Systematic Insights into Private Equity Investing

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KEY FINDINGS

- The line between public and private company investing is blurring, in part through the proliferation of alternative data that can facilitate data-driven strategies for private company investing.
- Forecasting models appear effective in predicting exits for private companies.
- The fundamental law of active management applies to private equity, with breadth measured by the number of companies raising capital at any given time, even if private equity portfolios are ultimately limited to a small number of positions.

ABSTRACT

Systematic approaches have greatly benefitted investors in publicly traded equities since at least the development of the first index fund in 1971. Private equities pose a far greater challenge for systematic investing due to lack of return data and regulatory filings and to significant illiquidity. Today, however, the availability of alternative data covering private companies, as well as the development of advanced forecasting methods, are facilitating systematic approaches to private equity investing. This article will present a systematic framework for private equity investing and extend the fundamental law of active management to show the benefits of breadth available to systematic investors. It will then demonstrate what public equity data can tell us about skill in private markets. Systematic approaches to private equity investment can be expected to continue to evolve and improve over time and to start to gain market share in this asset class of increasing investor interest.

Systematic approaches have greatly benefitted investors in publicly traded equities since at least the development of the first index fund in 1971. At that time, all investing was active, investors believed that a skilled MBA should outperform the market over a business cycle,[1] and investment managers charged high fees. Index funds are low-fee products that have demonstrated that broad market indices outperform most active managers most of the time. They are now very popular, by some measures even more popular than actively managed funds,[2] and investors are clearly better off for having them as widely available choices. Their presence has even lowered active management fees, as active products must compete with index funds. For example, from 2000 to 2023, the asset-weighted average US domestic equity mutual fund fee dropped more than 50%, from 0.99% to 0.42%.[3]

[1] Often attributed to Benjamin Graham.
[2] Rekenthaler (2024).
[3] Investment Company Institute (2024, 82).

Systematic or quantitative active investing has also helped improve the environment for investors through improved risk management and portfolio construction and better understanding of the components of active management. The result has been lower-fee active products for clients and arguably more-consistent positive active returns.[4] These developments over the past half century have thus significantly improved the landscape for investors in public markets by increasing competition, popularizing benchmarks for performance, and innovating new methods to extract alpha.

Today, private equity is the pre-1970s public market: an active, high barrier-to-entry asset class ripe for disruption. The private equity market has grown in US dollars from $716 billion in total assets under management in December 2000 to $15.3 trillion as of September 2023, according to Preqin. Of that $15.3 trillion, the largest category is classified as buyout at $4 trillion. Venture capital and growth equity follow at $1.8 trillion and $1.4 trillion, respectively.

The growth of private equity has occurred at the same time as increasing numbers of companies remain private at various stages of development and fewer companies choose to list through an IPO—further ballooning the demand for private equity access to investment opportunities.[5] Due to companies remaining private for longer, late-stage venture and growth equity companies increasingly resemble publicly traded small-capitalization growth stocks.

These trends, alongside the explosion in alternative data and computation, create an opportunity to apply quantitative tools, data, and methods traditionally deployed for public equities to private equity. While there are dozens of asset classes within the private markets and various investment approaches within each, this article will focus on late-stage venture capital and growth equity through a quantitative lens. The current market share of quantitative investment strategies in this space is believed to be very close to zero.

Despite its increasing presence, investing in private companies involves many challenges in both liquidity and security selection.[6] Only a subset of private companies raises funds in any given year, and the most promising limit access. The road to establishing a position is long and winding. Investing in a private company starts by identifying a company of interest or receiving an introduction to a company that may be raising capital and then connecting with the management team before or during a fundraise. From there, the process continues with several meetings with the company, due diligence on the business and the team, followed by a review of legal documents. This involves much more than pushing a button on a screen. Most investors hold positions for many years. Most deals are shown to very small groups of investors based on existing relationships and networks.

Beyond liquidity, pricing itself is problematic. The best reads occur only at funding rounds, which take place on average every 20 months.[7] For late-stage venture capital investing, there is enough information for potential investors to analyze valuation, however, pricing is not publicly available or as timely as for public companies. Due to the lack of synchronization of funding rounds, cross-sectional comparisons are difficult.

Against this backdrop of challenges and material differences with public equities, can systematic investing gain traction in private company investing? There are some reasons for optimism. Many alternative databases, very useful for public company

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[4] BlackRock research. Our analysis of global active equity funds in the eVestment database from 2019 through 2023 shows that median and top-quartile five-year information ratios for quantitatively managed funds, respectively, exceed those of discretionary managed funds in 19 out of 20 and 17 out of 20 quarters.

[5] Ewens and Farre-Mensa (2020).

[6] Metrick and Yasuda (2010).

[7] Source: CB Insights, BlackRock, average time between rounds, US late-stage venture universe, between January 2002 and April 2024.

investing, cover private companies as well. Advanced forecasting techniques can provide views on every private company. And with more companies remaining private for longer, experience with public small-cap growth companies can provide insight into late-stage private companies.

This article will discuss how to approach private equity security selection through a systematic lens and then formalize a theoretical framework for private equity investing by extending the fundamental law of active management into private markets. We then demonstrate what public equity data can tell us about skill in private markets and conclude by discussing how systematic tools can unlock value for clients interested in private equity.

PUBLIC VERSUS PRIVATE EQUITY BASIC DATA

Stark disparities in granularity exist between public and private equity returns. For public equities, daily (and even more frequent) returns are readily available at the stock level. For private equity, it is difficult to see returns more frequent than quarterly and at the index level (aggregated over many funds). For public equity, news about cash flows and discount rates impact prices. Private company valuations mainly reflect cash flow information and reflect relevant broad public market news only very slowly. While alternative data sources cover both public and private companies, standardized financial data releases are quite limited in private markets.

In public equities, standardized financial disclosures appear on scheduled frequencies and occasionally at other times. Annual reports traditionally provide a detailed overview of financial performance, including audited financial statements and management discussions and analysis (MD&A), and are typically filed within one quarter of the end of a firm's fiscal year; quarterly reports, which include unaudited financial statements, are filed within two months at the end of the first three fiscal quarters and follow earnings releases published at the end of each quarter. Proxy statements covering corporate governance issues are filed before annual shareholder meetings. Meanwhile, forms such as 8-K disclosures of significant events of interest to shareholders (e.g., bankruptcy, acquisitions) or 13-D disclosures of share acquisitions exceeding 5% are filed within days of the event.

In private equity, annual and quarterly filings to investors and stakeholders are also shared but are not publicly disclosed. To investors engaged in initial security selection, publicly available information is limited. Compared with public equity investing, the private market's focus on deal sourcing, valuation, structuring, entry, and exit requires significantly more resources to reduce search costs and facilitate trade execution. Initially sourcing a deal often requires skill in understanding untested, emerging industries. Thus, while the data on private companies can be quite granular once discovered by existing or prospective investors in due diligence during a capital raise, they are almost never shared with the public (at least in the United States). During the diligence period after an investor signs a nondisclosure agreement with a potential target company, the company grants the investor access to documents and information needed to aid in the evaluation of the transaction.

PRIOR SYSTEMATIC RESEARCH INTO PRIVATE EQUITY INVESTING

Consistent with the challenges of systematically investing in private equity, despite limited research published in this area, plenty of research has been published on private equity more broadly (long-term expected returns, changing investor allocation to private equity over time, growth of the industry, etc.). That said, we should mention three articles that have influenced our thinking in this area. The first is Kinlaw, Kritzman, and Mao (2015). The authors look at the aggregate performance of private equity relative to public equity and show that most of the outperformance comes from industry allocation relative to public equities with the rest representing an illiquidity premium. Note that industry allocation reflects a combination of available deal flow and active industry selection. This is one of many articles to deal with the understated return volatility of private equity due to valuation smoothing.[8] This leads to overstating Sharpe ratios for private equity with implications for strategic asset allocation.[9]

The second influential article is Boyer et al. (2023). This article is interesting in its attempt to mark a private equity index to market with pricing information coming from secondary market transactions. The article is an econometric tour-de-force, attempting to account for issues like the typical forced selling associated with secondary transactions in private equity. It won a 2022 Jack Treynor Prize from the Q-Group. Unfortunately, the methodology works only at the asset class level and not the individual asset level. It cannot provide us with comprehensive mark-to-market returns for individual private companies.

The third article is Ewens, Rhodes-Kropf, and Strebulaev (2016). It looks at insider financing rounds—that is, fund raises where only existing investors participate—and shows that the existence of such rounds tends to lead to higher probability of failure and lower probability of IPOs. Their approach of using insider rounds as features to help predict exits inspired our forecasting framework.

THE SYSTEMATIC APPROACH TO PRIVATE EQUITY INVESTING

Active investing relies on accurate forecasting. In the case of public equities, the challenge is to forecast future returns. Systematic investors have developed many techniques for forecasting returns (or return components such as residual or specific returns) and tested these on historical returns. A fundamental challenge of systematic investors in private companies is that we do not observe a similar comprehensive cross-sectional history of daily or monthly returns.

A key insight, therefore, into our systematic approach is to forecast things we can observe, namely the probabilities of a positive outcome (an IPO or an acquisition) in the next T years, with T typically in the range of 5–10 years.

As noted earlier, private companies, especially those based in the United States, don't provide regular regulatory filings like public companies. Fortunately, however, the explosion of alternative datasets can provide useful information to help forecast positive outcomes. Many datasets—for example, ones providing information on hiring, on company management, or on investor attention—cover both public and private companies. It turns out that we can access enough data/information on private companies to improve our forecasts of positive outcomes. For example, the unconditional probability of a positive outcome for a private investment in the next seven years is about 40%.[10] Conditioning our forecasts on available data on private companies can increase that probability to 75%; that is, we can identify a subset of private investments, 75% of which will lead to an IPO or an acquisition in the next seven years, a significant uplift.

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[8] While many analyses of private equity view this as a "bug" leading to overstated Sharpe ratios, investors may in fact view it as a feature. They understand that the Sharpe ratio is overstated. They also know that smoothed returns have many benefits.

[9] At (unconstrained) optimality, investors allocate risk in proportion to $\boldsymbol{\rho}^{-1} \cdot \mathbf{SR}$, where $\boldsymbol{\rho}$ is the correlation matrix of asset class returns and $\mathbf{SR}$ is the vector of asset class Sharpe ratios.

[10] CB Insights, BlackRock, late-stage venture universe, between January 2002 and April 2024.

IDEALIZED MODEL OF INVESTING IN PRIVATE COMPANIES

In this section, we will develop an idealized model of investing in private companies to help understand the potential advantage of the systematic approach. In particular, we will develop a private equity version of the fundamental law of active management and show that systematic investors can gain some benefit of breadth even if the final portfolio contains only limited numbers of companies. A significant advantage of the systematic approach is in developing a view of every private company with available data. Fundamental private equity investors will mainly have views on the small set of companies they can meet or where they have been manually gathering information.

To start, we will make the following simplifying assumptions:

- Investments in private companies have binary outcomes: a good return, μ_G, and a not good return, μ_{NG}. These are outcomes over the T~7–10-year holding period, and we assume they are annualized (so that the actual return over the period will be $\mu_G \cdot T$ or $\mu_{NG} \cdot T$). Furthermore, we associate good returns with exits. These investments have risk ω, which we will relate to the two possible outcomes. Every investment will have the same risk. The investments are uncorrelated.
- Private investment funds build equal-weighted portfolios of M holdings, where M is much less than the number of possible investments, N. The number N measures the number of private companies raising capital at the time of building the private investment fund.
- As our investment benchmark, we will use the expected performance of an equal-weighted portfolio of the N possible positions.

In the spirit of Box (1976), “all models are wrong, but some are useful,” we believe these assumptions simplify the analysis while retaining the important insights. We will flag any additional assumptions in the following.

Analysis

Let’s start by analyzing our investment skill. We can capture the investment possibilities, given the binary nature of the investments, with the contingency table shown in Exhibit 1.

We assume there are N available private investments. Our research has identified M of them we believe will have good returns, μ_G, and we build an equal-weighted portfolio of them. It subsequently turns out that M_G of them actually deliver good returns, and the remainder, M_{NG}, deliver poor returns, μ_{NG}. Similarly, of the $N - M$ opportunities we think will deliver poor returns, some of them do that but some of them actually deliver good returns. In Exhibit 1, we show the row and column sums at the right and bottom, respectively. We account for each of the N opportunities in this exhibit.

EXHIBIT 1
Contingency Table

Forecasts \ Realizations	μ_G	μ_{NG}	
μ_G	M_G	M_{NG}	$M = M_G + M_{NG}$
μ_{NG}	$N_G - M_G$	$N_{NG} - M_{NG}$	$N - M$
	N_G	N_{NG}	

Here are two statistics that will be useful and connect with our empirical models The probability p measures the probability that one of the opportunities delivers good returns and the probability q measures the probability that one of our picks delivers good returns:

$$p \equiv \frac{N_G}{N} \tag{1}$$

$$q \equiv \frac{M_G}{M} \tag{2}$$

Essentially, p measures the unconditional probability of a good outcome and q measures the conditional probability of a good outcome (i.e., conditional on our having forecasts that it will experience a good return, μ_G).

The Information Coefficient

Based on Exhibit 1, we can calculate our information coefficient, the correlation of our forecasts, and the subsequent realizations:

$$IC = Corr\{f,r\} = \frac{Cov\{f,r\}}{Std(f)\cdot Std(r)}. \tag{3}$$

In Equation (3), f represents our forecasts and r represents the realizations. We now need to calculate the three terms on the right-hand side of Equation (3). To start,

$$Cov\{f,r\} = E\{(f-\bar{f})\cdot(r-\bar{r})\} = E\{f\cdot r\} - E\{f\}\cdot E\{r\} \tag{4}$$

Let's start with the expected values of f and r:

$$E\{f\} = \left(\frac{M}{N}\right)\cdot\mu_G + \left(1-\frac{M}{N}\right)\cdot\mu_{NG} \tag{5}$$

$$E\{r\} = p\cdot\mu_G + (1-p)\cdot\mu_{NG} \tag{6}$$

We will also need to calculate the variances of f and r to get the standard deviations required in Equation (3). The calculations are similar, so we will show the first in more detail:

$$\begin{aligned} Var\{f\} &= E\{f^2\} - (E\{f\})^2 \\ &= \mu_G^2\cdot\left(\frac{M}{N}\right) + \mu_{NG}^2\cdot\left(1-\frac{M}{N}\right) - \left[\mu_G\cdot\left(\frac{M}{N}\right) + \mu_{NG}\cdot\left(1-\frac{M}{N}\right)\right]^2 \end{aligned} \tag{7}$$

With a bit of algebra, this becomes

$$Var\{f\} \Rightarrow \left(\frac{M}{N}\right)\cdot\left(1-\frac{M}{N}\right)\cdot(\mu_G-\mu_{NG})^2 \tag{8}$$

The other variance calculation is similar and results in

$$Var\{r\} = p\cdot(1-p)\cdot(\mu_G-\mu_{NG})^2 \tag{9}$$

Now let's go back to Equation (4) to continue our covariance calculation. We need to calculate the expected product:

$$E\{f\cdot r\} = \left(\frac{M_G}{N}\right)\cdot\mu_G^2 + \left(\frac{M_{NG}}{N}\right)\cdot\mu_G\cdot\mu_{NG} + \left(\frac{N_G-M_G}{N}\right)\cdot\mu_G\cdot\mu_{NG} + \left(\frac{N_{NG}-M_{NG}}{N}\right)\cdot\mu_{NG}^2 \tag{10}$$

Hence, the covariance of f and r is

$$Cov\{f,r\} = \left(\frac{M_G}{N}\right)\cdot\mu_G^2 + \left(\frac{M_{NG}}{N}\right)\cdot\mu_G\cdot\mu_{NG} + \left(\frac{N_G - M_G}{N}\right)\cdot\mu_G\cdot\mu_{NG} + \left(\frac{N_{NG} - M_{NG}}{N}\right)\cdot\mu_{NG}^2$$
$$-\left(\left(\frac{M}{N}\right)\cdot\mu_G + \left(1-\frac{M}{N}\right)\cdot\mu_{NG}\right)\cdot(p\cdot\mu_G + (1-p)\cdot\mu_{NG}) \tag{11}$$

With a bit of algebra, this simplifies to

$$Cov\{f,r\} = \left(\frac{M}{N}\right)\cdot(q-p)\cdot(\mu_G - \mu_{NG})^2 \tag{12}$$

Now we can insert Equation (12) and the square roots of Equations (8) and (9) into Equation (3) to see that the information coefficient is

$$IC = \sqrt{\frac{\frac{M}{N}}{1-\frac{M}{N}}}\cdot\frac{(q-p)}{\sqrt{p\cdot(1-p)}} \Rightarrow \sqrt{\frac{M}{N-M}}\cdot\frac{(q-p)}{\sqrt{p\cdot(1-p)}} \tag{13}$$

Equation (13) is at least somewhat intuitive in that the information coefficient is proportional to $q-p$; that is, it is proportional to our probability of picking investments with good outcomes (q) relative to what we would get with random picks from the larger universe of possible investments (p). Note that if $q = p$, then our $IC = 0$, appropriately.

Equation (13) also looks reasonable for a few other reasons based on the information coefficient being a correlation.

- It is dimensionless.
- It has reasonable properties in the extremes:
  - If $p = 0$, then there are no good investments and q must also be zero. Hence, the $IC = 0$.
  - Similarly, if $p = 1$, then all the investments are good, and q must also be one. Hence, the $IC = 0$.

We can use Equation (13) to estimate the information coefficient of our approach. According to our research on the growth equity universe, $p \approx 0.4$ while $q \approx 0.75$ using our approach. If we choose a 30-position portfolio out of maybe 1,000 potential investments, Equation (13) implies $IC \approx 0.13$. That's high compared with public equity investments but perhaps plausible assuming inefficiencies in private markets.[11] We will return to this later and estimate roughly similar *IC*s empirically.

The Volatility of a Private Investment

What can we say about the volatility of an individual private investment in this model? We will need this when we consider portfolio volatility later. We know that private investors don't discuss volatility much, and it's very hard to get a read on it by looking at just occasional valuations.

We will make another assumption here, that the time-series volatility of a private investment matches the cross-sectional volatility we observe. We already calculated this (actually, the variance) in Equation (9). Hence,

$$\omega = \sqrt{p\cdot(1-p)}\cdot(\mu_G - \mu_{NG}) \tag{14}$$

[11] Grinold and Kahn (2000, 272).

We need to make one comment on annualization of this risk number. Remember that μ_G and μ_{NG} are annualized and the outcomes over the T-year investment period will be $\mu_G \cdot T$ and $\mu_{NG} \cdot T$. The risk over the full period is, then,

$$\omega = \sqrt{p \cdot (1-p)} \cdot (\mu_G - \mu_{NG}) \cdot T, \tag{15}$$

because $\mu_G \cdot T$ and $\mu_{NG} \cdot T$ are the possible outcomes over the period. We annualize this by dividing by $\sqrt{T}$:

$$\omega_{annual} = \sqrt{p \cdot (1-p)} \cdot (\mu_G - \mu_{NG}) \cdot \sqrt{T} \tag{16}$$

The Information Ratio of the Optimal Portfolio

Our optimal portfolio will be an equal-weighted portfolio of the M available investments we believe will have superior returns. We know from the contingency table that the expected return on that portfolio will be

$$E\{r_P\} = \left(\frac{M_G}{M}\right) \cdot \mu_G + \left(\frac{M_{NG}}{M}\right) \cdot \mu_{NG} = q \cdot \mu_G + (1-q) \cdot \mu_{NG} \tag{17}$$

What about our benchmark portfolio and, more importantly, our active positions?

Let's say we rank all the potential N positions in order, with the M positions of our portfolio at the beginning followed by another $N - M$ positions. Our active position for each of those first M investments is $\frac{1}{M} - \frac{1}{N}$. For the remaining $N - M$ positions, our active positions will be $\frac{-1}{N}$. We can check that this works by checking that the aggregate active position is zero: $M \cdot \left(\frac{1}{M} - \frac{1}{N}\right) + (N-M) \cdot \left(\frac{-1}{N}\right) = 0$.

With that, we can calculate the annualized active risk of the portfolio. Remember that we are assuming all the returns are uncorrelated. Hence,

$$\begin{aligned} \omega_P^2 &= \sum h_{PA}^2 \cdot \omega_{annual}^2 \Rightarrow \omega_{annual}^2 \cdot \left[\left(\frac{1}{M} - \frac{1}{N}\right)^2 \cdot M + \left(\frac{-1}{N}\right)^2 \cdot (N-M)\right] \\ &= \frac{\omega_{annual}^2}{M} \cdot \left(1 - \frac{M}{N}\right) \end{aligned} \tag{18}$$

Using Equation (16), this becomes

$$\omega_P^2 = \frac{p \cdot (1-p) \cdot (\mu_G - \mu_{NG})^2}{M} \cdot \left(1 - \frac{M}{N}\right) \cdot \sqrt{T} \tag{19}$$

What about the expected return to the benchmark? Its expected annualized return will just be the expected return on average:

$$E\{r_B\} = p \cdot \mu_G + (1-p) \cdot \mu_{NG} \tag{20}$$

With Equation (20) plus Equation (17), the expected active return to our portfolio will be

$$E\{r_P - r_B\} = q \cdot \mu_G + (1-q) \cdot \mu_{NG} - [p \cdot \mu_G + (1-p) \cdot \mu_{NG}] = (q-p) \cdot (\mu_G - \mu_{NG}) \tag{21}$$

Hence, our expected information ratio is

$$E\{IR\} = (q-p)\cdot(\mu_G - \mu_{NG})\cdot\sqrt{\frac{M}{p\cdot(1-p)\cdot\left(1-\frac{M}{N}\right)\cdot T}}\cdot\frac{1}{(\mu_G - \mu_{NG})}$$

$$\Rightarrow \frac{q-p}{\sqrt{p\cdot(1-p)\cdot T}}\cdot\sqrt{\frac{M}{1-\frac{M}{N}}} \tag{22}$$

Now we can substitute Equation (13), our calculation of the *IC*, into Equation (22) to find the simple result:

$$E\{IR\} = IC\cdot\sqrt{\frac{N}{T}} \tag{23}$$

The familiarity of Equation (23) is reassuring. This closely resembles the fundamental law of active management we know from public equity investing.[12] Based on an *IC* of about 0.13, a universe on the order of 1,000 companies, and a 10-year holding period, this implies an information ratio of 1.3.[13] This is high relative to active systematic public equity funds, but not completely unreasonable given the advantages of private investing.

One question, though, is why there doesn't seem to be any haircut associated with the simplistic long-only portfolio construction? That might be the result of our simple bimodal model of returns. If there are only two possible outcomes, every investment is independent and with the same risk, and the benchmark is also equal weighted, the long-only portfolio has a transfer coefficient of one.

One other interesting feature is that *N* in Equation (23) measures available deals for investing. That implies that a firm with greater access to deal flow should have a higher information ratio—also intuitive. A more detailed modeling of deal flow could also involve some networks having access to higher expected return deals. That's not in this simple model.

USING PUBLIC EQUITY DATA TO INVESTIGATE PRIVATE EQUITY FUNDS

To gain further insight into the performance of private equity funds, we will use stocks in the Russell 2000 Growth Index to see if we can mimic observed performance of venture capital indices of different vintages. We will use these publicly traded stocks in Monte Carlo simulations and see if the observed performance looks similar to reported aggregated venture capital fund returns.

Here is the setup. Our model of a generic venture capital fund has a 10-year horizon and invests in 30 companies with 10 investments per year over the first 3 years. After that, the fund holds the companies for the remainder of the 10-year period. (The investment manager starts another fund after those first 3 years.)

We will run simulations assuming different levels of skill and then compare results with average performance of actual funds to estimate levels of skill in the industry.

[12] Grinold (1989) and Grinold and Kahn (2000).
[13] Based on this very simplified model. This is not a guarantee of future results.

For every stock in the Russell 2000 Growth universe, we simulate manager views as

$$f_n = E\{r_n(t,T)\} = IC \cdot [IC \cdot r_n(t,T) + \sqrt{1-IC^2} \cdot \omega_n \cdot \sqrt{T-t} \cdot Z_n], \quad (24)$$

where the information coefficient, IC, is the correlation between the forecast, f_n, and the subsequent realization, $r_n(t,T)$, and hence a measure of skill. The term Z_n is a mean zero, standard deviation one Gaussian random variable. We make the forecast at time t for the return from t to T. Equation (24) models expected returns as a weighted combination of the actual future return plus noise. The extra factor of IC provides the appropriate scaling for the forecast.

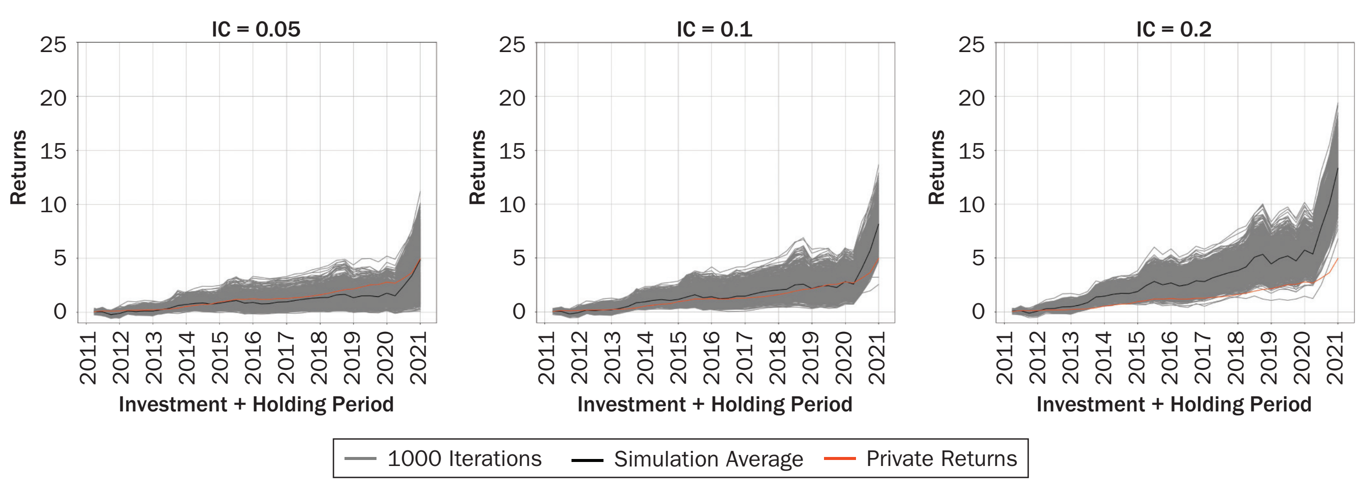
In Year 1, we generate these forecasts for every stock and then invest $1 in each of the 10 stocks with the highest 10-year f_n. In Year 2, we invest $1 in each of the stocks with the highest 9-year f_n among those stocks not previously chosen. In Year 3, we continue the same process, focusing on 8-year forecasts. Once we have built our portfolio after 3 years, we hold it until the end of year 10. We repeat this simulation process 1,000 times for each choice of IC and vintage (starting year). This will then lead to distributions of returns for each vintage and skill level, as well as many other statistics not generally available for private company investments.

Exhibit 2 shows example output for Vintage Year 2010 and for three skill levels: $IC = 0.05$, 0.1, and 0.2. Each graph shows the return to the Burgiss Venture Capital Index in red, as well as the cloud of 1,000 simulated return streams generated by the public equity data. From 2010, the Burgiss index achieved an annualized rate of return of 19.6%. Note that the Burgiss index is not a vintage index and includes companies from many vintages. We show the average of these 1,000 simulations in the thick black line. Note that from 2010, the simulations using $IC = 0.05$ on average underperform the Burgiss Index, with an annualized rate of return of 19.4% while the $IC = 0.1$ simulations on average outperform the index with an internal rate of return of 24.8%. Interpolating between them implies that $IC = 0.052$ would match the private equity data.

We can also look at the industries represented among the most frequently chosen 100 stocks for Vintage Year 2010. Biotech is the standout at 28%, with Healthcare equipment and pharmaceuticals in second place at 6%. This is a roundabout way of saying that small biotech stocks were top performers from 2010 to 2020. In Vintage Year 2002, in contrast, the top performers were internet stocks (15%) over the period from 2002

EXHIBIT 2

Vintage Year 2010 Simulations



SOURCES: BlackRock and Burgiss.

EXHIBIT 3
Simulation Analysis

Vintage	Estimated *IC*
2002	–0.02
2003	0.05
2004	0.08
2005	0.13
2006	0.03
2007	0.01
2008	0.06
2009	0.14
2010	0.05
2011	0.05
2012	0.15
AVERAGE	**0.07**

to 2012. These industry choices vary from vintage year to vintage year. As noted earlier, Kinlaw, Kritzman, and Mao (2015) showed that part of the private equity performance gap over public equities comes from superior industry allocation.

Overall, Exhibit 3 shows the yearly *IC* estimates from our simulations along with the average estimate of $IC = 0.07$.[14] Our earlier analysis of the *IC* of a model based on predicting positive outcomes (exits) led to an estimate of $IC = 0.13$. Interestingly, these results from very different analyses are close, especially given the simplified modeling, with the theoretical calculation higher than the more empirical result.

CONCLUSIONS AND NEXT STEPS

While there are many challenges in applying the systematic approach to investing in public equities to the world of private company investments, we have tried to show that systematic approaches can enhance current private equity investing, in part by increasing breadth. We have also tried to show that public equity data can act as a laboratory for understanding private investing.

We expect systematic approaches to private equity investing to continue to evolve and improve over time and start to gain market share in this asset class of increasing investor interest.

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[14] In a few cases, Vintage Years 2002, 2006, and 2007, we extrapolate to estimate the *IC* rather than interpolate, as even $IC = 0.05$ shows better performance than the index.

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