a market beta to estimate the actual volatility and return profile of private equity funds compared to public equities. They find that private equity investments typically carry higher risks (beta) than equities when accounting for leverage and long holding periods. They also discuss the "stale price" effect, which can understate volatility in private equity fund returns due to infrequent asset valuations. These last points are echoed in numerous papers: since private equity investments lacks the daily pricing data available for public equities, it results in "smoothing" of returns and makes PE appear less volatile than it might be in reality; and private equity's inherent illiquidity and long investment horizons add to its risk profile, complicating direct comparisons with public market returns (see for example Korteweg (2011)).

In conclusion, existing research on private equity investment has so far been unable to cover the topic of market risk at the asset-level i.e., before the impact of fund structures and cash flows also impact the risk and return profile of the investment.

As a result, it is difficult to know if the risks identified in the research papers mentioned above and others spring from the market for private equity itself i.e., buying and selling private companies, or the liquidity and cash flow risks created by the fund structure employed to invest in private markets.

3. Data

The datasets used for this research include (1) an asset-level financials dataset, (2) a transaction-level private equity entry/exit price dataset and (3) the privateMetrics monthly priced universes. We use raw financial data for a large sample of over 1M firms in 150+ countries, as well as observable transaction data for 10k private equity "entry/exits", to document the risks of private equities. We investigate the level of risk found in private equities, whether these risks tend to be priced and what proportion of market prices can be explained by systematic risk factors. We use privateMetrics modelled data, described in the subsequent pages, to further validate and cross-check our findings.

Financials (Asset-level dataset)

The financials database consists of financial results for over 1 million unique companies covering the period 2013 to 2024. Table 1 highlights the key statistics for the database as of the year end December 31, 2023, across 3 segments – Global (all companies), Advanced economies, and European Union. Table 2 provides the same statistics for the full period 2013 to 2023.

TABLE 1: FINANCIAL DATABASE KEY STATISTICS FOR YE DECEMBER 31, 2023

Universe Profile (US$M)	Global	Advanced	EU
Companies	824k	637k	171k
Revenue	10.3/53.2	10.6/48.9	14.3/83.8
EBITDA	0.71/5.29	0.79/5.13	0.98/8.3
EBIT	0.58/4.1	0.64/3.77	0.64/5.29
Net Income	0.42/3.02	0.47/2.81	0.46/4.1
Revenue Growth%	2.5%/5.8%	2.2%/4.9%	2.7%/6.8%

As of December 31, 2023. Data presented as Median/Mean

TABLE 2: FINANCIAL DATABASE KEY STATISTICS FOR ALL YEARS FROM 2013-2023

Universe Profile (US$M)	Global	Advanced	EU
Companies	1,626k	899k	312k
Revenue	10.4/80.4	10.8/66.6	10.3/69.3
EBITDA	0.49/4.27	0.67/9.0	0.57/6.89
EBIT	0.36/1.48	0.46/5.17	0.32/4.54
Net Income	0.23/2.85	0.32/3.55	0.21/3.21
Revenue Growth%	3.2%/11.7%	2.5%/8.9%	3.7%/11.7%

For years ending December 31, 2013-2023. Data presented as Median/Mean. Table 1 Companies count as of December 31, 2023. Table 2 represents unique Companies count for 10-year period.

Transactions

To test the systematic vs. idiosyncratic risk pricing in observed transactions, we used a dataset consisting of over 10k transactions from Pitchbook and Capital IQ covering the 2005-2024 period. Table 3 outlines the key metrics for the companies in the database, including mean and median revenues, transaction price figures and other operating metrics. However, after excluding missing values on key observations, we end up with a sample of over 5,000 transactions.

3. Data

TABLE 3: TRANSACTION DATA KEY STATISTICS

TRANSACTION DATABASE BY PECCS ACTIVITY PILLAR							
N=5,437	P/S	Rev (A)	Rev (M)	Price (A)	Price (M)	EBITDA %	Rev Gr%
All Transactions	1.78	463.9	96.6	808.0	182.5	12.8%	6.1%
Education and public	1.92	306.7	66.6	512.3	123.9	13.2%	9.4%
Financials	2.38	464.5	80.7	885.9	196.4	14.9%	10.4%
Health	2.09	420.5	79.2	715.8	166.6	12.1%	7.9%
Hospitality and entertainment	1.89	417.1	99.3	816.2	213.0	12.7%	6.0%
Information and communication	2.65	345.9	75.6	1,053.5	185.0	15.9%	6.8%
Manufacturing	1.47	406.5	96.6	540.0	159.1	12.3%	4.7%
Natural resources	1.89	751.2	122.0	860.0	233.7	13.9%	3.0%
Professional and other services	1.58	361.3	81.7	592.2	128.2	12.3%	7.9%
Real estate and construction	1.78	396.9	144.8	918.4	246.8	16.0%	5.6%
Retail	0.96	1,228.3	187.7	1,441.8	228.5	7.4%	5.6%
Transportation	1.44	597.4	158.7	1,011.3	280.3	13.9%	5.7%
Utilities	1.93	563.8	182.5	1,492.2	326.0	18.4%	3.0%

Source: Pitchbook, Capital IQ. Revenue and Price data in USD millions. A= Mean. M = Median.

privateMetrics®

The **privateMetrics** database includes more than 1 million private companies from over 100 countries. It combines data from audited accounts, commercial databases, and documents processed manually or with AI algorithms trained inhouse. These companies are valued monthly dating back 10 years and form the basis of the indices. It offers equity index series that combines the performance of a large number of private companies globally to reflect the overall, segment-wise, and regional performance of the private asset class in a precise, granular, and frequent manner. To facilitate classification, the PrivatE Company Classification Standard (PECCS®) is used to classify companies across the 5 key pillars – Activity, Lifecycle, Revenue Model, Customer Model, and Value Chain. The flagship index is the private2000®, representing 2000 private companies selected across 30 countries based on country and sector weight, with the largest companies in each included in the index. The index constituents are priced monthly, providing for monthly pricing of the private2000 index. More details on privateMetrics approach are described in Appendix B.

The Broad private Market Universe (BMU) represents the full set of private companies included in the privateMetrics database. The BMU includes all for profit companies that are not government owned, publicly listed, or would classify as infrastructure. The Private Equity backed Universe (PEU) is a more refined set that controls for companies that are more likely to be owned by private equity investors. The PEU inclusion controls for size, profitability, and sector to ensure its aligned with private equity companies that are transacted in the marketplace.

The index construction then derives from the PEU. For the private2000, the companies in the PEU are ranked in each country and activity combination by their latest valuation as estimated by a factor model. The largest companies are included subject to country and activity weights.

3. Data

The private2000 is comprised of companies from 30 countries, with the U.S. having the largest weighting in the index (46% = 2024YE). Tables 4 and 5 outline key statistics for all segments.

TABLE 4: KEY UNIVERSE STATISTICS

Universe Profile (US$)	BMU	PEU	MIU
Constituents	935k	193k	2k
Market Capitalization	$60T	$19T	$2.1T
Enterprise Value	$112T	$39T	$3.7T
Total Assets	$104T	$33T	$2.7T
Revenue	$58T	$18T	$2.3T

Source: privateMetrics. As of December 31, 2024.

TABLE 5: KEY CONSTITUENT STATISTICS

Constituent Profile (Median)	BMU	PEU	MIU
Enterprise Value (EV)	$28.5	$42.2	$388.3
Market Capitalization	$21.9	$31.2	$275.7
Revenue	$14.6	$19.8	$213.2
EBITDA	$0.86	$1.06	$12.54
Debt/EBITDA	4.09x	2.39x	2.39x

Source: privateMetrics. As of December 31, 2024.

Operating Performance Volatility in Private Equities

In this chapter, we examine risk in private equities from a micro-economic perspective. We first look at risk as variance and as the volatility of key operating performance metrics that can be expected to impact private company valuations, namely the volatility of revenues, profits and revenue growth.

Descriptive Statistics

To document the cross-sectional variations in volatility between firms, we consider the average volatility of several operating metrics for all firms alive in a given period, going back at least 3 years and as far back as possible.

Table 6 displays the Profit volatility, Revenue volatility, and Growth volatility for different PECCS Pillars, which are classifications related to revenue model, value chain, customer model, and lifecycle.

TABLE 6: VOLATILITY IN PRIVATE EQUITIES BY PECCS PILLARS

PECCS		Volatility		
Pillar	Classes	Profit	Revenue	Growth
Revenue Model	Markup	0.0438	0.3523	0.2436
Value Chain	Products	0.046	0.3127	0.2253
Customer Model	B2C	0.0575	0.3183	0.232
Lifecycle	Mature	0.065	0.3246	0.2329
Revenue Model	Advertising	0.063	0.3721	0.2605
Revenue Model	Production	0.0768	0.3858	0.2878
Customer Model	B2B	0.0782	0.4162	0.3029
Lifecycle	Growth	0.0848	0.4847	0.3409
Value Chain	Services	0.0974	0.4581	0.335
Value Chain	Hybrid	0.0702	0.3637	0.2676
Lifecycle	Early Stage	0.0986	0.7121	0.5683
Revenue Model	Subscription	0.1173	0.4544	0.3165

Source: privateMetrics

The non-Activity Pillars in the PECCS taxonomy are:[1]

Revenue Model: How the company generates revenue e.g., Markup, Advertising, Production, Subscription.

Value Chain: The stage of the company's product or service in the value chain e.g., Products, Services, Hybrid.

Customer Model: The target audience of the company e.g., B2B, B2C.

Lifecycle: The stage of development the company is in e.g., Mature, Growth, Early Stage.

1 - Find out more about the PECCS taxonomy here: https://edhecinfraprivateassets.com/private-equity/peccs/ (PECCS, 2023).

Table 6 highlights that systematic differences in risk levels exist across different market segments, as demonstrated by the varying volatility figures for each PECCS Pillar and Class.

For instance, companies in the "Early Stage" lifecycle exhibit higher volatility across profit, revenue, growth, and returns compared to those in the "Mature" lifecycle. Similarly, companies with a "Subscription" revenue model show greater volatility than those with a "Markup" model.

Similar variations in volatility exist across each PECCS pillars, suggesting that a company's position within the classification can provide insights into its expected level of risk. Thus, start-up companies exhibit higher volatility compared to mature companies, and services are more volatile than products. In other words, a company's stage of development and its core offerings are a systematic driver of the volatility of its financials.

Operating Performance Risks by Activity Class

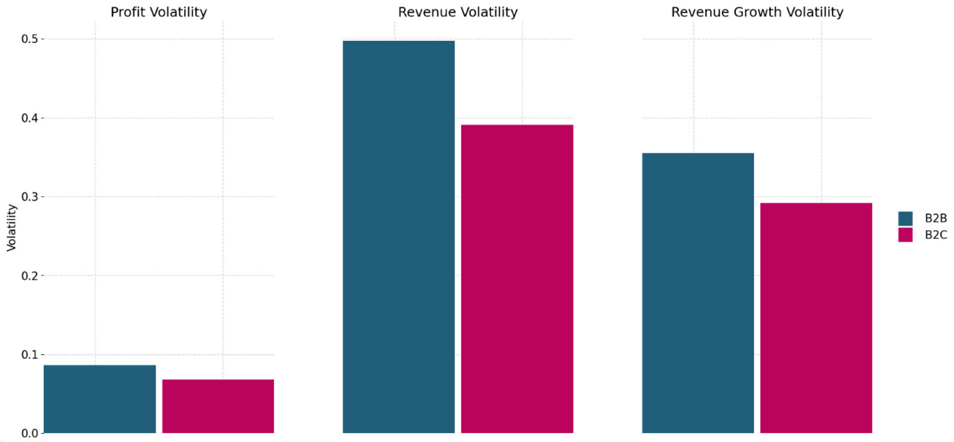
Figure 1 presents firm level volatility in operating performance across the PECCS Industrial Activity pillar, revealing clear differences in risk profiles among sectors. Certain industries exhibit significantly higher volatility than others. In particular, Financials, Professional and Other Services, and Real Estate and Construction show the highest levels of revenue volatility, while sectors such as Health and Manufacturing demonstrate comparatively lower volatility. Similar patterns emerge in revenue growth volatility, albeit less pronounced. Notably, sectors with elevated revenue and growth volatility also tend to display the highest profit volatility. Taken together, the results underscore that volatility—whether in revenue, profit, or growth—varies meaningfully across PECCS Activity classes, highlighting the presence of systematic differences in risk across sectors.

FIGURE 1: OPERATING PERFORMANCE VOLATILITY BY INDUSTRIAL ACTIVITY

Source: privateMetrics. Based on 1 million firms as of 2023 with a minimum of 5yrs data.

Figure 2 demonstrates that volatility is higher for B2B companies than for B2C companies across all key dimensions—revenue, revenue growth, and profit volatility. This suggests that firms operating under a B2B model are generally more exposed to fluctuations in financial performance compared to their B2C counterparts.

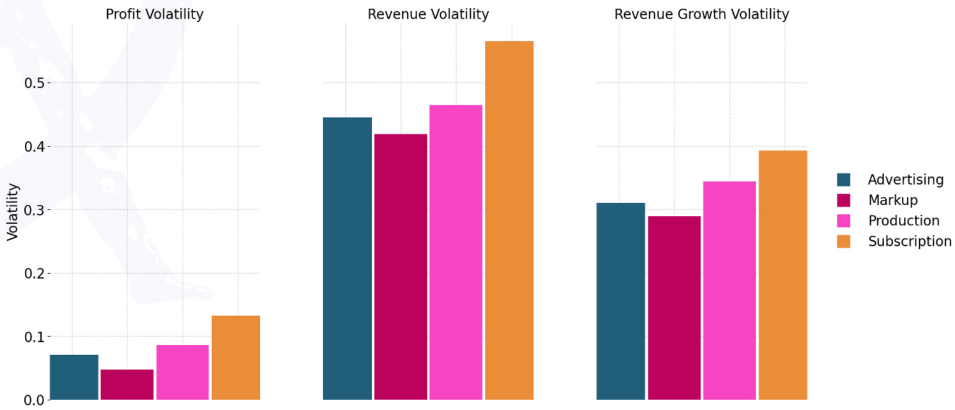
FIGURE 2: OPERATING PERFORMANCE VOLATILITY BY CUSTOMER MODELS



Source: privateMetrics. Based on 1 million firms as of 2023 with a minimum of 5yrs data.

Figure 3 outlines operating performance volatility at the Revenue Model Classes, specifically across advertising, markup (retail), production, and subscription models. The subscription model displayed the highest revenue, growth, and profit volatilities across the class. The Markup (reseller) model had the lowest volatility, followed by Advertising. Once again, clear differences in risk are apparent across the classes.

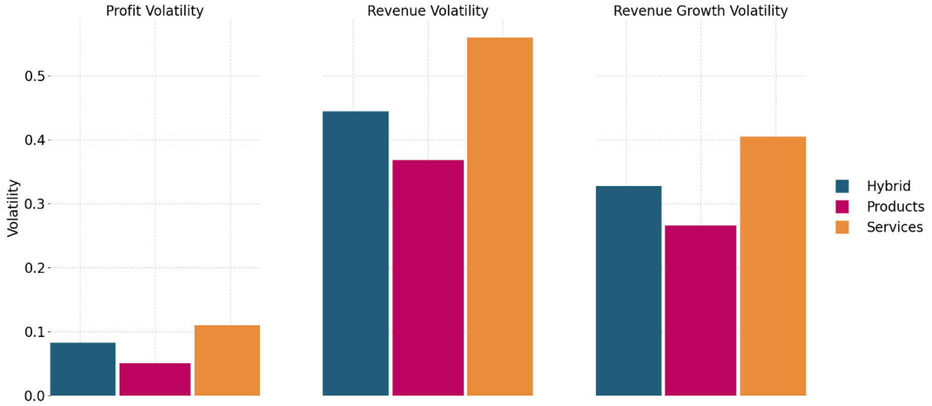
FIGURE 3: OPERATING PERFORMANCE VOLATILITY BY REVENUE MODELS



Source: privateMetrics. Based on 1 million firms as of 2023 with a minimum of 5yrs data.

Turning to the Value Chain Classes, Figure 4 illustrates microeconomic volatility across Products, Services, and Hybrid classifications. Volatility is highest across all key risk metrics—revenue, growth, and profit—for firms classified under the Services value chain. This aligns with earlier findings from the Activity Pillar analysis, where sectors such as Financials, Professional and Other Services, and Hospitality and Entertainment exhibited elevated volatility. A significant share of businesses within these sectors operates under service-based models, which helps explain the heightened volatility observed here.

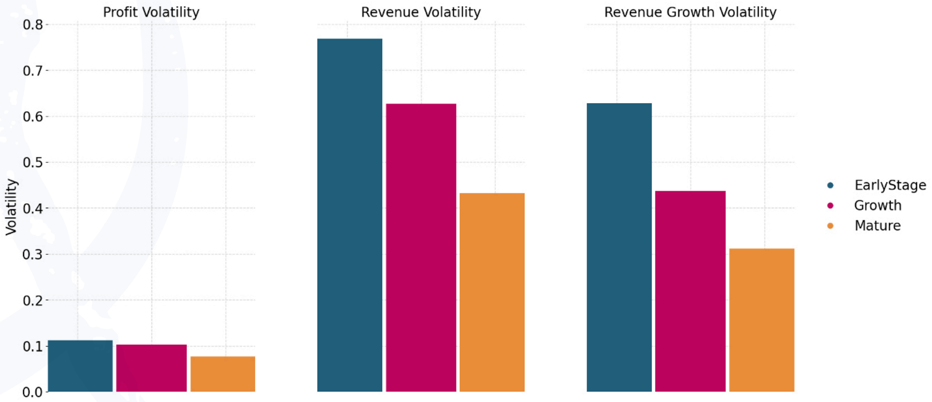
FIGURE 4: OPERATING PERFORMANCE VOLATILITY BY VALUE CHAIN



Source: privateMetrics. Based on 1 million firms as of 2023 with a minimum of 5yrs data.

At the Lifecycle pillar, it is no surprise that early-stage companies exhibit the highest volatility across operating metrics, followed by growth companies, and mature companies. Figure 5 highlights the differences across lifecycle stage.

FIGURE 5: OPERATING PERFORMANCE VOLATILITY BY LIFECYCLE



Source: privateMetrics. Based on 1 million firms as of 2023 with a minimum of 5yrs data.

Operating Performance Volatility Across Risk Factors

After establishing the presence of variability in operating performance across PECCS pillars, we evaluated their volatility by risk factors. These factors include size, growth, profit, leverage, and maturity.

Beginning with the size factor, Figure 6 shows that small-cap companies exhibit the highest levels of revenue, revenue growth, and profit volatility. On average, smaller firms tend to be less profitable than their larger counterparts and may be more heavily influenced by the volatility of young, emerging firms as well as mature value companies, contributing to elevated risk levels. The data reveal a “U-shaped” pattern in revenue and growth volatility by size quintile—small firms show the highest volatility, mid-sized firms the lowest, and large firms a moderate increase in volatility. This pattern does not hold for profit volatility, where differences are less pronounced across size buckets. Overall, the largest disparity in risk is observed between the first and second quintile, with the smallest firms being substantially riskier than all other size categories.

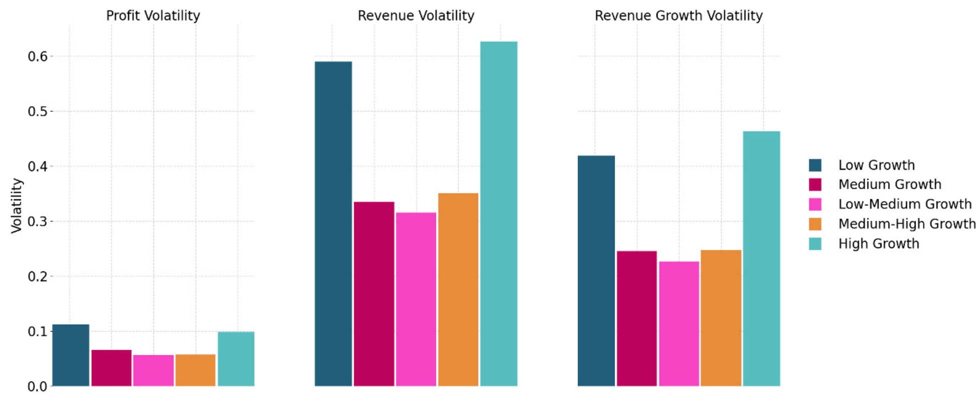
FIGURE 6: OPERATING PERFORMANCE VOLATILITY BY RISK FACTORS: SIZE

Source: privateMetrics

Next, looking at operating performance risk split by buckets of the Growth Factor, we observe a similar "U-Shape" pattern emerging across all three risk factors, profit, revenue, and growth. For medium growth to high growth companies, an increasing trend is observed, with increasing revenue and growth volatility corresponding to higher growth firms. However, low-growth firms also show very high revenue and profit volatility. Within the low-growth category, this bucket also captures firms that are experiencing negative growth, which may contribute to the heightened volatility. This bucket may also capture value or distressed firms that are facing disruptions to their business, impacting revenue and net income, increasing volatility.

For profitability, a similar trend unfolds. Low profit firms experience the greatest revenue, growth, and profitability volatilities. The difference with other profitability segments is rather dramatic in this case as can be observed in Figure 8. This result is not surprising given low profit firms are of lower quality and may be comprised of value or distressed firms. For the remaining profit buckets, low-medium and medium profit firms show the lowest volatility across the 3 categories, increasing with size.

FIGURE 7: OPERATING PERFORMANCE VOLATILITY BY RISK FACTORS: GROWTH



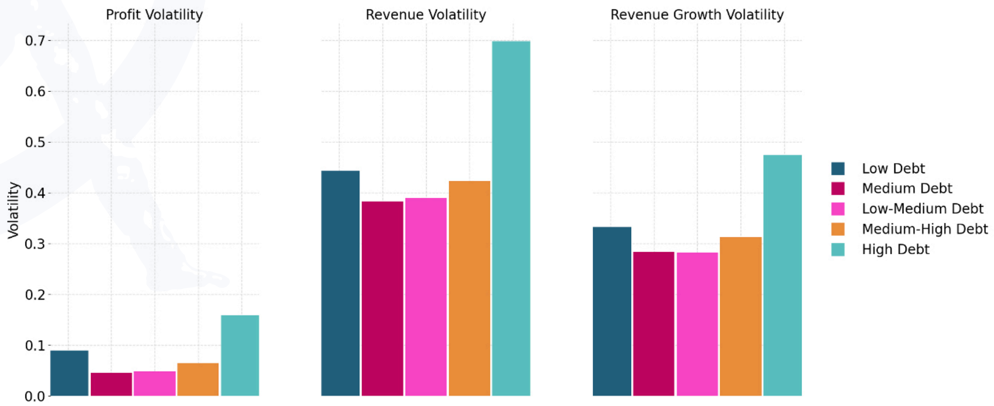
Source: privateMetrics

Turning to the leverage factor, firms with higher leverage experienced higher volatility in operating performance. Figure 9 shows that the trend increases with leverage bucket, with a rather marked increase for firms with the greatest leverage. The lowest leverage bucket has the second highest volatility across all three metrics. This may be due in part to higher growth companies eschewing or unable to attain leverage, while investing in growth, leading to both higher revenue and profit volatility. Further, lower quality firms may be unable to obtain leverage, indicating the underlying fundamentals are more risky or volatile than other buckets.

FIGURE 8: OPERATING PERFORMANCE VOLATILITYBY RISK FACTORS: PROFIT

Source: privateMetrics

FIGURE 9: OPERATING PERFORMANCE VOLATILITY BY RISK FACTORS: LEVERAGE



Source: privateMetrics

Finally, based on maturity, there is a negative relationship between maturity and operating performance risks. Figure 10 details this relationship. Younger firms have dramatically higher revenue volatility than more mature firms. The gap is widest between the first and second maturity bucket. The difference is also pronounced for revenue growth volatility, while less so for profit volatility.

FIGURE 10: OPERATING PERFORMANCE VOLATILITY BY RISK FACTORS: MATURITY

Source: privateMetrics

Overall, we find that smaller, highly levered, and younger companies are more volatile across all metrics. The regression results in Table 7 confirm the relationship at conventional levels of statistical significance.

TABLE 7: REGRESSION RESULTS OF OPERATING PERFORMANCE VOLATILITY WITH PECCS PILLARS AND RISK FACTORS

Regression Results	Dependent Variable			Dependent Variable		
	Revenue Volatility			Profit Volatility		
	(1)	(2)	(3)	(1)	(2)	(3)
Size	-0.017***	-0.016***	-0.015***	-0.013***	-0.011***	-0.012***
Profit	-0.206***	-0.251***	-0.227***	-0.049***	-0.055***	-0.054***
Leverage	0.0001***	0.0001***	0.0001***	0.00001***	0.00001***	0.00001***
Leverage2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
Growth	0.143***	0.141***	0.146***	0.028***	0.024***	0.027***
Maturity	-0.189***	-0.180***	-0.181***	-0.015***	-0.010***	-0.011***
Financials	0.219***	0.219***	0.219***		-0.004***	
Health	0.021***	0.021***	0.021***		-0.038***	
Hospitality and Entertainment	0.109***	0.109***	0.109***		0.003***	
Info and Comm	0.179***	0.179***	0.179***		-0.022***	
Manufacturing	0.086***	0.086***	0.086***		-0.046***	
Nat. Res.	0.087***	0.087***	0.087***		-0.034***	
Pro. Services	0.179***	0.179***	0.179***		-0.024***	
Construction	0.203***	0.203***	0.203***		-0.023***	
Retail	0.103***	0.103***	0.103***		-0.066***	
Transportation	0.108***	0.108***	0.108***		-0.051***	
Utilities	0.148***	0.148***	0.148***		-0.031***	
Markup		0.052***	0.052***		0.004***	
Production		0.014**	0.014**		0.019***	
Subscription		0.010	0.010		0.032***	
B2C		-0.050***	-0.050***		0.001***	
Products		-0.027***	-0.027***		-0.011***	

Services		0.037***	0.037***		0.016***	
Constant	1.037***	0.888***	1.000***	0.147***	0.169***	0.115***
Observations	193,668	193,668	193,668	193,668	193,668	193,668
R^2	0.073	0.086	0.079	0.116	0.204	0.178
Adjusted R^2	0.073	0.086	0.079	0.116	0.204	0.178
Note:	*** p<0.01, ** p<0.05, * p<0.1					

Regression Results	Dependent Variable		
	Growth Volatility		
	(1)	(2)	(3)
Size	-0.011***	-0.008***	-0.009***
Profit	-0.119***	-0.146***	-0.131***
Leverage	0.00002***	0.00002***	0.00002***
Growth	0.140***	0.133***	0.141***
Maturity	-0.127***	-0.122***	-0.120***
Financials	0.052***		
Health	-0.045***		
Hospitality and Entertainment	0.070***		
Info and Comm	0.025***		
Manufacturing	-0.006*		
Nat. Res.	0.014***		
Pro. Services	0.046***		
Construction	0.113***		
Retail	-0.009***		
Transportation	-0.007*		
Utilities	0.025***		
Markup	0.039***		
Production	0.033***		
Subscription	0.013***		
B2C	-0.027***		
Products	-0.018***		
Services	0.037***		
Constant	0.720***	0.681***	0.666***
Observations	193,668	193,668	193,668
R^2	0.112	0.138	0.125
Adjusted R^2	0.112	0.138	0.125
Note:	*** p<0.01, ** p<0.05, * p<0.1		

Operating Performance Volatility Listed Equities vs Private Equities

Table 8 provides the profit, revenue, and growth volatility across GICS sectors and the PECCS equivalent in private equities. Table 9 provides the correlation between GICS and PECCS sectors for profit, revenue, and growth volatilities. With the exception of Energy, volatility of profit, revenue, or growth is positively correlated between public and private markets.

TABLE 8: COMPARISON OF OPERATING PERFORMANCE RISK IN LISTED EQUITY AND PRIVATE EQUITIES

GICS Sector	Profit Volatility (Listed)	Revenue Volatility (Listed)	Growth Volatility (Listed)	PECCS Equivalent	Profit Volatility (Private)	Revenue Volatility (Private)	Growth Volatility (Private)
Consumer Discretionary	0.0292	0.2067	0.1106	Hospitality and Ent.	0.1032	0.3624	0.3018
Consumer Staples	0.0199	0.1768	0.1034	Retail	0.0351	0.3251	0.2247
Energy	0.0830	0.3396	0.2820	Natural Resources	0.0861	0.4183	0.3100
Financials	0.0545	0.2146	0.1144	Financials	0.1163	0.6258	0.4068
Health Care	0.2995	0.3497	0.2677	Health	0.0687	0.2470	0.1855
Industrials	0.0216	0.2088	0.1226	Manufacturing	0.0632	0.3281	0.2340
Information Technology	0.0521	0.2576	0.1423	Information Comm	0.0786	0.4201	0.3017
Real Estate	0.0016	0.3021	0.1422	Real Estate & Const	0.1076	0.4962	0.3895
Utilities	0.0365	0.1384	0.1108	Utilities	0.0748	0.4162	0.2272

Source: privateMetrics, Compustat

TABLE 9: CORRELATION BETWEEN GICS AND PECCS BASED OPERATING PERFORMANCE VOLATILITY

GICS Sector	PECCS Equivalent	Correl: Profit	Correl: Revenue	Correl: Growth
Consumer Discretionary	Hospitality and Ent.	0.97	0.94	0.98
Consumer Staples	Retail	0.46	0.89	0.65
Energy	Natural Resources	-0.51	-0.20	0.07
Financials	Financials	0.81	0.92	0.89
Health Care	Health	0.87	0.92	0.93
Industrials	Manufacturing	0.90	0.88	0.91
Information Technology	Information and Comm	0.87	0.96	0.91
Real Estate	Real Estate and Const.	0.00	0.85	0.80
Utilities	Utilities	0.82	0.88	0.76

Source: privateMetrics, Compustat

Insolvency Risk in Private Equities

Bankruptcy events are not well documented in the data. Instead, we focus on "insolvency events" defined as the moment when a company's total assets become lower than its total liabilities for the first time, signalling a large negative shock for equity holders. Subsequent insolvency events are ignored as a subsequent financial statement of debt being lower than equity value is not a surprising event. As before, we look for evidence of systematic risk in private equities with an approach by factor loadings and market segments. We consider:

- Insolvency by PECCS Pillar and risk factor exposures (betas)
- Cumulative Insolvency Rates
- Comparison of Cumulative Insolvency Risk with listed equities
- Cumulative Insolvency rates relative to operating performance and return volatilities

4. Part I: Economic Risk Factors in Private Equity

We return to our financials database covering the period from 2013 to early 2024. Table 10 outlines the key characteristics of the data by region, including the number of firms and financial metrics over the period. Insolvency and bankruptcy data was not well documented in all regions, and we focused efforts on the EU, where the data and disclosures were materially better.

Descriptive Statistics

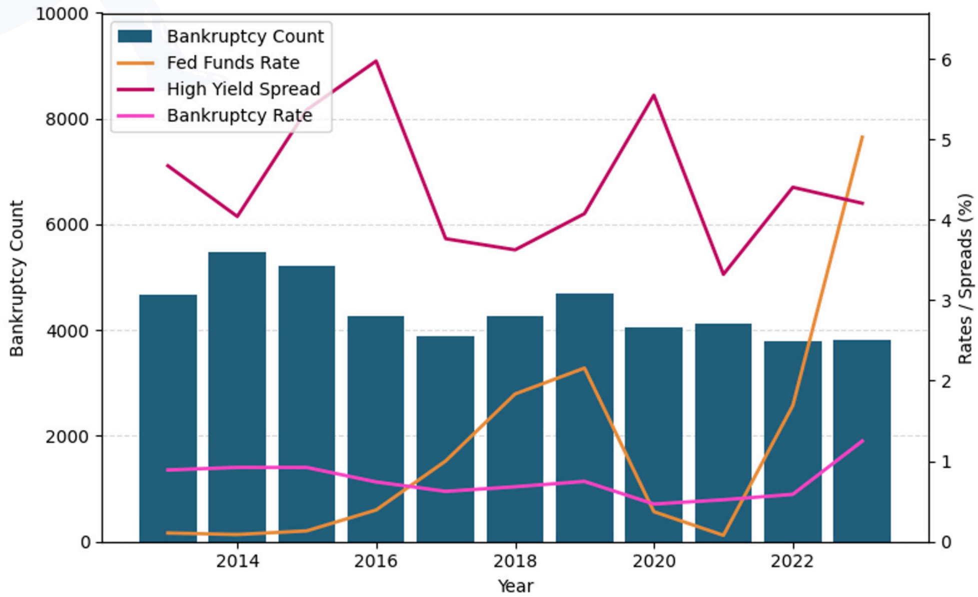
TABLE 10: INSOLVENCY DATASET

Universe Profile (US$)	Global	Advanced	EU
Countries	>100	35	28
Companies	1,069k	454k	345k
Revenue	11.0/93.0	11.5/81.6	10.5/70.6
# Firms w Revenue>100M	133k	38.6k	33.8k
EBITDA	0.43/4.4	0.64/11.8	0.59/7.0
EBIT	0.28/0.99	0.39/6.3	0.3/4.6
Net Income	0.18/3.15	0.26/4.2	0.2/3.2
Revenue Growth%	3.6%/13.5%	3.5%/11.1%	3.6%/11.7%
Technically Insolvent*	140.3k	34.1k	35.2k

Source: privateMetrics. Technically Insolvent figure cumulative for 2013-2024 period.
Figures presented as Median/Mean

For the 2013-2024 period, there were approximately 45k bankruptcies (actual defaults or debtor protections filed) observed, with over 70% of this total in Europe. Given the inconsistencies in reporting on bankruptcies across regions, we focused on the EU to discriminate insolvency events by PECCS pillars and key risk factors. Figure 11 details the annual bankruptcies for all regions over the 10-year period alongside key economic indicators.

FIGURE 11: ANNUAL BANKRUPTCIES

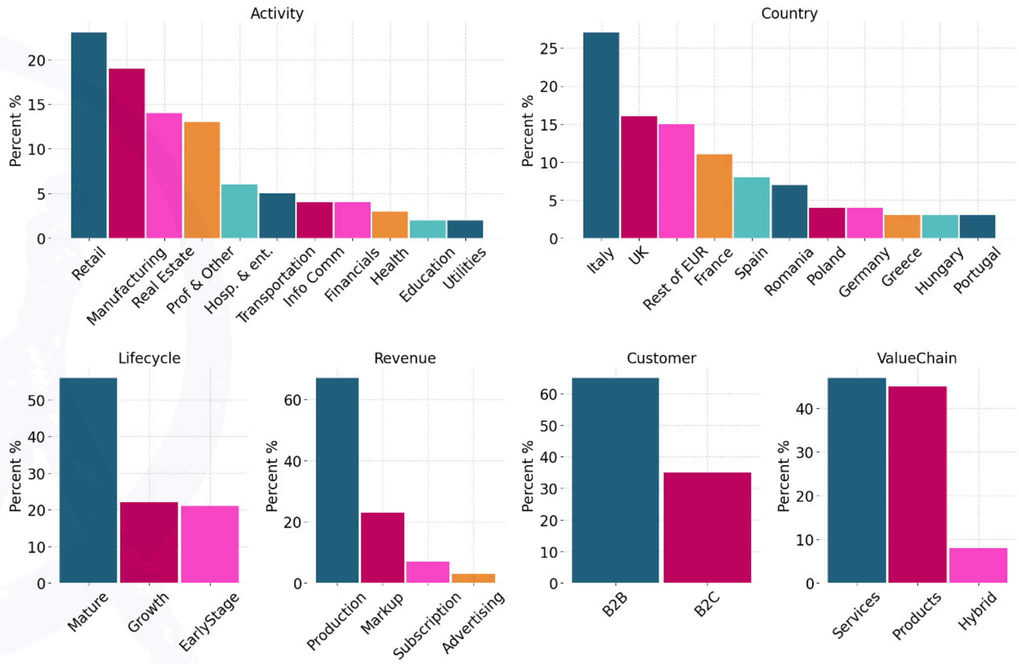


Source: privateMetrics, Orbis.

4. Part I: Economic Risk Factors in Private Equity

Before turning to insolvency events and rates, we present Figure 12, which provides more granularity on the above bankruptcies across PECCS pillars and countries within the European Union for the 2013 to 2024 period. By Activity Class, retail and manufacturing accounted for the highest percentage of bankruptcy events at 23% and 19%, respectively. Information and communications sector was just 4% despite accounting for an increasing weighting within the economy over this period. Mature companies accounted for the most insolvency events in the lifecycle pillar, while those firms with a production model accounted for 67% of cases by revenue model. By value chain, Products and services focused firms accounted for a similar proportion. Regionally, within the EU, Italy, the UK, France, and Spain were the 4 largest contributors.

FIGURE 12: ANNUAL BANKRUPTCIEES BY PECCS AND COUNTRY



Source: privateMetrics

Likelihood of Insolvency

Insolvency Rates by Risk Factors

Turning to insolvency events by risk factor beta, Figure 13 shows the five key risk factors and the incidence of insolvency by quintiles for each. The data includes all observed private companies from the UK and Europe during the 2013-2024 period.

Size – The smallest firms (quintile 1) account for the highest prevalence of insolvency events with 33% of the total observations. The incidence of insolvency declines with increasing size.

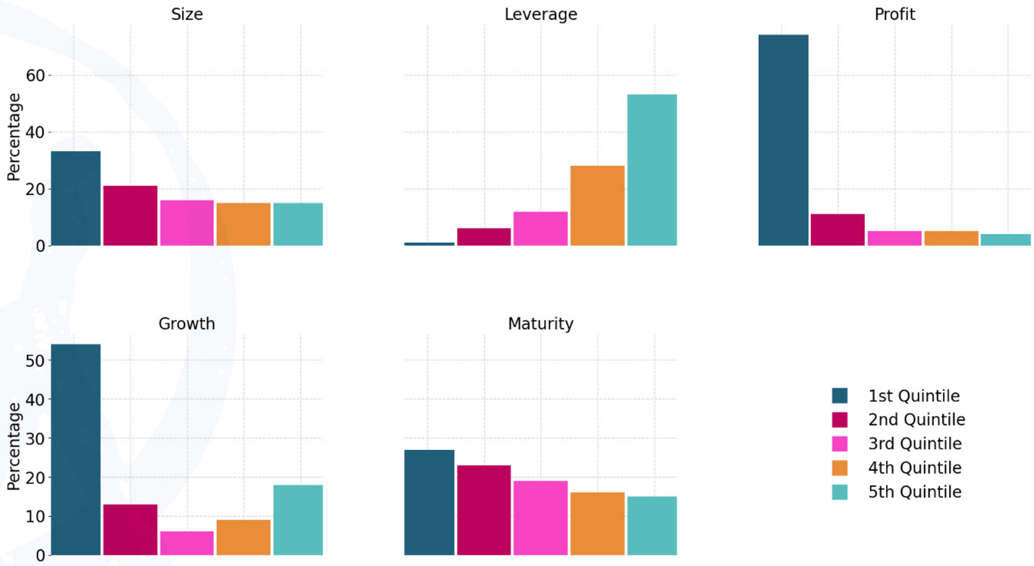
Leverage – Firms with the lowest leverage, not surprisingly, show lower incidence of insolvency. Just 1% of the 1st quintile firms based on leverage reached insolvency. The insolvency rates increase dramatically with increasing leverage, with the 4th and 5th quintiles collectively accounting for 81% of the insolvencies.

Profit – The least profitable (1st quintile) firms accounted for 74% of the insolvencies. This declined to 11% for the 2nd quintile. Low profitability is a key driver of insolvency risk.

Growth – Firms with the lowest growth accounted for 54% of the insolvencies. Interestingly, there was a "U-Shaped" pattern here, with the highest growth firms (quintile 5) accounting for the next largest percentage of insolvencies, at 18%. Thus, the lowest and highest growth firms accounted for the highest insolvency risk, with the former responsible for the majority of cases.

Maturity – The youngest firms accounted for the most cases of insolvencies. There was a negative relationship between firm age and rate of insolvency.

FIGURE 13: INSOLVENCY EVENT INCIDENCE BY RISK FACTOR BETA



Source: privateMetrics

Cumulative Insolvency Risks by Risk Factors

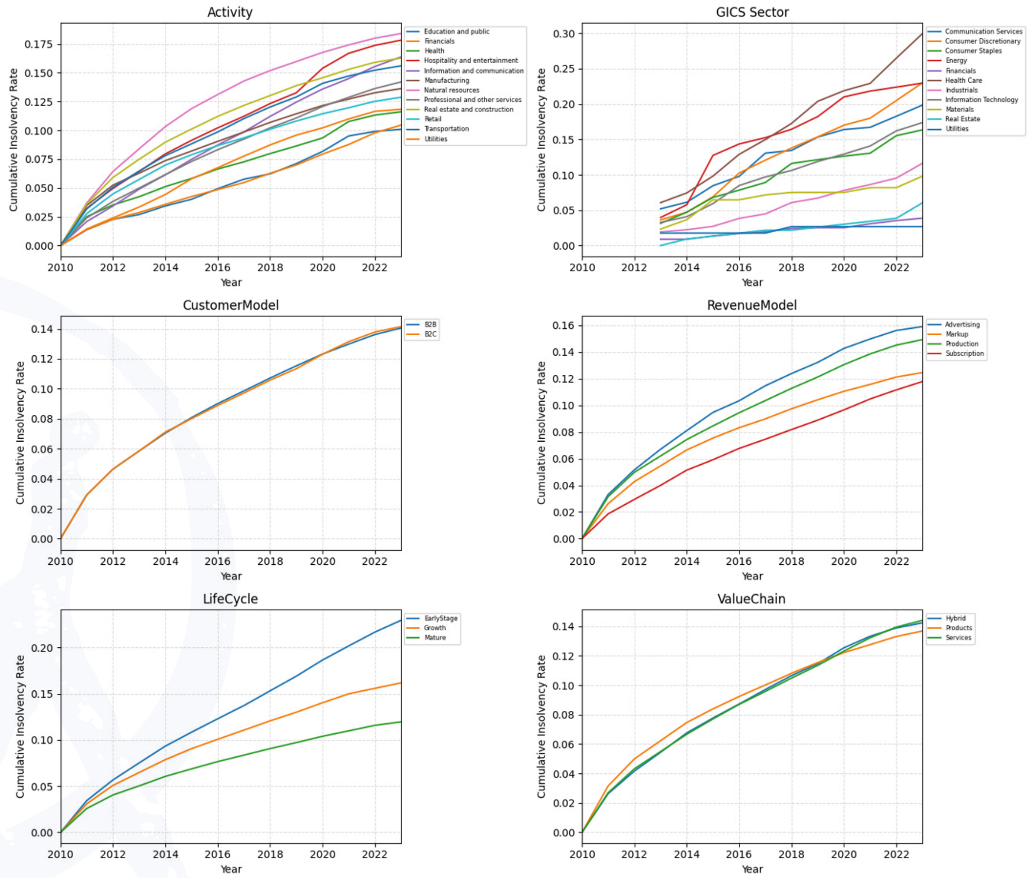
On a 10-year cumulative basis, insolvency rates reach between 10 and 20% across PECCS segments. In other words, holding a company for a decade leads to cumulative odds of insolvency of 1-in-10 cases (utilities) up to 1-in-5 cases (natural resources). Figure 14 details the cumulative insolvency rate by PECCS pillars

By comparison, the same insolvency measure computed over a large sample of US listed equities (5k obs Compustat) shows similar patterns and order of magnitude, albeit not a one-for-one match by sector. This is expected as listed firms are also larger than private ones. Figure 14 shows the comparison with listed equities organised by GICS.

By PECCS revenue model, the advertising sector shows the highest cumulative rate of insolvency, followed by the markup (reseller) and production related business models. The Subscription model shows the lowest rate in the segment.

By PECCS lifecycle stage, early-stage firms are much more likely to experience insolvency, as would be expected. There was an approximate 1 in 4 chance of insolvency in the early-stage segment over a 10-year hold period. This compares to close to a 1 in 8 chance for mature firms.

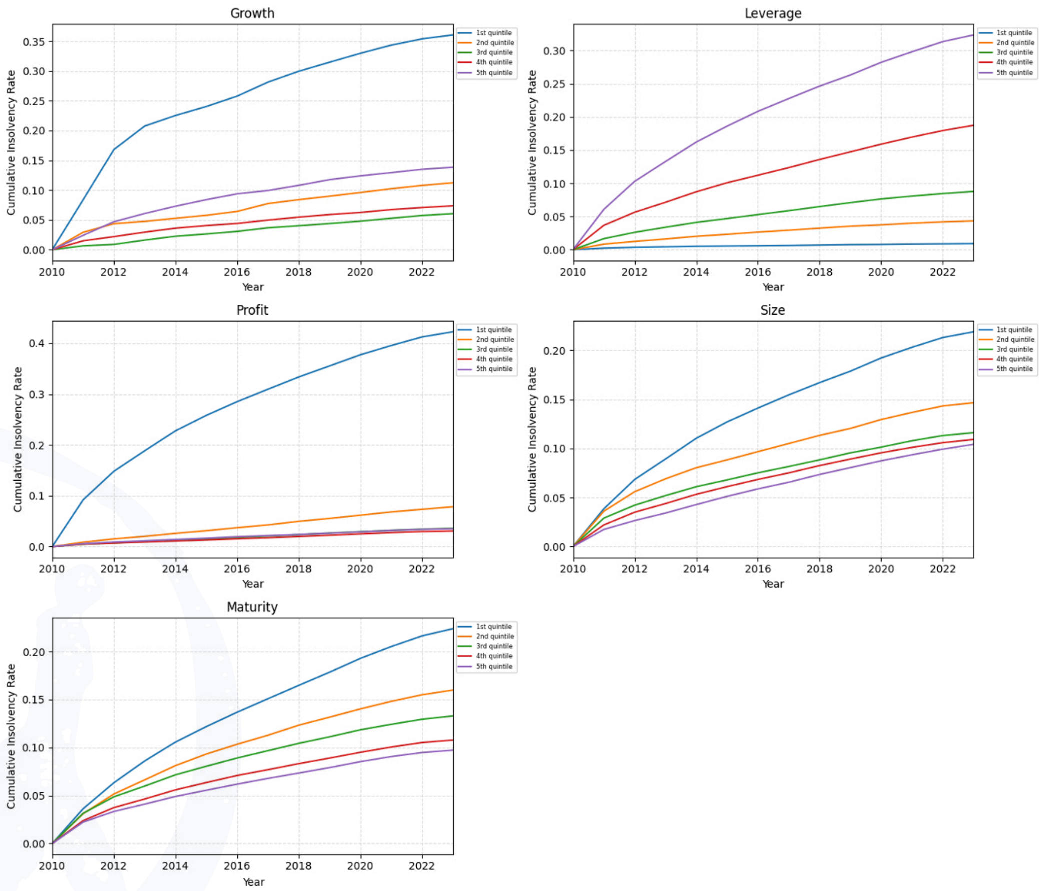
FIGURE 14: CUMULATIVE INSOLVENCY RATE BY PECCS PILLARS



Source: privateMetrics, Compustat

Similar findings can be made by risk factor exposures: there is a systematic and linear relationship between cumulative insolvency rates and risk factor exposure buckets. By size, the smallest firms have close to 2x the rate of insolvency over a 10-year period. The small firms have greater than 20% cumulative insolvency rate for this holding period. For leverage, the highest quintile has greater than 30% cumulative insolvency rate, almost 2x the next highest quintile, and many orders of magnitude greater than the companies in the lowest quintiles. For profit, the results are even more stark. The lowest profitability quintile has more than 40% cumulative rate of insolvency for a 10-year holding period, dwarfing the outcomes in the other 4 quintiles, which are all below 10%. Finally, the lowest growth firms have the highest cumulative incidence followed the highest growth quintile. However, the gap is quite significant. Figure 15 below outlines the relationship across the key factors.

FIGURE 15: CUMULATIVE INSOLVENCY RATE BY RISK FACTORS



Source: privateMetrics

Cumulative Insolvency Risks vs Operating Performance and Return Volatilities

We examine the relationship between the annual operating performance volatility measures and the cumulative insolvency risk. In addition to examining this relationship, we also examine whether return volatility is correlated to cumulative insolvency risks. Using return volatilities calculated using priced assets within the privateMetrics Private Equity Universe (PEU), which comprises approximately 193k assets as of year-end 2024, we examine how they correlate with insolvency.

Both operating performance volatility and return volatility are highly correlated within each PECCS activity, during 2013-2023. This is also the case across the other 4 PECCS pillars, Lifecycle, Revenue model, Customer model, and Value Chain. Tables 11 and 12 detail the correlations by class within each PECCS pillar.

Similarly, Volatility by risk factor betas is highly correlated with insolvency risk. Table 13 details the correlation between the cumulative 10-year insolvency rate and the operating performance and return volatilities by factor and quintiles.

TABLE 11: CORRELATION BETWEEN ANNUAL OPV AND CUMULATIVE INSOLVENCY RISK

Correlation OPV and Cumulative Insolvency rate		Volatility			
PECCS Pillar	Class	Profit	Revenue	Growth	Return
Activity	Education and public	0.9268	0.9437	0.7236	-0.5926
	Financials	0.7038	0.9423	0.9696	0.4889
	Health	0.9453	0.9455	0.9159	0.3900
	Hospitality and entertainment	0.9299	0.9544	0.9331	0.9338
	Information and comm.	0.9516	0.9722	0.9610	0.9697
	Manufacturing	-0.0033	0.8323	0.6399	0.8817
	Natural resources	-0.5511	0.0252	-0.2810	0.9845
	Professional and other services	0.9236	0.9098	0.9209	0.9662
	Real estate and construction	0.6684	0.9324	0.9272	0.9119
	Retail	0.1276	0.8888	0.7070	0.9496
	Transportation	0.7784	0.9111	0.7717	0.6926

Source: privateMetrics. OPV = Operating Performance Volatility

TABLE 12: CORRELATION BETWEEN ANNUAL OPV AND CUMULATIVE INSOLVENCY RISK

Correlation OPV and Cumulative Insolvency rate		Volatility			
PECCS Pillar	Class	Profit	Revenue	Growth	Return
Lifecycle	Early Stage	0.9065	0.8303	0.8890	0.9742
	Growth	0.8848	0.9616	0.9479	0.9958
	Mature	0.7225	0.9058	0.8381	0.9291
Revenue	Advertising	0.5774	0.9660	0.9252	0.9583
	Markup	0.2852	0.9099	0.7730	0.9319
	Production	0.7530	0.8716	0.8270	0.9465
	Subscription	0.8682	0.9491	0.9257	0.9028
Customer Model	B2B	0.6902	0.8980	0.8310	0.9450
	B2C	0.7880	0.9217	0.8687	0.9658
Value Chain	Hybrid	0.8653	0.9111	0.8131	0.8789
	Products	-0.0830	0.8060	0.5388	0.9549
	Services	0.9185	0.9273	0.9343	0.9441

Source: privateMetrics. OPV = Operating Performance Volatility

TABLE 13: CORRELATION BETWEEN ANNUAL OPV AND CUMULATIVE INSOLVENCY RISK

Correlation OPV and Cumulative Insolvency rate		Volatility			
PECCS Pillar	Quintile	Profit	Revenue	Growth	Return
Size	1st quintile	0.7489	0.7367	0.8128	0.9505
	2nd quintile	0.7091	0.8827	0.7647	0.9896
	3rd quintile	0.8085	0.8630	0.7442	0.9899
	4th quintile	0.8570	0.9200	0.8755	0.9884
	5th quintile	-0.1250	0.6022	0.3913	0.4393

Leverage	1st quintile	0.9404	0.8398	0.7320	0.8818
	2nd quintile	0.9489	0.9394	0.8321	0.9425
	3rd quintile	0.8590	0.9460	0.9124	0.9569
	4th quintile	0.0263	0.6572	0.5616	-0.0199
	5th quintile	0.8641	0.9668	0.9833	0.6134
	1st quintile	0.9181	0.9444	0.9557	0.9953
Profit	2nd quintile	0.9591	0.9642	0.8318	0.9677
	3rd quintile	0.6087	0.9189	0.7483	-0.5501
	4th quintile	0.0951	0.8450	0.5961	-0.4218
	5th quintile	0.1587	0.2167	-0.0462	-0.9829
	1st quintile	0.3616	0.7010	0.7982	0.8023
Growth	2nd quintile	0.9289	0.9892	0.9576	0.9490
	3rd quintile	0.9182	0.9069	0.9498	0.6758
	4th quintile	0.4170	0.3749	0.0657	0.4493
	5th quintile	0.5630	0.5716	-0.0984	0.4699
	1st quintile	0.7489	0.7367	0.8128	0.9505

Source: privateMetrics. OPV = Operating Performance Volatility

Logit model results

Analysis of asset-level data, employing a logit model with fixed effects, confirms the impact of PECCS segments and factor exposures on insolvency risk. The model, tested across global, advanced economy, and EU geographies, demonstrated good predictive power, with an area under the curve ranging from 0.8598 to 0.8758. Model predictions show distinct probabilities of insolvency based on PECCS classification and factor exposure. Profitability, revenue growth, leverage, and firm age have robust and strong relationship to insolvency rates at 1% level. Please see appendix A for model insolvency predictions by PECCS and risk factor exposure.

TABLE 14: LOGIT MODEL RESULTS

	Insolvency Event (first time)		
Model	(1) Logit	(2) Logit	(3) Logit
Profit Factor	-4.5*** (0.02)	-4.8*** (0.03)	-5.3*** (0.04)
Growth Factor	-0.24*** (0.01)	-0.31*** (0.02)	-0.34*** (0.02)
Size Factor	0.08*** (0.003)	0.10*** (0.004)	0.07*** (0.005)
Maturity Factor	-0.47*** (0.009)	-0.55*** (0.01)	-0.46*** (0.01)
Leverage Factor	0.72*** (0.006)	0.75*** (0.007)	0.62*** (0.009)
Education	-0.13*** (0.04)	-0.27*** (0.05)	0.28*** (0.08)
Financials	-0.71*** (0.04)	-0.72*** (0.05)	-0.86*** (0.07)
Health	-0.02 (0.04)	-0.18*** (0.06)	0.37*** (0.06)
Hospitality & Ent.	-0.01 (0.03)	-0.03 (0.04)	-0.04 (0.05)
Info. Comm.	-0.05 (0.03)	-0.05 (0.04)	0.13** (0.05)
Nat. Resources	0.09*** (0.02)	0.18*** (0.03)	0.08*** (0.03)
Pro. Services	-0.02 (0.03)	-0.03 (0.04)	0.04 (0.05)

Construction	-0.17*** (0.03)	-0.10*** (0.04)	0.03 (0.05)
Retail	0.13*** (0.02)	0.18*** (0.03)	0.22*** (0.03)
Transportation	0.37*** (0.03)	0.57*** (0.04)	0.62*** (0.05)
Utilities	-0.23*** (0.04)	-0.28*** (0.06)	-0.14** (0.06)
Advertising Model	0.09*** (0.03)	0.13*** (0.03)	0.13*** (0.04)
Subscription Model	-0.19*** (0.02)	-0.17*** (0.03)	-0.42*** (0.04)
Markup Model	-0.03 (0.02)	-0.08*** (0.03)	-0.03 (0.03)
Growth Stage	-0.04*** (0.01)	-0.12*** (0.02)	-0.05*** (0.02)
Early Stage	0.02 (0.02)	-0.10*** (0.02)	0.06*** (0.03)
B2C	0.15*** (0.01)	0.20*** (0.01)	0.24*** (0.02)
Hybrid Value Chain	-0.05* (0.03)	-0.12*** (0.04)	-0.11** (0.05)
Services Value Chain	0.10*** (0.03)	0.06* (0.03)	0.02 (0.04)
Fixed Effects			
Country	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit Statistics			
Observations	4,496,653	3,311,514	2,176,596
Squared Correl	0.05447	0.05463	0.06889
Pseudo R^2	0.18791	0.19664	0.21597
BIC	552,880.1	358,998.2	246,917.2
Clustered (Company) standard-errors in parentheses			
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1			

Takeaways from Part I

We find that that micro-economic volatility and insolvency risk in private companies is significant and varies systematically by PECCS market segment and by risk factor exposure bucket (betas). We also showed that both risk measures correlate strongly with privateMetrics index return volatility.

5. Part II: Systematic Risk Factors and Private Market Prices

Having established the existence of systematic differences in risk in private equities, we consider whether these risks are priced using observable transaction price data and examining whether market prices can also be systematically explained. We consider two types of pricing metrics:

- Transaction price multiples: we look at EV-to-Ebitda and Price-to-Revenue ratios in thousands of transactions over the past decade and find that average transaction price multiples can be systematically explained by the same differences of market segments and risk factor exposures that were found to describe the level of risks in private equities in the previous section.
- Expected returns: we compute an implied expected return for the same set of transactions and find that implied expected returns as observed in individual market transactions can also be systematically explained by PECCS segments and risk factors exposures.
- We conclude that the systematic risks found in the previous analysis are indeed priced, which confirms both their systematic nature and the importance of taking market risk into account when investing in private equities since risk pricing is found to correlate with the economic cycle.

Transaction Price Variance and Systematic Risk Factors

In this section, we ask whether the same segments and risk factors can be shown to explain observable transaction price variance in private markets. i.e., whether the variance of private equity transaction prices can be explained systematically by common market (risk) factors.

Table 15 details the data from over 5k transaction prices from Pitchbook. What we find is that observed transaction prices vary systematically with PECCS. We looked at the significance of price variance by PECCS and factor bucket using non-parametric tests (different in mean).

Looking at the Activity pillar, we can observe that Information and Communication and Health sectors have the highest P/EBITDA multiples, followed closely by the Education and public sector. Conversely, Natural Resources has the lowest P/EBITDA multiple of the Activity pillar. Systematic price differences also exist at the Lifecycle pillar, with startup and growth companies garnering higher multiples than mature firms. For revenue model, as expected, there is a higher valuation placed on subscription-based revenue models relative to reselling or production models.

Similar to our findings in **Part I**, the observed transactions systematically vary with risk factors exposures. Smaller companies, on average, transact at higher multiples, implying higher risk premiums for larger companies. This can be a function of liquidity in private markets, where fewer players can pursue the largest assets. High growth firms attracted the highest valuations and there was a positive relationship between growth and valuation multiple. More profitable firms also attracted higher valuations. For firm age or maturity, younger firms received higher prices and this negative relationship between firm maturity and valuation held across quartiles for the transaction database. Firms with greater leverage transacted at higher multiples. The implication is that higher quality companies have greater debt capacity, so leverage is a signal of a company's quality. Finally, there was a negative relationship between country risk and valuation. Transactions that took place in riskier countries (defined as higher term spread) were priced at lower valuations. Higher risk premiums were required to entice investors to pursue transactions in riskier markets.

5. Part II: Systematic Risk Factors and Private Market Prices

Table 16 summarises the relationship between key risk factors and transaction multiples.

TABLE 15: P/S AND P/EBITDA MULTIPLES BY PECCS® SEGMENT, 2013-2024

PECCS Activity	P/Sales	P/EBITDA
Education & Pub	1.9x	12.4x
Financials	2.4x***	11.1x***
Health	2.1x	13.1x***
Hospitality & Ent.	1.9x	11.5x**
Info comm	2.6x***	12.8x***
Manufacturing	1.5x***	10.1x
Natural resources	1.9x	7.4x**
Professional Ser	1.6x**	10.3x
Real estate & Const	1.8x	10.5x
Retail	0.9x***	10.3x
Transportation	1.4x***	8.8x**
Utilities	1.9x	10.2x
All Transactions	1.7x	10.9x

Revenue Model	P/Sales	P/EBITDA
Advertising	2.1x***	10.9x
Markup	1.4x***	10x
Production	1.6x***	10.5x
Subscription	2.9x***	13.6x***

Value Chain	P/Sales	P/EBITDA
Hybrid	2.4x	10.9x
Products	1.5x***	10.5x***
Services	1.9x	11.3x***

Customer Model	P/Sales	P/EBITDA
B2B	1.8x	10.6x***
B2C	1.7x***	11.4x***

Lifecycle Phase	P/Sales	P/EBITDA
Early-stage	2.4x***	12.1x
Growth	2.1x	12x***
Mature	1.6x***	10.5x*

Source: Pitchbook, CapitalIQ, based on >5k transactions from 2013 to 2024.
Calculations by EIPA
****1% confidence /**5% confidence intervals*

TABLE 16: P/S MULTIPLE BY QUARTILE OF RISK FACTOR EXPOSURE, 2013-2024

	P/S RATIO					
Quartiles	Size	Growth	Profitability	Maturity	Leverage	Country Risk
Top Quartile	2.1x***	3.0x***	4.2x***	2.1x***	3.8x***	2.3x***
Second Quartile	2.5x***	2.8x	2.5x***	2.5x***	2.7x	2.9x
Third Quartile	2.8x	2.6x	1.8x***	3.1x***	2.5x***	3.0x***
Bottom Quartile	3.5x***	2.5x***	2.5x**	3.2x***	2.2x***	2.8x

Source: Pitchbook, Capital IQ, based on 5k+ transactions 2013-2024.
*Calculations by EIPA. ***1% confidence /**5% confidence intervals*

Expected Return and Systematic Risk Factors

To calculate the expected return, we employ the Gordon model to derive a discount rate from completed private equity transactions and observed metrics. Recall that the original Gordon model is as follows:

$$P = \frac{D_1}{r-g}$$

This requires information on dividend payouts and dividend growth, which is rare in private markets. However, we can re-write the formula in terms of the information we do have:

$$P = \frac{\left(S \times Profit \times (1-RR)\right)}{r-g}$$

5. Part II: Systematic Risk Factors and Private Market Prices

where:

P = price or value of the company

S = Annual revenues of the company

Profit = Operating profit margin or net profit margin

RR = The percentage of profits that are reinvested into the company for growth = 1 – Cash Yield.

r = required return

g = growth rate of revenues

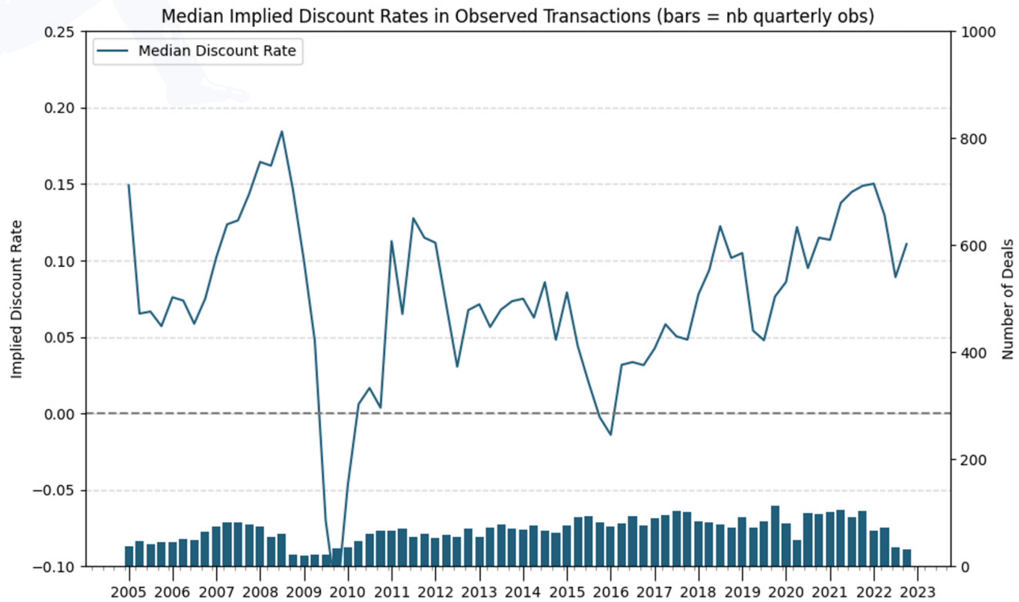
Thus,

$$r = \frac{\left(S \times Profit \times (1 - RR)\right)}{P} + g$$

Using pricing from observed transactions, and the recent 1-year growth rate (at time of deal), we have all the required inputs to calculate the expected return. With this, we can then determine implied discount rates in our transaction dataset of more than 5k transactions. Figure 16 provides the implied discount rates for observable transactions dating back to 2005.

Expected returns reflect both the risk-free government bond yield and the private equities risk premium. Discount rates were volatile over the 20-year period reflecting several major events (GFC, Covid, ZIRP) and policy initiatives. Discount rates spiked into the GFC consistent with listed markets as prices and valuations plunged reflecting a "risk-off" environment. The subsequent years from 2010 through 2019 reflected the low or zero interest rate environment and a risk-on setting for private equities. The spike in discount rates in 2018 is consistent with the volatility spike in early 2018 and the taper fears in late 2018 that led to price declines in equities. Post covid, the discount rates have risen largely reflecting higher bond yields.

FIGURE 16: IMPLIED DISCOUNT RATES IN TRANSACTION DATASET



Source: privateMetrics, Pitchbook, Capital IQ. Calculations by EIPA.

5. Part II: Systematic Risk Factors and Private Market Prices

Examining discount rates across PECCS pillars, clear differences emerge. At the Activity (sector) level, discount rates vary, with Utilities, Retail, Hospitality and Entertainment, and Transportation having the lowest discount rates based on a large sample of past transactions. Conversely, Real Estate and Education were among the highest. Table 17 details the discount rates by each of the 5 PECCS pillars, using both asset-level growth rates (DR_1) and sector level growth rates (DR_2).

TABLE 17: IMPLIED DISCOUNT RATES IN TRANSACTION DATASET

PECCS Activity	DR1	DR2	N
Education & Pub	0.137	0.143	65
Financials	0.134	0.118	344
Health	0.104	0.106	313
Hospitality & Ent.	0.0875	0.0771	339
Info comm	0.106	0.104	900
Manufacturing	0.0974	0.0833	1486
Natural resources	0.158	0.118	120
Professional Ser	0.130	0.127	432
Real estate & Const	0.155	0.150	140
Retail	0.0804	0.0724	256
Transportation	0.0906	0.0911	252
Utilities	0.0803	0.0791	106

Lifecycle Phase	DR1	DR2	N
Early-stage	0.147	0.106	355
Growth	0.121	0.101	1464
Mature	0.0960	0.0951	2934

Revenue Model	DR1	DR2	N
Advertising	0.121	0.113	235
Markup	0.108	0.0976	611
Production	0.108	0.0951	3182
Subscription	0.102	0.104	725

Supply Chain	DR1	DR2	N
Hybrid	0.0846	0.0752	331
Products	0.0990	0.0875	2193
Services	0.117	0.111	2229

Customer Model	DR1	DR2	N
B2B	0.111	0.104	3050
B2C	0.0972	0.0868	1703

Source: privateMetrics, Pitchbook, Capital IQ. Calculations by EIPA.

By lifecycle or maturity, early-stage companies were priced with higher discount rates than mature firms. Services firms showed higher discount rates than products firms, B2B higher than B2C, and firms with an advertising revenue model transacted with higher discount rates than markup (retail), production, and subscription-based revenue models.

PECCS segments are strong discriminants of expected returns/implied discount rates.

Sorted by risk factor exposures also discriminates strongly among the implied discount rates. Table 18 shows clear differences in discount rates across profitability, revenue growth, and overall revenues.

5. Part II: Systematic Risk Factors and Private Market Prices

TABLE 18: IMPLIED DISCOUNT RATES IN TRANSACTION DATASET

EBITDA								
Margin	DR	N	Growth	DR	N	Size	DR	N
0.66	0.0669	939	-0.0576	-0.0229	939	17	0.126	939
7.72	0.0962	939	0.0161	0.0479	939	44	0.125	939
13.7	0.116	938	0.0751	0.104	938	96.9	0.125	938
21.3	0.13	938	0.138	0.171	938	240	0.105	938
39.2	0.142	938	0.344	0.385	938	956	0.0839	938
DR = Discount Rate			Growth = Revenue Growth			Size = Revenues		

Source: privateMetrics, Pitchbook, Capital IQ. Calculations by EIPA.

We check the validity of the results by regressing the price to revenue ratio on the implied discount rate (DR_1), profitability (PROFIT), cash yield (CY), and revenue growth (G) of the aggregated data (all transactions median per period). The results are robust, and coefficient signs are correct. The mean Variance Inflation Factor for the model is 3.76, indicating multicollinearity is not an issue. Table 19 provides the regression results.

TABLE 19: REGRESSION TRANSACTION DATA

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.09175	0.25254	-0.363	0.7175
DR1	-4.37311	2.13069	-2.052	0.0440 *
G	4.61756	1.90227	2.427	0.0179 *
CY	2.82495	0.54348	5.198	2.06e-06 ***
PROFIT	7.67254	1.79254	4.280	6.08e-05 ***
Residuals				
Min	1Q	Median	3Q	Max
-1.00281	-0.20516	-0.00023	0.18816	0.77026
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Residual standard error: 0.3644 on 67 degrees of freedom				
Multiple R-squared: 0.5274, Adjusted R-squared: 0.4991				
F-statistic: 18.69 on 4 and 67 DF, p-value: 0.00				
Variance Inflation Factor: 3.76				

Source: privateMetrics, Pitchbook, Capital IQ. Calculations by EIPA.

Takeaways from Part II

Observed transaction prices are systematically different when discriminating by PECCS pillars and key risk factors. Transaction price multiples exhibited differences at the sector level, and across lifecycle, revenue model, value chain, and customer model. The differences were significant at the 1% confidence level. Moreover, calculated implied discount rates from transactions across PECCS pillars confirm differences among classes within PECCS pillars. Finally, risk factors, including profitability, size, and revenue growth varied systematically for the transaction data set.

6. Part III: Systematic vs. Idiosyncratic Risk in Private Equity

Having established that private assets are exposed to common segment and risk factors in **Part I** and that private asset prices systematically differ across these segments and risk factors in **Part II**, we want to determine what fraction of private asset transaction prices is determined by systematic factors and what is the role of idiosyncratic elements.

Additionally, we attempt to break down the idiosyncratic variation into a bid-ask spread based on market conditions that can account for some of the variation in asset prices. In other words, we want to identify the explainable portion of idiosyncratic differences that can account for some of the variation. For example, market liquidity and transaction costs (see Amihud and Mendelson, 1986 and Pastor and Stambaugh, 2003) can vary predictably according to market conditions, and thus command a broader or narrower spread around an estimated valuation.

We consider:
- The share of observable price variance that can be explained by common risk factors and PECCS classes,
- The bid-ask spread based on market conditions as an additional measure of systematic price movements, and
- The remaining asset-specific portion in private asset prices

In the next section, first we describe the approach providing an overview of the theoretical underpinnings and empirical methods. Then, we present our findings.

Approach

A simple factor model

To demonstrate the power of a factor model approach in explaining the variation in private asset prices, we use observed transaction data from private markets and construct a simple factor model. Focusing on the factors shown in Table 16 and geography and PECCS controls, we perform a simple Ordinary Least Squares (OLS) regression.

At this stage, we prioritise parsimony over other model features. That is, rather than identifying a highly complex model that overfits the data, we focus on a model using simple intuitive choice of risk factors motivated in **Part II** to explain the systematic variation in prices.

Prediction uncertainty

By design, the OLS can fit the prices well on average, but at the level of each observation, OLS regressions may produce noisy errors, i.e., idiosyncratic risk, especially for naturally occurring data, such as private market transactions. In other words, the predicted price from the OLS model can vary by a large amount from the observed value, especially when fitting log values of valuation ratios, which when averaged across observations cancel out. Thus, simple OLS models help in getting an understanding of the overall or broad segment level valuation trends (or systematic risks).

6. Part III: Systematic vs. Idiosyncratic Risk in Private Equity

To measure the level of uncertainty in the OLS estimates, we explore some common approaches, such as:

1. Use the standard deviation of the residuals in the regression. But as described above, generally the residuals are large in absolute terms in a fit of naturally occurring data, leading to overly broad confidence intervals in the prediction, rendering them to be impractical for many applications.
2. Use the standard error of the prediction that accounts for the uncertainty in the estimated regression coefficients and the position of the observation relative to the sample. As confidence intervals around statistically significant variables are narrow, this method may indicate overly confident and narrow ranges for predictions, thus not addressing the deviations from the true values.

Using discount rate volatility

To better motivate the expression of uncertainty in the prediction, we return to the source of uncertainty in each valuation. If each private company's valuation was regarded to be a result of a discounted cash flow (DCF) analysis, then each valuation is sensitive to the choice of discount rate and future projected cash flows.

Blanc-Brude et al. (2021) find that small changes in discount rates account for a large variation in valuation overshadowing similar changes to future projected cash flows for infrastructure assets. For assets with long or indefinite time horizons—such as private companies—valuation differences are amplified with horizon, as small differences in discount rates compound significantly. Thus, if we can measure the variation in discount rates that may probably be used in valuing a private company using a DCF framework, then we can estimate the sensitivity of the valuation to such choices.

However, estimating the discount rate level and uncertainty applicable for a large sample of private asset transactions is cumbersome. To achieve this, we rely on seminal academic work in finance that focuses on discount rate volatilities and arbitrage pricing theory as explained below.

Cochrane and Saa-Requejo (2000) extend traditional arbitrage pricing theory to incomplete markets, where not all payoffs can be perfectly replicated or hedged. Since arbitrage bounds in such markets can be too wide to be informative, they propose "good-deal bounds" as a tighter, more practical alternative. A good deal is defined as one that offers an unrealistically high Sharpe ratio compared to traditional investments and thus violates economic intuition and rationality in being passed along. Another way to think about the good-deal bounds is that these are the upper and lower bounds on asset prices that rule out arbitrage and also rule out excessively attractive investment opportunities.

Borrowing this idea, we express the discount rate volatility as a multiple (we choose 3x) of the S&P 500 index's Sharpe Ratio, which captures the idea that any price in private markets that provides a Sharpe ratio three times that of the S&P 500 index at any point in time will be fleeting and transacted immediately. Notationally, this is equivalent to:

$$\sigma_{DR} = \frac{h}{(1 + r_f)}$$

where σ_{DR} is the volatility of the discount rate r, r_f is the risk-free rate, and $h = 3 \times Sharpe\ Ratio_{S\&P\,500}$.

After establishing the volatility of the discount rate, upper and lower bounds of discount rates can be computed around a mean value $\overline{DR}$, assuming the discount rates are normally distributed. For a 95% confidence level, the upper and lower limits of discount rates, DR_{upper} and DR_{lower}, respectively, are then given by:

$$DR_{upper} = \overline{DR} + 1.96 \times \sigma_{DR}$$

$$DR_{lower} = \overline{DR} - 1.96 \times \sigma_{DR}$$

Estimating the bid-ask prices

To translate the range of discount rates into uncertainty in valuation, we need a good estimate of the average discount rate to be applied, which when equated with the current price can produce a *Terminal value*$_h$ at a horizon of h years, in a DCF framework (assuming no intermediate cash flows), as expressed below.

$$P_{pred} = \frac{Terminal\ value_h}{(1 + \overline{DR})^h}$$

Combining the above two equations, we can get the bid and ask prices as:

$$P_{bid\_pred} = \frac{Terminal\ value_h}{(1 + DR_{upper})^h}$$

$$P_{ask\_pred} = \frac{Terminal\ value_h}{(1 + DR_{lower})^h}$$

Estimating the average discount rate

A key ingredient to the above computation is to determine the average discount rate to be applied to each transaction, and which is unobservable. $\overline{DR}$ can be obtained by an approach similar to the one used in **Part II**. However, since the observed transactions are a biased sample of private market universe, this approach may not be robust.

Moreover, it would be incorrect to use each observed valuation itself to compute the discount rate, and then subsequently use it to improve our prediction's accuracy. Thus, to obtain more robust and granular estimate of discount rate for each transaction, we leverage the private2000 index, a market price-based index of private companies. The private2000 index is constructed from a large dataset in privateMetrics called the Private Equity Universe (PEU), that consists of over 100,000 private companies that are priced monthly based on a factor model calibrated and updated each month with private market transactions. The PEU is carefully curated to resemble typical Private Equity owned companies in terms of their size and profit profiles. From this universe, the private2000 is constructed by choosing the largest representative constituents, with consideration for country and activity representation in the index.

Using the private2000 index constituent prices, we perform the computations for discount rate for each constituent every month, following the approach in **Part II**. Specifically, using each company's revenue, profit, revenue growth, and payout ratios, we use a simple one-period model to back out the discount rate. We then compute the average discount rates for each activity every month and take that as the applicable discount rate for the transaction sample, i.e., $\overline{DR}$.

6. Part III: Systematic vs. Idiosyncratic Risk in Private Equity

Asset-specific unexplained valuation

The residuals from the OLS model using systematic risk factors, ε_{sys} are very straightforward and can be expressed as:

$$\varepsilon_{sys} = P_{obs} - P_{pred}$$

Note, that for notational convenience in the above equation, P_{obs} and P_{pred} are denoted as the observed and predicted prices, whereas in the modelling the log transformed ratios of P/S is used. Again, extending the notational convenience and having calculated the P_{bid_pred} and P_{ask_pred}, the idiosyncratic residuals ε_{idio} can then be computed as the residual unexplained variation as below:

$$\varepsilon_{idio} = \begin{cases} P_{obs} - P_{ask\_pred}, & if\ P_{obs} > P_{ask\_pred} \\ P_{obs} - P_{bid\_pred}, & if\ P_{obs} < P_{bid\_pred} \\ 0, & otherwise \end{cases}$$

To check if the ε_{idio} truly represents white noise, we can examine the error distribution for non-zero values. Moreover, the proportion of zero ε_{idio} is informative about whether the P_{obs} falls within the bid-ask predicted spreads.

Results

Ordinary least square regressions

Beginning with the private market transactions used in **Part II**, we restrict the deals to start from 2013 to align with the starting date of the private2000 index. We exclude deals with key missing information, resulting in a sample of 3,928 transactions between 2013 and 2024. The descriptive statistics of the transaction sample are shown in the Table 20.

TABLE 20: DESCRIPTIVE STATISTICS OF TRANSACTION SAMPLE USED IN FACTOR MODEL, 2013-2024

Variable	Count	Mean	Std. dev.	25th Percentile	Median	75th Percentile
P/S	3,928	4.05	5.42	0.98	2.07	4.57
Revenue ($ M)	3,928	547.12	2506.90	32.31	88.94	307.61
Leverage	3,928	0.86	3.84	0.01	0.06	0.39
Growth (%)	3,928	2.11	44.43	-0.03	0.06	0.21
Market P/S	3,928	1.46	0.36	1.17	1.42	1.63
Term spread (%)	3,928	0.01	0.01	0.01	0.01	0.02
Age (Years)	3,928	34.44	32.74	14.00	23.50	42.00
Profit (%)	3,928	0.15	0.24	0.05	0.13	0.24

Source: Pitchbook and Capital IQ. Variables calculated by EIPA.

The average transacted company in private markets have a revenue over $ 500 million and receive a valuation that is on average higher than that of public markets. In terms of characteristics, they are highly levered, profitable, have positive growth, and are mature, on average.

Using this sample, we conduct a simple OLS regression, where the valuation measured as the logarithm of the P/S ratio is regressed on the characteristics of the private company. We use the P/S ratio over other metrics for its distribution characteristics, as it is almost log-normal. Other metrics such as Ev-to-Ebitda are noisy and can be negative at times, making them less ideal for modelling. The results of the regression are presented in Table 21, and they confirm the patterns observed earlier in Table 16 when looking at quartile sorting of transaction prices based on key characteristics. Size and age are negatively related to valuation, while leverage and profit are positively related, with the relationship being statistically significant at conventional levels. Also, the model is able to explain 30% of the observed variation in transaction prices in the sample. To check for multi-collinearity we also compute the Variance Inflation Factor and find the average value to be 3.33, well below 5 and 10, that indicate high and severe multicollinearity problems.

In addition to these characteristics, to control for time invariant unobservable characteristics of homogeneous companies operating in similar markets, we control for each PECCS class the company belongs in all of the five pillars including industrial activity, revenue model, lifecycle phase, customer model, and value chain. More details about the PECCS taxonomy including the classes in each pillar are detailed in PECCS (2023).

Dummies are also used to control for the region of the company, based on a segmentation of the world on a geo-economic grouping into North America, South America, Western Europe, Rest of Europe, Asia, Oceania, and Others. To control for time variant trends in valuation, we also include time dummies based on calendar quarters.

TABLE 21: AN OLS FACTOR MODEL OF TRANSACTION VALUATION, 2013-2024

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
	Dependent variable: P/S			
Size	-0.234***	0.012	(-20.18)	0.00
Leverage	0.085***	0.008	(11.21)	0.00
Age	-0.145***	0.025	(-5.73)	0.00
Term spread	-1.184	4.897	(-0.24)	0.81
Growth	0.031	0.030	(1.03)	0.30
Profit	0.781***	0.070	(11.08)	0.00
Intercept	3.523	3.459	(1.02)	0.31
Fixed effects				
PECCS Classes	Yes			
Calendar Quarter	Yes			
Regions	Yes			
Fit Statistics				
Observations	3,928			
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05.				
Residual standard error:1.0122 on 3,849 degrees of freedom				
R-squared: 0.2973, Adjusted R-squared: 0.2830, Variance Inflation Factor: 3.33				
F-statistic: 20.88 on 78 and 3,849 DF, p-value: 0.00				

Source: PitchBook and Capital IQ. Calculations by EIPA. All variables except Profit are log-transformed.

6. Part III: Systematic vs. Idiosyncratic Risk in Private Equity

How well does the OLS fit the data?

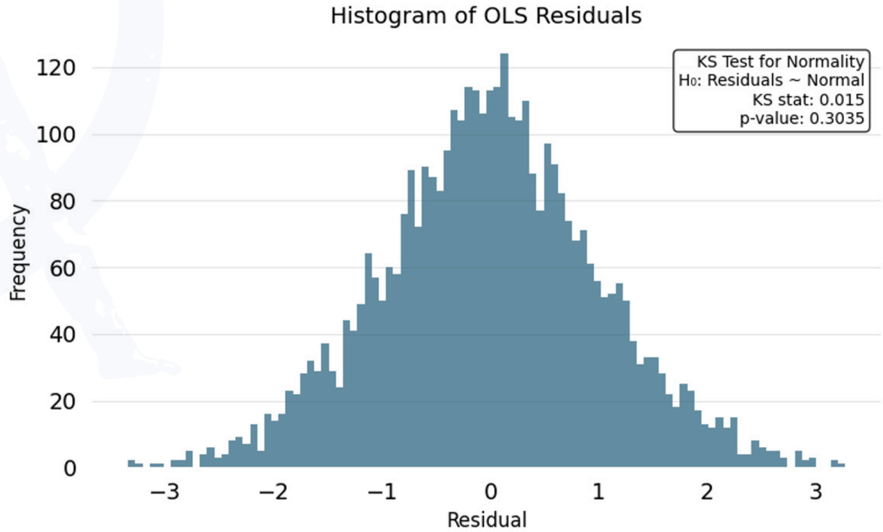
To examine how well the model fits the transaction sample, in Table 22 and Figure 17, we present the error statistics and distribution. Unsurprisingly, the model errors (or residuals) are on average zero, even when using the median. However, the Mean Absolute Error is a high 0.79 in the logarithm scale, indicating poor accuracy at the observation level of the model. The histogram of the residuals resembles a Gaussian distribution, also confirmed by the Kolmogorov-Smirnov statistic with a p-value of 0.30, failing to reject the null hypothesis that the residuals are drawn from a normal distribution.

TABLE 22: DIAGNOSTICS OF OLS FACTOR MODEL ERRORS

Metric	Value
Mean Error	0.0000
Median Error	0.0009
MAE (Mean Absolute Error)	0.7882
MSE (Mean Squared Error)	1.0040
RMSE (Root Mean Squared Error)	1.0020
R^2 (Explained Variance)	0.2973

Source: PitchBook and Capital IQ. Calculations by EIPA.

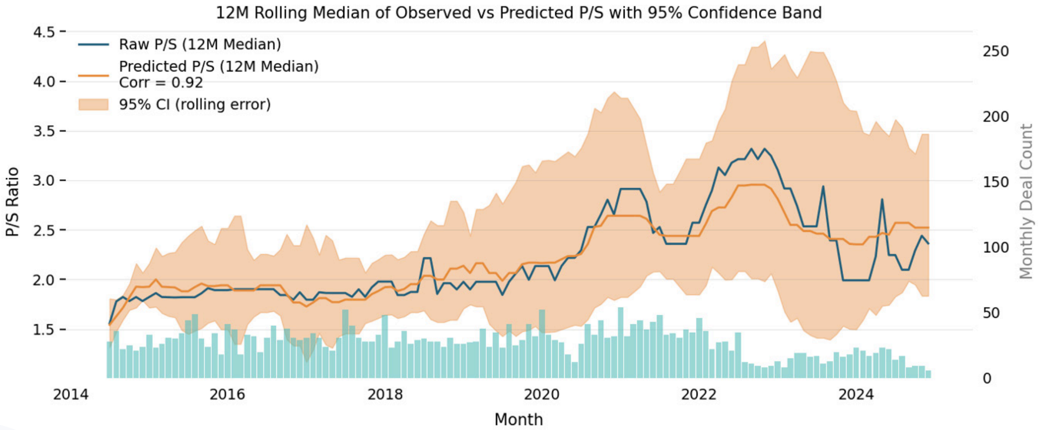
FIGURE 17: DIAGNOSTICS OF OLS FACTOR MODEL ERRORS



Although the errors are large, the OLS predictions do well in capturing the overall trends, as shown in Figure 18. We plot the 12-month rolling medians of the raw observed transaction valuation and the factor model predicted valuations, and we can see that both the lines track each other quite closely, with an overall correlation of 0.92. The orange shaded area around the predicted line is based on confidence intervals built around the predictions based on the median residuals (or errors) in those predictions. The bars on the horizontal axis represent the number of observed transactions each month during the sample period.

6. Part III: Systematic vs. Idiosyncratic Risk in Private Equity

FIGURE 18: AVERAGE TIME TRENDS BASED ON OLS FACTOR MODEL PREDICTIONS



Determining the discount rate

As the confidence interval based on the errors do not allow a practical measure of uncertainty in the predictions, we build the good deal bounds around the predictions.[2] A key ingredient for estimating the good deal bounds is to determine the discount rate for each transaction. Although the method demonstrated in **Part II** can be used, it suffers from look-ahead bias as we are using the observed price to compute the discount rate in order to improve the model predictions. Thus, we use the discount rates of the private2000 index, which are estimated as in **Part II**, using the monthly prices of the constituents of the index.

Excluding some negative discount rates, we compute activity-month average of all PECCS activity classes in the private2000. As private2000 index, explicitly excludes utility sector and majority of financial companies, we assign the monthly average across other activities. Table 23 briefly summarises the discount rate thus computed for the private2000. As can be seen across sectors, the estimated average discount rates for the private2000 index range between 7% and 17%, and are fairly typical of discount rates that investors can be expected to use.

TABLE 23: DESCRIPTIVE STATISTICS OF private2000 DISCOUNT RATES BY PECCS ACTIVITY, 2013-2024 (N=141)

Activity	Mean	Std. dev.	Min	25th percentile	Median	75th percentile	Max
Education and public	0.16	0.03	0.08	0.14	0.15	0.17	0.24
Health	0.07	0.02	0.05	0.06	0.07	0.08	0.11
Hospitality and entertainment	0.13	0.03	0.07	0.10	0.12	0.15	0.21
Information and communication	0.14	0.03	0.08	0.12	0.15	0.16	0.18
Manufacturing	0.17	0.03	0.10	0.14	0.16	0.19	0.23
Natural resources	0.14	0.06	0.03	0.09	0.13	0.18	0.23
Professional and admin services	0.13	0.03	0.07	0.12	0.13	0.16	0.18
Real estate and construction	0.18	0.04	0.07	0.16	0.18	0.21	0.29

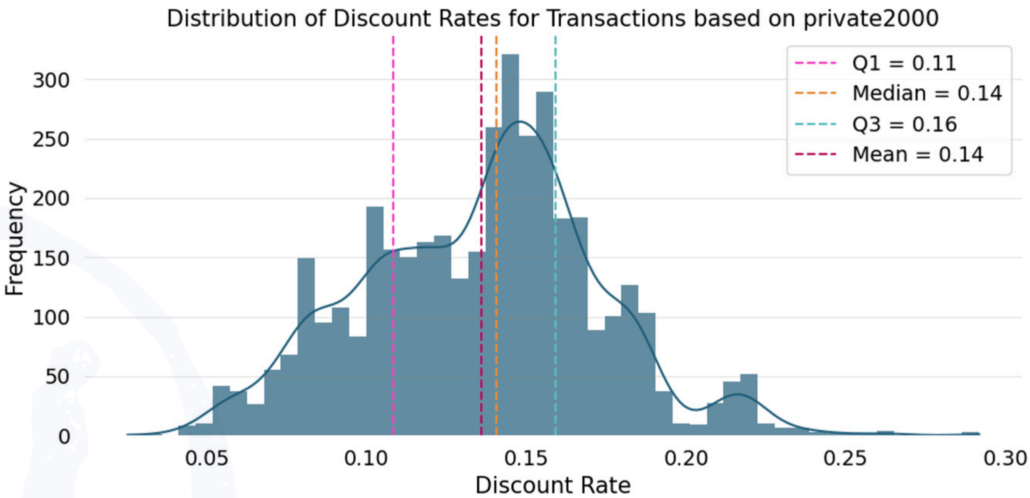
Source: Pitchbook and Capital IQ. Variables calculated by EIPA.

2 - Although uncertainty in the OLS estimates can be expressed through the standard deviation of the regression errors or through the standard error of the coefficient estimates, both these methods give unrealistic confidence intervals (either too broad or too narrow). For example, we find that the average half width of the confidence interval based on these two methods are 576% and 42% of the modelled variable log (P/S), respectively. The extent of observations falling within the two confidence intervals are a high 95% (for 576% confidence interval half width) and 24% (for 42% confidence interval half width), indicating that either method is unsuitable to express the uncertainty of the modelled estimates.

6. Part III: Systematic vs. Idiosyncratic Risk in Private Equity

Using the average estimated values for the private2000 by activity and month, we merge it with our transaction sample. The histogram of the discount rate, thus computed for the transactions are presented in Figure 19. The mean and median predictions for the transactions are a discount rate of 14% while the 25th and 75th percentiles are 11% and 16%, respectively. These discount rates seem realistic and plausible for the observed transactions.

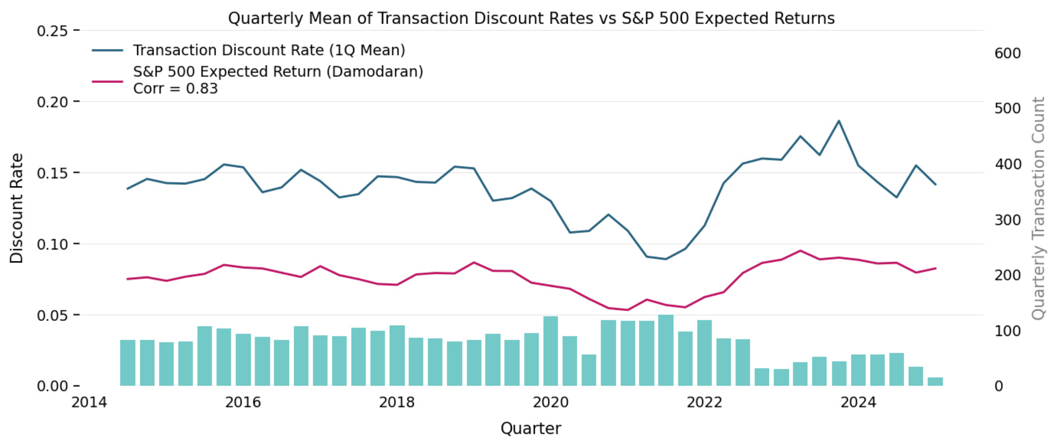
FIGURE 19: ESTIMATED DISCOUNT RATES FOR TRANSACTIONS, 2013-2024



For reference, we also plot the quarterly mean of these discount rates along with the implied expected returns on the S&P 500, sourced from Damodaran's dataset in Figure 20. The implied discount rates of public equities vary very narrowly, averaging 7.69% over the same period, with a median of 7.84% and an interquartile range of 7.24% to 8.31%. In contrast, the estimated discount rates derived from private market transactions are higher in level, with the difference with implied public market returns also exhibiting time-varying properties.

This time-varying disparity between public market and private market discount rates challenges the conventional approach of applying a fixed illiquidity premium to public market expected returns, suggesting that private market valuations reflect more heterogeneous and dynamic discount rate assumptions. The two curves also exhibit a high correlation with a correlation coefficient of 0.83, indicating that discount rates in private and public markets move in tandem.

FIGURE 20: TIME TRENDS IN ESTIMATED DISCOUNT RATES FOR TRANSACTIONS AND PUBLIC MARKETS, 2013-2024



6. Part III: Systematic vs. Idiosyncratic Risk in Private Equity

Estimating the bid-ask valuation spread

With the estimate of transaction level discount rates, we begin computing the good deal bounds of the estimated price. First, using the OLS predicted estimate, we compute a terminal value for each transaction. This needs an assumption about the investment horizon for each transaction.

Based on McKinsey's 2025 Global Private Markets report[3] the long-term average holding period of private equity investments has approached 6.7 years in 2025. We use the 6.7 years, the estimated discount rate for each transaction, and the OLS predicted estimate to arrive at each transaction's terminal value as per the expression below:

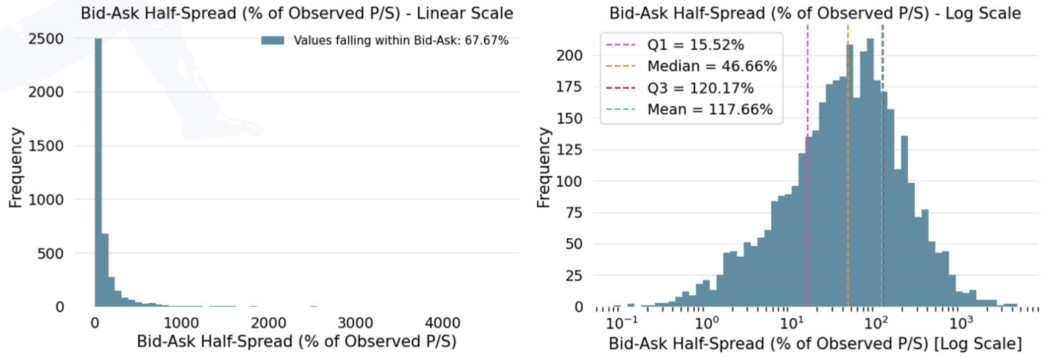
$$\textit{Terminal value} = \left(\frac{\mathrm{P}}{\mathrm{S}}\right)_{\mathrm{pred}} \times \mathrm{S} \times (1 + \overline{\mathrm{DR}})^{6.7}$$

Next following, Cochrane and Saa-Requejo (2000) we set the discount rate volatility as $\sigma_{DR} = \frac{3\times \text{S\&P500 Sharpe Ratio}}{(1+r_f)}$, thereby allowing us to determine upper and lower limits of discount rates based on a 95% confidence interval using the expression $\overline{\mathrm{DR}} \pm 1.96 \times \sigma_{DR}$. Substituting these different discount rates, allows us to estimate the bid (using the upper discount rate) and ask (using the lower discount rate) prices around the predicted valuation.

Uncertainty based on good deal bounds

To gauge how wide this prediction interval is, we perform an analysis of the bid-ask half spreads relative to the estimated valuation, i.e., $\frac{P_{ask\_pred} - P_{bid\_pred}}{2P_{pred}}$. In Figure 21, we find that the average half spread is wide at almost 1.18x whereas the median width is about 0.47x. Moreover, about 67.67% of observations fall within the bid-ask spreads, indicating that for more than half the transactions, the predicted valuation and the bid-ask bands around them explain the observed valuation.

FIGURE 21: UNCERTAINTY IN MODEL PREDICTIONS BASED ON THE GOOD DEAL BOUNDS BASED BID-ASK SPREADS

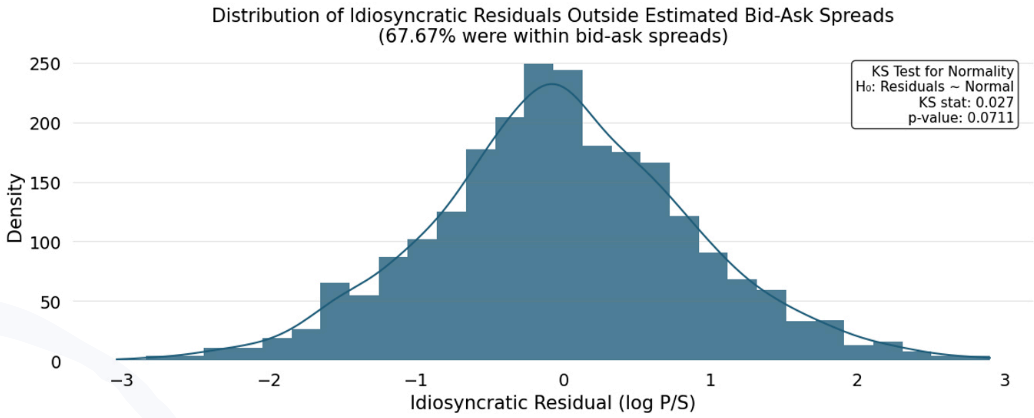


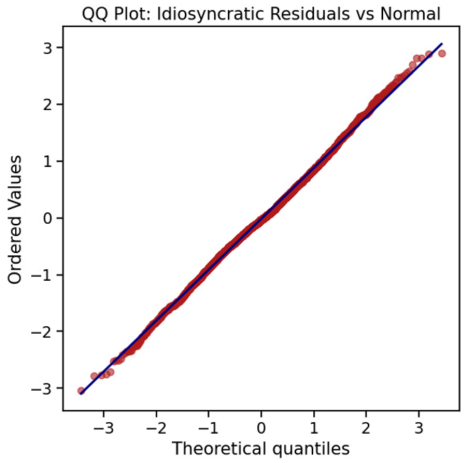
Finally, to estimate whether the residuals outside the bid-ask bounds are normally distributed, we examine the residuals for observations that fall outside the bid-ask spreads (i.e., 32.33%). As shown in Figure 22, the residuals behave Gaussian and also based on the Kolmogorov-Smirnov tests also fails to reject the null hypothesis that the idiosyncratic residuals are part of a normal distribution at 5% level of statistical significance. However, at 10% level of significance, we reject the null hypothesis of the residuals being normally distributed. However, bear in mind that the sample used here represents only one-third of all the transactions we modelled, as the bid-ask bounds perfectly

3 - McKinsey's Global Private Markets Report 2025 estimates that the backlog of assets that are in the divestment phase is growing globally in Private equity and the average holding time is about 6.7 years based on an average over the last 20 years (https://www.mckinsey.com/industries/private-capital/our-insights/global-private-markets-report).

explain the remaining two-thirds of the prices. The QQ plots also provide similar inference that the residuals are very close to a normal distribution.

FIGURE 22: DIAGNOSTICS OF IDIOSYNCRATIC ERRORS BASED ON BID-ASK SPREADS





Pricing error based on the bid-ask bounds

Finally, we examine the errors based on the dynamic prediction interval, i.e., when we extend the evaluation beyond the OLS point prediction to examine the idiosyncratic residuals that fall outside the predicted bid-ask ranges.

To recall, our approach accounts for the heterogeneity in prediction uncertainty by estimating the discount rate based on the contemporaneous average of activity-matched constituents of private2000 and allowing it to vary based on upper and lower "good-deal" pricing bounds that borrow the idea of an asset in an incomplete market offering an irresistible payoff in comparison to a traditional asset class.

Using these idiosyncratic residuals, we then compute error metrics based solely on these out-of-band residuals. As shown in Table 24, the Mean Absolute Error of the unexplained component is approximately 0.39 in log scale. The band-based R^2 is 0.67, implying that the model and its uncertainty bounds together explain around 67% of the total variation in log price-to-sales ratios—much better than the explanatory power of the OLS point prediction alone, after accounting for prediction confidence.

TABLE 24: DIAGNOSTICS OF ERRORS USING THE DYNAMIC PREDICTION INTERVAL BASED ON BID-ASK PRICES

Metric	Value
Mean Error	-0.0095
Median Error	0.0000
MAE (Mean Absolute Error)	0.4177
MSE (Mean Squared Error)	0.4803
RMSE (Root Mean Squared Error)	0.6930
R^2 (Explained Variance)	0.6639

Source: PitchBook and Capital IQ. Calculations by EIPA.

Takeaways from Part III

We determine that a simple factor model calibrated with common risk factors can explain about 30% of the variation in transaction prices in private equity entry/exits. When the uncertainty in the implied prices based on systematic factors are expressed through a combination of relative attractiveness of the private asset class and average market prices in private markets, more than two-thirds of the variation can be accounted for in observed prices. The residual unexplained variation almost resembles a normal distribution.

Conclusion

Having established that private assets are exposed to common segment and risk factors (**Part I**) and that private asset prices systematically different across these segments and risk factors (**Part II**), we also determine what fraction of private asset transaction prices is determined by systematic factors (**Part III**).

Additionally, we focus on the role of the bid-ask spread in explaining the uncertainty around the estimated prices based on systematic risk factors. In other words, we determine what can be regarded as a systematic component of idiosyncratic prices. Truly, idiosyncratic risks remain after accounting for the dynamic prediction interval based on systematic risk factors, and its characteristics are then examined.

Implications For Asset Pricing

The results demonstrate that market risk in private equities—distinct from fund-level liquidity and cash flow risks—can be identified, quantified, and priced. Using detailed asset-level financials and transaction data, the analysis shows that the pricing of private equities assets is influenced by a set of observable risk factors and market segment classifications (PECCS). This challenges the conventional view that private equities risk is unobservable or unmeasurable due to the paucity of transaction activity.

Three key implications emerge:

- **Systematic risk is observable and varies meaningfully** across firms depending on size, growth, profitability, leverage, and maturity, as well as sector classification and other PECCS pillars and classes. These risk exposures correspond to measurable differences in both volatility and insolvency likelihood.
- **Market participants price risk systematically**. Transaction multiples (e.g., P/EBITDA, P/S) and implied expected returns are shown to align with PECCS classifications and firm-level factor exposures. This indicates that investors differentiate across risk profiles, similar to pricing behaviour in public markets.
- **A substantial portion of price variance is explainable** by systematic factors, suggesting that private equity markets, while less liquid, are governed by coherent pricing dynamics. This has direct implications for asset valuation and fund manager benchmarking.

Existing valuation practices often ignore the presence of multiple priced systematic risk factors, in favour of one 'market' factor. The discounted cash flow (DCF) valuation method normally uses discount rates computed using the capital asset pricing model (CAPM). This one 'market' factor in CAPM is unobservable and usually proxied with a broad, listed market index. This fails to account for the presence of systematic risk factors observed in private equities pricing and historical transactions, as demonstrated throughout this paper. Moreover, the 'market' factor is not derived from the private equities market, but rather, listed equities. Combined, this makes the traditional DCF approach unsuitable for valuing private assets.

A second common approach involves the use of comparable company multiples (comps) or precedent transactions. Comps, typically drawn from listed firms, suffer from a lack of robustness: it is difficult to find more than a few firms that closely match the private firm in size, growth, capital structure, and sector exposure. Moreover, these comparables are traded in public markets, which differ from private markets in terms of liquidity, investor base, and pricing dynamics. While precedent transactions, particularly private equities deals, are more relevant, the analysis in Part II shows that observed pricing reflects systematic risk exposures. Valuation exercises that use transaction multiples without adjusting for risk factor differences risk drawing misleading conclusions.

Overall, the existence of priced systematic risks in private assets strengthens the case for improved asset-level pricing, incorporating risk factors into a well calibrated factor model. This should lead to modelled prices that more accurately reflect the volatility inherent in private equities.

Implications For Benchmarking Private Asset Funds

The ability to identify and price systematic risk at the asset-level lays the groundwork for more accurate and objective benchmarking of private asset funds. By isolating market risk from liquidity and cash flow risks—typically conflated in traditional fund-level analysis—this approach enables performance evaluation relative to the actual private equities market rather than relying solely on public market proxies or manager-contributed benchmarks.

Current benchmarking practices fail to isolate and accurately capture market risk in private equities. Proxies based on listed equities benchmarks reflect the market beta of public equities, not private ones. These benchmarks also ignore key priced risk factors specific to private equity – such as size, growth, leverage, maturity, and profitability – which, as discussed, are essential to understanding market risk.

Benchmarks based on private equity fund managers partially reflect private market exposures but do not isolate market risk. These are not true market indices; rather, they are collections of portfolio companies shaped largely by manager-specific active bets. As a result, such benchmarks are not representative of the broader private equity market. They are not appropriately representative across geography, sector (activity), lifecycle stage, revenue model, customer model, and value chain position, which are critical to constructing a private equities asset level benchmark.

Private asset funds can be benchmarked against a private equities index comprised of private companies priced with a well calibrated factor model that incorporates key systematic risk factors. This allows limited partners (LPs) to assess whether general partners (GPs) are adding value beyond what is explained by the private equities market.

Appendix A: Logit Model Insolvency Predictions by PECCS

Predicted Insolvency rates:

PECCS Activity	WORLD	ADV	EU
Financials	1.18	1.14	0.996
Real estate and Const.	1.2	1.0	1.41
Utilities	1.25	0.934	1.03
Manufacturing	1.26	1.11	1.11
Retail	1.4	1.12	1.27
Education and public	1.4	1.21	1.42
Health	1.42	1.19	1.56
Professional and other ser.	1.69	1.56	1.55
Information & Comm.	1.71	1.67	1.67
Transportation	1.82	1.63	1.71
Natural resources	1.96	1.71	2.1
Hospitality and Ent.	2.21	2.08	2.18

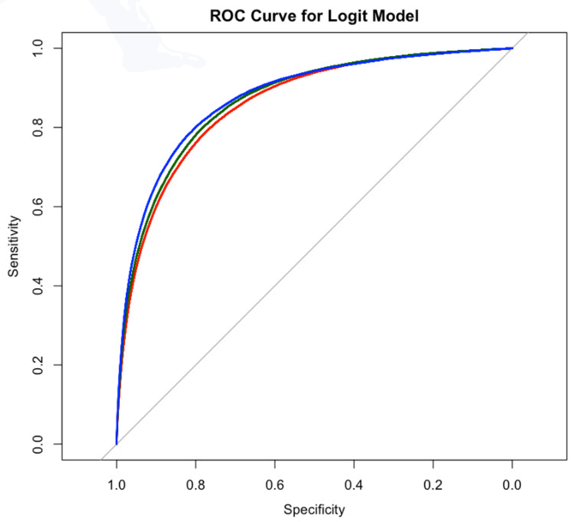
PECCS_Customer Model	WORLD	ADV	EU
B2B	1.39	1.20	1.30
B2C	1.54	1.36	1.47

PECCS_Lifecycle	WORLD	ADV	EU
Mature	0.994	0.908	0.984
Growth	1.77	1.65	1.73
Early Stage	3.32	3.16	3.39

PECCS_Revenue Model	WORLD	ADV	EU
Markup	1.37	1.10	1.26
Subscription	1.44	1.27	1.09
Production	1.46	1.30	1.42
Advertisting	1.74	1.59	1.68

PECCS_Value Chain	WORLD	ADV	EU
Products	1.38	1.16	1.26
Services	1.47	1.32	1.49
Hybrid	1.71	1.48	1.53

EBITDA%	Prob%	Age	Prob%	Size	Prob%	Growth	Prob%	Leverage	Prob%
-0.0968	3.57	6.75	2.91	2.08	2.31	-0.257	1.95	0.0579	0.796
0.0102	1.20	15.2	1.58	6.47	1.34	-0.0233	1.30	0.169	0.905
0.0304	1.02	22.6	1.2	12.2	1.19	0.0345	1.83	0.302	1.01
0.0637	0.866	32.4	0.851	24.4	1.17	0.118	1.05	0.520	1.25
0.208	0.55	63.4	0.669	320.0	1.21	0.734	1.09	1.34	3.25



Global: Area under the curve: 0.8598

ADV: Area under the curve: 0.8686

EU: Area under the curve: 0.8758

The privateMetrics® Valuation Model

Our approach to the valuation of private companies is designed to maximise the available transaction and financial data in private markets and provide a standardised and systematic manner to update prices with every observed transaction.

First, we construct a multi-factor model of prices using a sample of observed transactions over time which can infer the unbiased and precise factor prices that investors pay for different characteristics of a private asset. Although every transaction is idiosyncratic or unique, in a large sample of transactions, the individual errors in each transaction price can be diversified away to discern the price attributable to each factor. Factor prices refer to the premium (or discount) that an investor is willing to pay to seek exposure to a specific factor of return in private companies. For example, observing the relationship between size and valuation among reported transactions, it can be inferred how much premium or discount an investor is willing to pay for purchasing a larger private company.

Second, an important and key application of this approach is that, with the estimated factor prices, say for size, it would then be possible to price unlisted private companies whose size information is available, irrespective of whether they are traded or not. This approach provides a more robust estimate for FV and enables the creation of representative indices of private companies.
Our approach's novelty is calibrating the model to newly observed transactions obtaining the factor price evolution over time, which allows us to update the valuation for all tracked unlisted private companies.

Common Risk Factors

If investors trade unlisted private companies from each other in mutually negotiated transactions, there must be some common characteristics that at least partially explain prices. For example, private companies that have higher profits or growth opportunities may be more valuable to investors than those that are not.

To arrive at a potential list of factors, we follow simple criteria that there needs to be an economic rationale for the factor to affect valuation. The factor should also be statistically related to the valuation. Moreover, the factor should also be objectively observable or measurable. With a potential list of factors, our factor selection is the result of a statistical approach, where the factors that can satisfactorily explain the variation in observed transaction valuations are included in the final model while trading off being parsimonious with being able to explain a higher variance in valuation. The privateMetrics asset pricing model uses five key risk factors as below:

- **Size**: Larger companies may be more complex, have higher transaction costs, and be less liquid, all of which can make them trade at a lower valuation per $ of revenue.
- **Growth**: As traditional PE strategies rely on growing the entry multiple, that may involve both increasing its top and bottom lines, i.e., revenue and profits. Thus, companies that can grow faster can be more sought after, making them more valuable.
- **Leverage**: Leverage can make a company riskier as it increases the risk of default. However, there

is also a signalling effect of leverage, as companies with stable consistent cash flows can support a higher leverage, and vice versa. Thus, leverage is expected to influence the valuation of a company.

- **Profits**: More profitable companies have more predictable (less risky) future payouts and hence attract a lower risk premium, making them more valuable.
- **Maturity**: Younger companies have fewer track records and face higher information uncertainty. Studies have shown that firms with high uncertainty tend to be overvalued and earn lower future returns. Thus, the maturity negatively affects valuation.
- **Country risk**: Investors may require a high return when investing in a high-risk country, thus depressing the current valuation. In other words, in countries with lower risk, investors may be willing to purchase assets at a higher valuation as government policies may be more predictable with lower macroeconomic risks.

Table A1: Key factors, their effect on valuation, & the economic rationale for including them in the model

Factor	Definition (Proxy)	Effect on price	Economic Rationale	References
Size	Revenues	Negative	Larger firms are more illiquid and trade a lower price	Fama & French (1993)
Growth	Change in Revenues	Positive	Companies with higher revenue growth trade at a higher price	Fama & French (1992), Petkova & Zhang (2005)
Leverage	Total debt / Revenues	Positive	Companies that can borrow more have a lower cost of capital and a higher value	Gomes & Schmid (2010), George & Hwang (2010)
Profits	Ebitda Margin	Positive	Companies that have higher profits have a higher value	Novy-Marx (2013), Hou et al. (2015)
Maturity	Years since incorporation	Negative	Companies that are mature exhibit less growth potential and trade a at a lower price	Jiang et al. (2005)
Country Risk	Term Spread	Negative	Companies in high-risk countries face more uncertain prospects	Chen & Tsang (2013)

Source: calculated using over 10k deals from PitchBook, CapitalIQ, Factset, and other primary sources between 1999-2022

Our factors have been documented in prior academic studies to be associated with valuation. We also include factors that have been identified as key determinants of valuation from a survey of private equity practitioners that we conducted in 2023. Table A1 summarises the key factors that we use in the model, how they are measured, each factor's effect we document in the data on average, the economic rationale for their inclusion, and citations for the work that underpins their inclusion.

Model Set Up

The privateMetrics asset pricing model uses the Price-to-Sales ratio of observable transactions (the entry price multiple) as the modelled variable. The model is estimated as the linear sum of the product of factor exposures and factor prices. The estimation can then separate the systematic part of the valuation while leaving out "noise" in each valuation.

$$\frac{P}{S} = a + \sum_{k=2}^{K} b_k l_k + e$$

Following standard asset pricing notation, the factor exposure or factor loading is called a beta (β), and the factor premium is called a lambda (l) for the k factors in the model. ***a*** is the intercept and ***e*** is the noise or idiosyncratic part of the valuation.

Model Calibration

The privateMetrics model uses a carefully curated dataset of more than 10k+ unlisted private company investments going back two decades sourced from a wide variety of datasets including PitchBook, Factset, Capital IQ, fund manager reports, and other publicly available data sources.

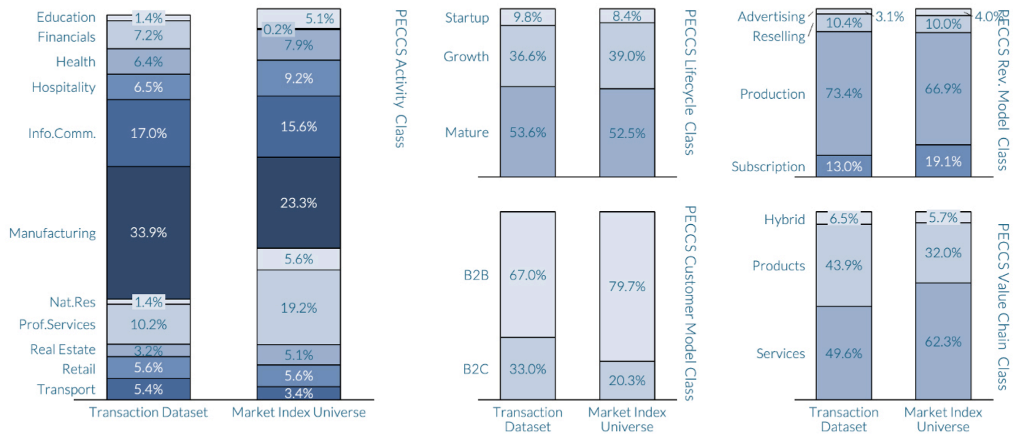
We calibrate this model using new observations monthly to update its estimation of the price of risk of each factor. In other words, each transaction observed is then used to 'update' this model (i.e., obtain new ls) through a dynamic estimation (using a Kalman filter), which retains the memory of past ls while also allowing the new transaction to influence the relationship while keeping the average e close to zero. More details on the implementation of the model are available in our online documentation and Selvam and Whittaker (2024). The dataset covers all key segments of the market as shown in Figure1.

A good application of using the model to value unlisted private companies is to create a representative marked-to-market index of private companies that are regularly valued. The privateMetrics index universe in Figure 1 includes the constituents of the private2000® index constructed by Scientific Infra and Private Assets, which is developed on this shadow pricing idea and captures the performance of private companies in 30 countries globally that are important for private equity investors (read more about the index here).

How Precise are the Predictions across PECCS® Pillars?

To examine how closely the predicted valuations track the raw modelled valuations in transactions, we compute the average estimation errors of the full sample, and also by classes within each PECCS® pillar. What stands out is that although the model by design is expected to have lower estimation errors in the full sample, the within PECCS® class estimation errors are also very small. All the errors are within ±10%, reassuring that the model predictions on average even within each segment of PECCS® are reasonable. The errors are summarised in Table A2.

FIGURE A1: PRIVATEMETRICS TRANSACTION DATASET COMPARED TO THE PRIVATEMETRICS INDEX UNIVERSE BY PECCS PILLAR & CLASS



Appendix B: privateMetrics Valuation Model

The most commonly used metric of valuation in private markets is EV/EBITDA as PE owners have the flexibility to alter the capital structure of their holding company and hence are more interested in operational profitability without factoring interest costs. However, our model is based on P/S because P/S is statistically better, stable, and not affected by loss-making companies. Thus, one may be concerned whether our predictions for EV/EBITDA might be biased.

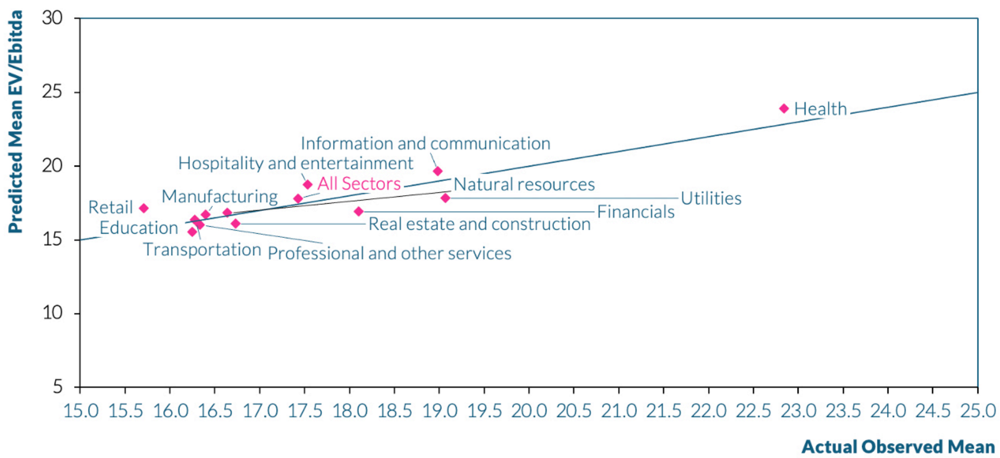
To ensure that is not the case, we compute the EV based on the book value of debt and predicted equity valuation and divide the sum by the EBITDA to get a predicted EV/EBITDA and compare it to transaction implied ratios. Figure A2 presents the average predicted and observed EV/EBITDA by PECCS® activity classes. We find that the predictions are very close to the observed values, thus mitigating this concern.

TABLE A2: AVERAGE ESTIMATION ERRORS ACROSS PECCS® CLASSES, BASED ON THE DIFFERENCE BETWEEN TRANSACTED VALUATIONS AND FACTOR MODEL PREDICTIONS

PECCS Pillar	PECCS Class	Mean Estimation Error	PECCS Class	Mean Estimation Error	PECCS Pillar
PECCS Activity	Education and public	0.9%	Startup	0.1%	PECCS Lifecycle Phase
	Financials	1.8%	Growth	-1.7%	
	Health	2.6%	Mature	2.8%	
	Hospitality and entertainment	-1.1%	Advertising	1.2%	PECCS Revenue Model
	Information and communication	-4.4%	Reselling	4.6%	
	Manufacturing	2.5%	Production	2.9%	
	Natural resources	9.4%	Subscription	-6.9%	
	Professional and other services	3.3%	B2B	1.5%	PECCS Customer Model
	Real estate and construction	1.9%	B2C	0.9%	
	Retail	0.5%	Hybrid	0.6%	PECCS Value Chain
	Transportation	7.2%	Products	1.1%	
Full Sample		**1.1%**	Services	3.4%	

SOURCE: CALCULATED USING OVER 10K DEALS FROM PITCHBOOK, CAPITALIQ, FACTSET, AND OTHER SOURCES BETWEEN 1999-2022

FIGURE A2: PREDICTED VERSUS ACTUAL EV/EBITDA RATIOS BY PECCS® ACTIVITY CLASSES



SOURCE: CALCULATED USING OVER 10K DEALS FROM PITCHBOOK, CAPITALIQ, FACTSET, AND OTHER SOURCES BETWEEN 1999-2022

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