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WHERE HAVE ALL THE ALPHAS GONE? A META-ANALYSIS OF HEDGE FUND PERFORMANCE

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Where Have All the Alphas Gone? A Meta-Analysis of Hedge Fund Performance

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Abstract:
We examine the factors influencing published estimates of hedge fund performance. Using a sample of 1,019 intercept terms from regressions of hedge fund returns on risk factors (the "alphas") collected from 74 studies, we document a strong downward trend in the reported alphas. The trend persists even after controlling for heterogeneity in hedge fund characteristics and research design choices in the underlying studies. Estimates of current performance implied by best practice methodology are close to zero across all common hedge fund strategies. Additionally, our data allow us to estimate the mean management and performance fees charged by hedge funds. We also document how reported performance estimates vary with hedge fund and study characteristics. Overall, our findings indicate that, while hedge funds historically generated positive value for investors, their ability to do so has diminished substantially.

JEL: J23, J24, J31
Keywords: hedge funds, alpha, fees, meta-analysis, model uncertainty

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Data and code are available in an online appendix at meta-analysis.cz/alphas.

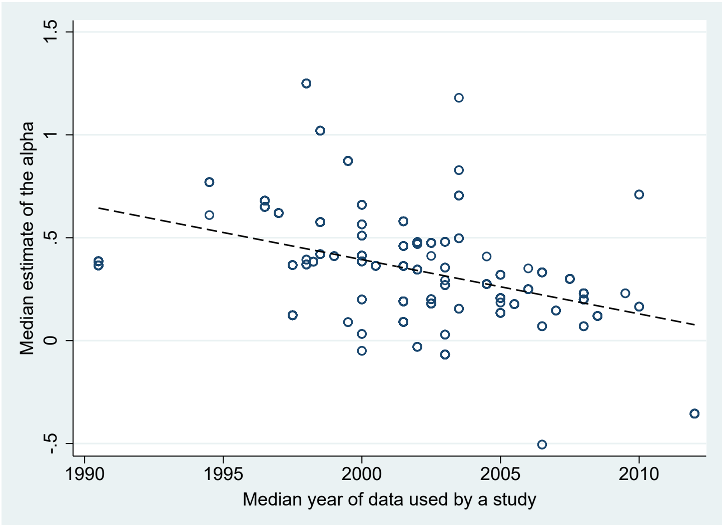
1 Introduction

The prominence of hedge funds in the economy and the capital invested in them has dramatically increased over the past years. Stulz (2007) and Barth *et al.* (2020) document a one-hundred-fold increase in the assets under management (AUM) since the early 1990s. Hedge funds often target high-net-worth individuals and institutional investors, which allows them to take advantage of favorable regulatory requirements and remain rather secretive about their trading strategies (Connor & Woo, 2004; Stulz, 2007; Brown *et al.*, 2018). The surge in hedge funds' popularity and the economic repercussions of some of their notorious failures prompted questions regarding their performance (Connor & Woo, 2004; Stulz, 2007). On the one hand, their relative opacity may let hedge funds better exploit innovative investment strategies, take risks that would otherwise be untenable, and benefit from favorable tax treatment. On the other hand, limited transparency may hamper monitoring by investors, and the substantial management and performance fees may diminish any return they generate (Ben-David *et al.*, 2020). Hence, how much value hedge funds create for investors is ultimately an empirical question.

In this paper, we perform a systematic analysis of prior empirical research on hedge fund performance based on 1,019 intercept terms (i.e., the "alphas") from regressions of returns on risk factors that we collect from 74 empirical studies published between 2001 and 2021. We use a range of meta-analytical techniques that allow us to adjust for potential biases and to simultaneously control for heterogeneity in hedge fund characteristics and research design choices in the underlying studies.

We document a steep decrease in the reported alpha estimates over time. The unconditional sample mean of all alpha estimates is equal to 36 basis points (i.e., 0.36%) on a monthly basis, which corresponds to the annual abnormal return of 4.4% ($= 1.0036^{12} - 1$). The positive mean alpha that we observe is broadly consistent with values reported in prominent prior studies on hedge fund performance Fung & Hsieh (2001); Getmansky *et al.* (2015). Nevertheless, we also observe a strong declining trend in hedge fund alphas that we visualize in Figure 1. The figure shows the median hedge fund alpha reported in a given primary study against the median year of the data used in the study. The dashed line showing the downward-sloping trend crosses the horizontal axis around the year 2015. This suggests that estimates of hedge fund performance based on data samples with a median year greater than 2015 are, on average, negative. Our empirical analysis discussed below establishes this finding stands even after considering various hedge fund characteristics and research design choices in the underlying studies. We also demonstrate that our best practices estimate of

Figure 1: Are markets getting more efficient?



Notes: The vertical axis shows the median estimate of the alpha (hedge funds' excess return) reported in individual studies. The horizontal axis shows the median year of the data used in the studies. The dashed line denotes a linear trend. Outliers are omitted from the figure for ease of exposition but are included in all tests.

hedge funds' current net-of-fees performance is not reliably different from zero. Furthermore, when classifying hedge funds into common categories based on their investment strategies, we observe that the current performance estimate is not significantly positive for any of these categories. Thus, our results suggest that while hedge funds have generated positive value for investors in the past, on average, they no longer do so.

Our multivariate analysis considers several factors related to hedge fund characteristics and research design choices that may affect the magnitude of alpha coefficients reported in prior empirical studies. We show that the reported alpha estimates tend to be lower when: (i) computed net of fees, (ii) estimated for the fund-of-funds, (iii) adjusted for the backfilling bias, (iv) estimated based on the 1-factor model, (v) estimated for the declining "bear" markets, (vi) more source databases are used, and (vii) the CISDM database is not used as a data source.

It is commonly argued that the magnitude of the value generated by hedge funds is substantially affected by the management and performance fees they charge. Ben-David *et al.* (2020) estimate that, on average, hedge funds appropriate in fees almost two-thirds of the excess return they generate. Prior literature also suggests that these fees are difficult to quantify due to their conditional nature. We offer an alternative way of estimating the effective fees paid by hedge fund investors by exploiting the composition of our sample that includes both alphas estimated using gross returns and alphas estimated net of fees. Our indicator variable captures the effective impact of hedge fund fees after controlling for all other relevant characteristics that affect the magnitude of reported alpha estimates. Our regression analysis shows that the indicator variable that captures whether hedge fund performance is estimated on a gross or a net-of-fee basis is the most powerful variable explaining the variation in the reported alpha coefficients. We show that, on average, monthly percentage alphas reported on the net-of-fee basis are 0.439 lower than alphas based on gross returns.

The existing research has frequently voiced concerns that the measurement of hedge fund performance may be distorted by the survivorship and backfilling biases (Fung & Hsieh, 2000, 2002, 2004b; Fung *et al.*, 2008). The backfilling bias arises when hedge funds are included in databases together with their performance history only after succeeding during an "incubation period" intended to accumulate a performance track record before offering the fund to investors. Backfilling performance histories of successful funds introduces a positive bias into the database since the performance of the funds that perform poorly in the incubation period are never recorded in the database (Fung & Hsieh, 2000; Posthuma & Van der Sluis, 2003). The survivorship bias may arise when commercial databases terminate coverage of previously included funds. Providers may wish to purge the database of funds that no longer operate because they are no longer relevant to their clients (Edelman *et al.*, 2013; Getmansky *et al.*, 2015). Hodder *et al.* (2014) report that on average 15% of hedge funds exit the database every year. A bias arises when the funds that exit the database on average underperform the "surviving" funds.

Fung & Hsieh (2000), Fung & Hsieh (2002), and Fung *et al.* (2008) argue that the impact of the backfilling and survivorship biases may be mitigated by using data on the funds of hedge funds (FoFs) because hedge funds included in FoFs must be by definition investable in any given time. Thus, FoFs' returns should adequately reflect even returns of funds that choose not to report their performance to commercial databases and those that cease to exist at some point in time (Posthuma & Van der Sluis, 2003). However, while these are valid arguments, using FoFs' returns generates new problems. FoFs endogenously decide what hedge funds to include in their holdings, which implies that the funds they hold may not be representative of the entire hedge fund population. Furthermore, FoFs charge investors an additional layer of management and performance fees (Stulz, 2007) that reduce the realized return, which may distort the quantification of the abnormal return generated by individual hedge funds (Amin & Kat, 2003a). Brown *et al.* (2005) find that due to the extra layer of fees, individual funds actually dominate FoFs in terms of net-of-fee returns, which makes

FoFs unattractive to investors. Getmansky *et al.* (2015) observe a decline in the number of FoFs over time, which the authors ascribe to their fee structure, competition from multi-strategy funds, and their limited ability to protect investors from losses during financial downturns. Due to these considerations, it is questionable how good a proxy of individual hedge funds' performance FoFs actually are.

In this paper, we offer an alternative approach to estimating the impact of these biases by comparing estimates that adjust for them with those that do not. Consistent with the concerns that these biases may indeed matter for the performance estimates voiced in the prior research literature, our results show that the reported alpha estimates tend to be significantly lower when the research design of the primary studies explicitly adjusts for the backfilling bias. Furthermore, we also observe lower alpha estimates for the fund of funds. Both of these findings are consistent with the proposition that these biases have a meaningful impact on the reported results, and empirical findings in studies that do not adjust for these biases should be interpreted with caution.

Furthermore, one of the major challenges in measuring hedge fund performance is the choice of the appropriate risk model. Hedge funds frequently engage in complex and dynamically evolving investment strategies. Thus, they may exhibit exposures to fundamental risk factors that differ from those that are typical for more conventional asset classes, such as common equities and fixed-income securities. Fung & Hsieh (2001, 2004b); Fung *et al.* (2008) propose a risk model that is specifically designed to capture risk exposures relevant to hedge funds. Given that this model was explicitly designed for measuring hedge fund alpha, it is plausible to expect that it should best capture the risk factors relevant to investment strategies commonly used by hedge funds. Nevertheless, the specificity of this model for hedge fund research also implies that results based on it are not directly comparable to performance estimates of other investment forms, such as mutual funds. Thus, prior hedge fund research also frequently reports alpha estimates based on several other asset pricing models, such as the Capital Asset Pricing Model (CAPM) (Sharpe, 1966; Lintner, 1965; Mossin, 1966; Black, 1972), the three-factor model (Fama & French, 1995, 1996), and the four-factor model (Carhart, 1997). Our results show that the choice of the risk model indeed matters for estimating how much value hedge funds actually create.

Our results also show that the estimates of the value created by hedge funds depend on the market conditions when they are measured. Hedge funds sometimes aspire to be "market neutral", i.e., to generate fairly stable returns regardless of the general stock market conditions. Market neutrality should be valued by investors because robust returns during market downturns help investors diversify away risks. Nevertheless, empirical research does not provide strong support for hedge funds' market neutrality (Capocci *et al.*, 2005; Patton, 2009). We document that hedge fund alphas tend to be lower when estimated for the declining "bear" markets.

Finally, we observe that reported hedge fund alpha coefficients tend to be lower when more databases are used as a source of data in a given primary study, and they are, on average, higher when the CISDM database is used as one of the data sources. These findings suggest that using more comprehensive datasets typically implies reporting lower hedge fund performance. Furthermore, researchers should be aware that alpha estimates based on the CISDM database are commonly higher than those based on other databases.

We make several important contributions to the prior research literature. First, we document that even though hedge funds used to generate positive value for investors in the past, on average, they do not do so anymore. This finding may potentially be driven by several underlying forces. First, the number of hedge funds has steeply increased over time, which may have intensified the competition among them and diminished abnormal returns that the early hedge ones were able to achieve. This explanation would be consistent with the prediction of a rational model of active portfolio management proposed by Berk & Green (2004). The model suggests that when managers have a differential ability to identify profitable investment opportunities with decreasing returns to scale, the likelihood of generating abnormal returns decreases in the volume of resources that these managers allocate. The increasing volume of resources managed by a given hedge fund manager may have, over time, eroded their ability to identify profitable investment opportunities and earn abnormal returns for their investors. These findings are also consistent with Eugene F. Fama's famous quote[1] that suggests that in efficient markets where everything is appropriately priced, hedge funds (that represent an extreme form of active investment management) cannot be expected to generate abnormal returns.

It is also possible that the decrease in hedge fund abnormal performance is due to progressively tighter hedge fund regulation that requires greater transparency. Much tighter hedge fund regulation was enacted in the aftermath of the 2008 financial crisis, in which some considered hedge funds one of the culprits (Fagetan, 2020). Better transparency may reduce monitoring costs to investors and promote better oversight that may discipline hedge fund managers. Some argued that stricter regulation requiring greater transparency may be

[1]Eugene F. Fama: "*I can't figure out why anyone invests in active management, so asking me about hedge funds is just an extreme version of the same question. Since I think everything is appropriately priced, my advice would be to avoid high fees. So you can forget about hedge funds.*" Source: https://www.azquotes.com/quotes/topics/hedge-fund.html.

instrumental in discouraging hedge fund managers from overly aggressive investment strategies based on high leverage and extensive use of financial derivatives that may be particularly damaging in times of market turmoil. In the US, the government proposed the Dodd-Frank Act in 2009, and the registration and greater disclosure requirements became effective in 2012. The EU implemented the Alternative Investment Fund Managers Directive (AIFMD) in 2012. Nevertheless, greater transparency may also reveal some of the funds' proprietary information, make it easier for free riders to imitate successful investment strategies, make it more difficult for hedge fund strategies to reap the benefits of their ideas, and ultimately dilute managerial incentives to innovate (Bianchi & Drew, 2010; Shi, 2017). Furthermore, the new regulation may entail a significant compliance cost that may further depress hedge fund performance (Kamal, 2012; Cumming *et al.*, 2020).

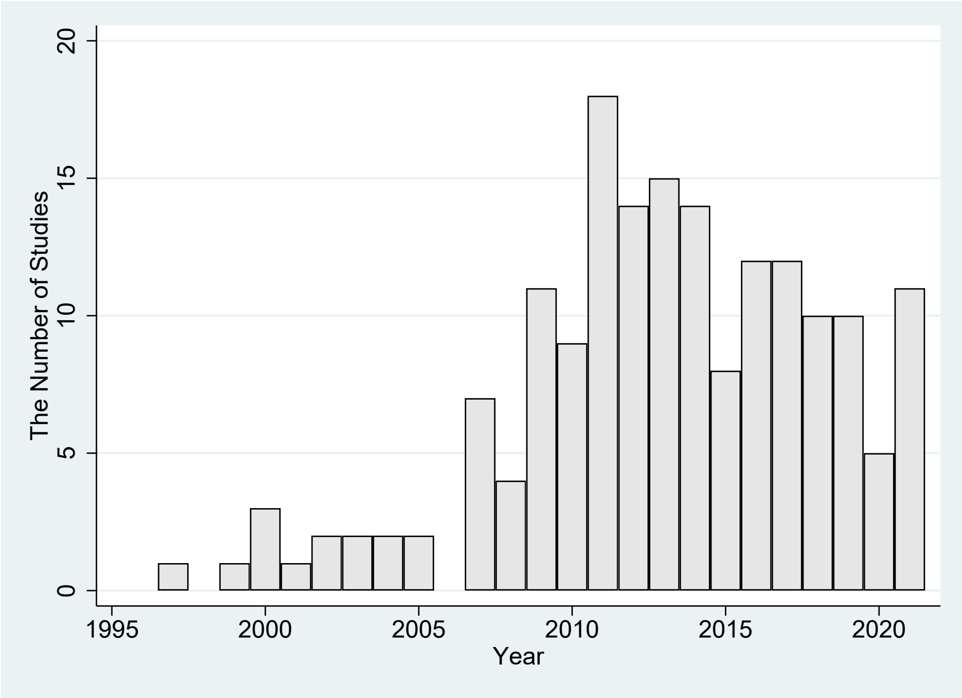
Second, we also provide an alternative approach to estimating the impact of the management and performance fees that hedge funds charge for the value they generate for their investors. These fees tend to be difficult to quantify because their magnitude may depend on a fairly complex set of conditions agreed upon by the investors. Our methodological approach allows us to measure the effective impact these fees have on the realized hedge fund performance.

Third, we identify several research design choices in the primary studies that systematically affect the magnitude of the reported hedge fund alphas. In particular, we show that the estimated alpha coefficients depend on the choice of the asset pricing model. They also depend on the general market conditions during which hedge fund performance is measured. Furthermore, we also show that the reported hedge fund performance estimates are sensitive to the choice of data sources. The reported coefficients tend to be lower when more databases are used as a source of data and are, on average, higher when the CISDM database is used as one of the data sources. These findings help researchers and practitioners interpret prior empirical findings and inform them about the likely impact of their methodology and sample choices in future research.

2 Literature

In the Online Appendix, we discuss the institutional background concerning hedge funds, and we provide an overview of the arguments that discuss whether they are likely to either outperform or underperform other types of investments. We conclude that due to conflicting arguments, it is not *a priori* obvious whether hedge funds, on average, should be expected to generate value for investors. This controversy likely motivated extensive prior

Figure 2: Articles on hedge fund performance



Note: The figure shows the number of research articles that include hedge fund alpha estimates published in the leading journals in finance (*Journal of Finance*, *Journal of Financial Economics*, *Review of Financial Studies*, *Review of Finance*, *Journal of Financial and Quantitative Analysis*).

empirical research on hedge fund performance. Figure 2 shows the number of studies that report hedge fund alphas published in individual years in the prominent research journals in the field of finance – the *Journal of Finance*, the *Journal of Financial Economics*, the *Review of Financial Studies*, the *Journal of Financial and Quantitative Analysis*, and the *Review of Finance*. The figure demonstrates the increased interest in examining hedge fund performance over the past two decades.

The reported estimates of hedge fund performance substantially vary across individual studies. Some of the variation in the published results likely arises due to the use of different methodological approaches. A commonly voiced concern related to the measurement of hedge fund performance is related to the deviations from normality in the distribution of hedge fund returns (Malkiel & Saha, 2005). Several studies explicitly address this issue. Agarwal & Naik (2004) document a significant left-tail risk in a wide range of hedge fund strategies. To account for this left-tail risk, they develop a conditional value-at-risk framework, which shows that the conventional mean-variance measures may underestimate expected left-tail losses by more than half. Amin & Kat (2003a) use an approach that does not require specific characteristics of the underlying returns distribution, and they conclude that the vast majority of individual funds and indices are inefficient relative to the general market index. Also Bali *et al.* (2013) use an approach that accommodates the non-normality in returns distribution. Out of eleven hedge fund indices they consider, they find outperformance only for two of them – the long-short equity and emerging markets hedge fund indices. In a similar vein, Agarwal *et al.* (2009a) document that hedge funds are exposed to the risks associated with the higher moments of their returns distribution and that adjusting for this exposure substantially reduces the observed abnormal performance, especially for equity-based hedge fund strategies.

Another research stream investigates the dependence of hedge fund performance on macroeconomic conditions. Bali *et al.* (2011) report that hedge funds with higher exposure to default risk premium and lower exposure to inflation earn higher returns. Avramov *et al.* (2013) consider four variables related to the macroeconomic conditions: the default spread, the dividend yield, the volatility index (VIX), and the aggregate fund flows into hedge funds, and they show that they predict future hedge fund returns. Similarly, Agarwal *et al.* (2017b) measure hedge funds' exposure to uncertainty about aggregate volatility and they show that funds with low exposure to this uncertainty outperform those with high exposure. Building on these findings that underscore the relevance of macroeconomic conditions for hedge fund performance Bali *et al.* (2014) include measures of macroeconomic uncertainty directly in the risk model used to measure hedge fund performance, and they demonstrate the relevance of most of the macroeconomic factors in this setting.

Related to the macroeconomic conditions, other papers also examine how hedge fund performance depends on conditions in financial markets. Hedge funds sometimes aspire to be "market neutral", i.e., generate fairly stable returns regardless of the general market conditions. Market neutrality should be valued by investors because robust returns during market downturns help investors diversify away risk. Nevertheless, empirical research does not provide strong support for hedge funds' market neutrality. Capocci *et al.* (2005) examine hedge fund performance in bull and bear markets, and they conclude that hedge fund outperformance is concentrated in periods of rising markets. Patton (2009) considers five different ways of measuring market neutrality and he concludes that hedge fund returns tend to be positively correlated with market returns. The author also finds that about one-quarter of funds classified in the market-neutral style exhibit substantial exposure to market risk.

Another reason for the divergence in the reported results may be the data deficiencies that may arise due to the voluntary nature of reporting of hedge fund performance in hedge fund databases. Fung & Hsieh (2000) and Fung & Hsieh (2002) and Fung *et al.* (2008) argue that the impact of these biases may be mitigated by using data on the funds of hedge funds (FoFs). FoFs' returns should not be affected by backfilled returns and they should appropriately reflect returns of hedge funds that decide not to report returns in commercial databases and that cease to exist (Posthuma & Van der Sluis, 2003). However, using FoF returns generates new problems. FoFs endogenously decide on what hedge funds to include in their holdings, which may not be representative of the overall hedge fund population. Furthermore, FoFs charge investors an additional layer of management and performance fees (Stulz, 2007) that reduce the realized return, which may distort the quantification of the abnormal return generated by individual hedge funds (Amin & Kat, 2003a). Brown *et al.* (2005) find that due to the extra layer of fees, individual funds actually dominate FoFs in terms of net-of-fee returns, which makes FoFs unattractive to investors. Getmansky *et al.* (2015) observe a decline in the number of FoFs over time, which the authors ascribe to their fee structure, competition from multi-strategy funds, and their limited ability to protect investors from losses during financial downturns. With fewer available FoFs, any analysis of their holdings and performance is less generalizable for the universe of hedge funds. Thus, the research literature also considers other approaches that we further discuss below.

A self-selection bias arises when successful hedge funds are more likely to report their performance to commercial databases. However, it is not obvious that better-performing funds are always more inclined to report their performance to commercial databases. Some very successful hedge funds may avoid reporting to databases to prevent disclosing clues about their proprietary trading strategies. Furthermore, well-performing hedge funds may reach their capacity limits and they may not seek any additional capital inflows. Such hedge funds may stop reporting performance to databases because they no longer have incentives to advertise themselves among investors (Ackermann *et al.*, 1999). Jorion & Schwarz (2014) indeed find that investment companies act strategically and they list in multiple commercial databases their small, best-performing funds, which helps them raise awareness about the funds and attract new investments (Fung & Hsieh, 1997, 2000). Agarwal *et al.* (2013) examine the impact of self-selection bias by comparing data in five commercial databases with information in Form 13F that are reported quarterly by advisors (rather than funds) with the Securities and Exchange Commission (SEC). They find that even though reporting initiation is more likely after a superior performance, it subsequently declines. They conclude that the differences in performance between the reporting and non-reporting funds are small.

Similarly, Edelman *et al.* (2013) combine previously unexplored data sources with manual data collection to construct a comprehensive dataset of returns earned by large hedge fund management companies. Based on the sample covering more than half of the industry's AUM they observe little differences between the reporting and non-reporting firms. In contrast, Aiken *et al.* (2013) use the mandatory regulatory filings by registered funds-of-funds (FoFs) that are obliged to report their holdings in individual hedge funds. They observe that only about one-half of these fund-level returns are reported to one of the five major hedge funds databases. Comparing the two subsamples they observe that non-database funds significantly underperform funds that report their performance to one of the databases. The result seems to be driven by the left tail of the returns distribution, that is, by funds in decline that quit reporting to databases before their performance further deteriorates.

The backfilling bias or the "instant-history bias" arises when hedge funds are included in databases together with their performance history only after succeeding during an "incubation period" intended to accumulate a performance track record before offering the fund to investors. Recording performance histories of only the successful funds introduces a positive bias into the database (Fung & Hsieh, 2000; Posthuma & Van der Sluis, 2003). To quantify its effect prior research compares returns generated in the first years of hedge fund existence in the database with other years. Estimates based on this approach range between 1.0% and 1.5% per annum (Fung & Hsieh, 2000; Edwards & Caglayan, 2001). Posthuma & Van der Sluis (2003) access additional information on the length of the incubation period in the TASS database and they find the bias to be more prevalent and significant. They observe that a typical incubation period lasts for about 3 years. They also find that more than half of the recorded returns are backfilled, which results in a bias of about 4% per annum. To mitigate the effect, prior research sometimes eliminates the first year of data that are most likely to be affected by the backfilling bias (Kosowski *et al.*, 2007; Teo, 2009; Avramov *et al.*, 2011). Nevertheless, Fung & Hsieh (2009) argue that this approach is problematic. The length of the incubation period may differ greatly and the information on funds' inception dates may be unreliable or missing in the databases. Some hedge funds may also enter the sample due to database mergers. Hence, removing the first year of observations is a rather blunt instrument that also results in a substantial loss of data and impairs the power and generalizability of empirical tests. Similarly, Jorion & Schwarz (2019) suggest that truncating early returns does not resolve the backfilling bias and it can lead to misleading conclusions. They recommend removing returns prior to the listing date and they propose an approach of inferring these dates when they are missing in the database.

The survivorship bias may arise when commercial databases terminate coverage of previously included funds. Providers may wish to purge the database of funds that no longer operate because they are not relevant to their clients anymore. Hodder *et al.* (2014) report that on average 15% of hedge funds exit the database every year. A bias arises when the funds that exit the database on average underperform the "surviving" funds. Edelman *et al.* (2013) and Getmansky *et al.* (2015) argue that two types of hedge funds are likely to stop reporting their performance to databases: those that are no longer attractive to investors and those that do not seek to attract new investors anymore. Funds that approach liquidation after having incurred substantial losses and experiencing an outflow of funds by investors lack the incentive to continue reporting their performance because they are no longer attractive to investors. On the other hand, well-performing funds that approach their capacity limit and no longer seek additional capital inflows also have incentives to quit reporting their performance to databases. Hence, the impact of survivorship bias in the context of hedge funds is not *a priori* quite obvious.

Prior research suggests that database exits due to poor performance tend to be more common. Fung & Hsieh (2000) observe that 60% of defunct funds are liquidated whereas 28% are removed from the database because the managers stopped reporting return information. To estimate the performance of successful funds that may exit the database due to capacity constraints Edelman *et al.* (2013) compare performance of large non-reporting funds identified through an industry survey with funds of comparable size that do report their performance to one of the commercial databases. They observe fairly similar performance for both groups. These findings suggest that databases likely overstate true hedge fund performance. Brown *et al.* (1999) examine survivorship bias in a database of active and defunct offshore funds and observe positive risk-adjusted returns even after adjusting for the bias. Liang (2000) observes that poor performance is the main reason for a fund's disappearance from the databases and finds that the survivorship bias exceeds 2% per annum and it varies with investment styles. Edwards & Caglayan (2001) compare the performance of defunct funds with those that are still in operation and they estimate the impact of the bias at 1.85% per annum. Similarly, Amin & Kat (2003b) estimate the impact of the survivorship bias to be around 2.0% per annum on average, but substantially higher for small, young, and leveraged funds (between 4.0% and 5.0%). Fung *et al.* (2006) estimate the impact of the survivorship bias at 1.8% and 2.4% per annum. In comparison, Agarwal *et al.* (2015) propose a range between 2.0% and 3.6% per annum. They also state that the bias varies across databases, sample periods, and fund characteristics.

The survivorship bias may be expected to decrease over time as databases improve the consistency of their coverage and retain historical data. However, even databases that retain the data for defunct funds may be contaminated by the delisting bias or liquidation bias. Aiken *et al.* (2013) find that about half of the hedge funds continue to operate two years after the delisting date and their returns are 1.8% lower than returns of funds that continue reporting their performance to the database. Edelman *et al.* (2013) argue that the reliability and consistency of performance data provided by hedge funds approaching liquidation often deteriorates, which may prompt data vendors not to record them due to questionable reliability. This implies that even databases that include records for the "dead" funds may miss some of the last performance data that tend to be rather poor. Hodder *et al.* (2014) use estimated portfolio holdings for funds-of-funds and they estimate the average delisting return for all hedge funds of -1.61%. They also find that the negative delisting return is substantially larger for funds with poor prior performance and with no clearly stated delisting reason. Other studies estimate the impact of missing delisting returns on estimates of average hedge fund performance. Edelman *et al.* (2013) estimate the magnitude of the delisting bias at a modest 0.02% per annum. Jorion & Schwarz (2013) exploit the differences in the timing of hedge fund delisting from various databases and estimate the impact of the bias to be at least 0.35% per annum. They suggest that hedge fund indices should be adjusted downward by 0.5% per annum to adjust for the effect.

3 Data

Hedge fund performance is commonly measured by the intercept terms (the "alphas") from regressions of hedge fund returns on risk factors, see Equation 1.

$$(R_p - R_f) = \alpha_p + \sum_{n=1}^{N} \beta_{n,p} \cdot F_n + \epsilon_p \tag{1}$$

where R_p denotes the realized return on portfolio p, R_f denotes the risk-free rate of return, α_p represents the intercept term, F_n represents the n-th risk factor, $\beta_{n,p}$ denotes the sensitivity of portfolio p to the n-th risk factor, and ϵ_p represents the error term. The factor models adjust for the portfolio returns exposure to the systematic risk. The alphas that represent the unexplained portion of the realized return may thus be interpreted as the "abnormal" returns that hedge funds earn for their investors.

Various factor models differ in the set of factors they consider. Thus, the alpha estimates obtained based on the different models may also vary. The simplest approach based on the

Capital Asset Pricing Model (CAPM) (Sharpe, 1966; Lintner, 1965; Mossin, 1966; Black, 1972) uses the difference between the stock market return and the risk-free rate ($R_m - R_f$) as the only risk factor. Notwithstanding the conceptual appeal this approach has, since it models the expected excess return based on an asset's contribution to the overall portfolio risk, which should correctly reflect the relevant risks exposure of well-diversified investors, prior research establishes that the single risk dimension might be too restrictive in capturing all the relevant risk exposures. Thus, the three-factor model (Fama & French, 1995, 1996) and the four-factor model (Carhart, 1997) are frequently proposed as more comprehensive alternative approaches to capturing the systematic risk. Furthermore, due to the complexity of measuring a risk exposure in Hedge funds that frequently engage in complex and dynamically evolving investment strategies, Fung & Hsieh (2004b) propose a model featuring seven factors that are particularly relevant for risk exposures that common hedge fund strategies involve. These seven dimensions involve (i) the stock market excess return, (ii) the spread between the small-capitalization and large-capitalization stock returns, the excess return pairs of look-back call and put options (iii) on currency futures, (iv) on commodity futures, and (v) on bond futures, (vi) the duration-adjusted change in the yield spread of the U.S. 10-year Treasury bond over the 3-month T-bill, and (vii) the duration-adjusted change in the credit spread of Moody's BAA bond over the 10-year Treasury bond.

We collect our sample of hedge fund alphas from peer-reviewed research articles published between January 1, 2001, and September 1, 2021. The alpha estimates are the intercept terms from regressions of hedge fund returns on risk factors. The alphas represent risk-adjusted returns generated by hedge funds, which makes them comparable and suitable for aggregation by means of a meta-analysis. We ensure that all the alphas are expressed as a percentage, and we normalize them by dividing annual and quarterly alphas by twelve and three, respectively. We consider only published estimates as these successfully cleared the peer-review process that assures the quality of published findings. This increases the likelihood that the alphas we consider are estimated using established methodologies and free of error. In addition, estimates published in academic journals likely represent empirical evidence that is most influential in shaping the views of investment professionals and academics on hedge fund performance.

Our procedure of identifying primary studies, from which we source the alpha estimates, follows the guidelines proposed by Havranek *et al.* (2020). We outline the procedure in Figure A1. First, we consider studies cited in two prominent reviews of empirical research on hedge fund performance: Connor & Woo (2004) and Agarwal *et al.* (2015). We then perform a systematic Google Scholar search based on the following combinations of keywords: "hedge fund returns" OR "hedge fund performance". To ensure that our search has a good coverage of relevant articles we verify that the used combination of keywords identifies the vast majority of studies cited in the two above-mentioned review articles. We go through the first 750 articles in the Google Scholar list and we manually collect hedge fund alpha estimates reported in them. We terminate our screening of primary studies after having covered the first 750 articles from the Google Scholar list because we observe that after this point, the relevance of articles substantially decreases and the likelihood of finding additional usable alpha estimates is rather small in articles further down in the list.

We further complement our main keyword search with another search that is more general in the combination of used keywords: "hedge fund" OR "hedge funds", and that is limited to five journals where empirical research on hedge fund performance is likely to be published: the *Journal of Finance*, the *Journal of Financial Economics*, the *Review of Financial Studies*, the *Journal of Financial and Quantitative Analysis*, and the *Review of Finance*. Finally, to ensure comprehensive coverage of estimates published in journals aimed primarily at investment professionals, we perform the third - search using the following keywords: "hedge fund" OR "hedge funds" in the journals listed on the Portfolio Management Research website[2]: the *Journal of Portfolio Management*, the *Journal of Financial Data Science*, the *Journal of Impact and ESG Investing*, and the *Journal of Fixed Income*.

In our multivariate analysis, we build on the companion paper Yang *et al.* (2023), who investigate the impact of the publication selection bias in hedge fund research and we control for selectivity in reporting alpha coefficients. This requires a measure of the precision of collected alpha estimates. Consequently, we only collect alpha estimates accompanied by a measure of statistical significance, i.e., a t-statistic, a standard error (SE), and/or a p-value. When more than one measure of statistical significance is provided, we apply the following procedure. We collect corresponding t-statistics directly from the primary studies whenever available. When standard errors are reported, we compute the t-statistic by dividing the alpha by its standard error. Correspondingly, in Bayesian studies, we approximate the t-statistic by dividing the alpha by its standard deviation. When a primary study reports p-values, we check if the paper discusses whether these are based on one-tailed or two-tailed tests. When the information on the type of the test is not explicitly stated, we try to infer it from the discussion of the statistical significance of reported results. We assume a two-tailed test whenever the type of the test cannot be ascertained from the discussion

[2]Source: https://www.pm-research.com/).

Table 1: Studies included in the meta-analysis

Agarwal *et al.* (2017a)	Edelman *et al.* (2013)	Malladi (2020)
Ahoniemi & Jylha (2014)	Edwards & Caglayan (2001)	Meligkotsidou & Vrontos (2008)
Aiken *et al.* (2013)	Eling & Faust (2010b)	Mitchell & Pulvino (2001)
Ammann & Moerth (2005)	Frydenberg *et al.* (2017)	Mladina (2015)
Ammann & Moerth (2008a)	Fung & Hsieh (2004b)	Molyboga & L'Ahelec (2016)
Ammann & Moerth (2008b)	Fung & Hsieh (2004a)	Mozes (2013)
Aragon (2007)	Fung *et al.* (2002)	Patton & Ramadorai (2013)
Asness *et al.* (2001)	Fung *et al.* (2008)	Racicot & Theoret (2009)
Bali *et al.* (2013)	Gupta *et al.* (2003a)	Racicot & Theoret (2013)
Bhardwaj *et al.* (2014)	Hong (2014)	Racicot & Theoret (2014)
Blitz (2018)	Huang *et al.* (2017)	Ranaldo & Favre (2005)
Bollen & Whaley (2009)	Ibbotson *et al.* (2011)	Diez De Los Rios & Garcia (2011)
Brown (2012)	Jame (2018)	Rzakhanov & Jetley (2019)
Buraschi *et al.* (2014a)	Joenvaara & Kosowski (2021)	Sabbaghi (2012)
Cao *et al.* (2016)	Joenvaara *et al.* (2019)	Sadka (2010)
Chen & Liang (2007)	Jordan & Simlai (2011)	Sadka (2012)
Chen *et al.* (2017)	Jylha *et al.* (2014)	Sandvik *et al.* (2011)
Chincarini & Nakao (2011)	Kanuri (2020)	Stafylas *et al.* (2018)
Clark & Winkelmann (2004)	Klein *et al.* (2015)	Stafylas & Andrikopoulos (2020)
Dichev & Yu (2011)	Kooli & Stetsyuk (2021)	Stoforos *et al.* (2017)
Ding & Shawky (2007)	Kosowski *et al.* (2007)	Sullivan (2021)
Ding *et al.* (2009)	Kotkatvuori-Ornberg *et al.* (2011)	Sun *et al.* (2012)
Do *et al.* (2005)	Liang (2004)	Teo (2009)
Duarte *et al.* (2007)	Ling *et al.* (2015)	Vrontos *et al.* (2008)
Edelman *et al.* (2012)	Lo (2001)	

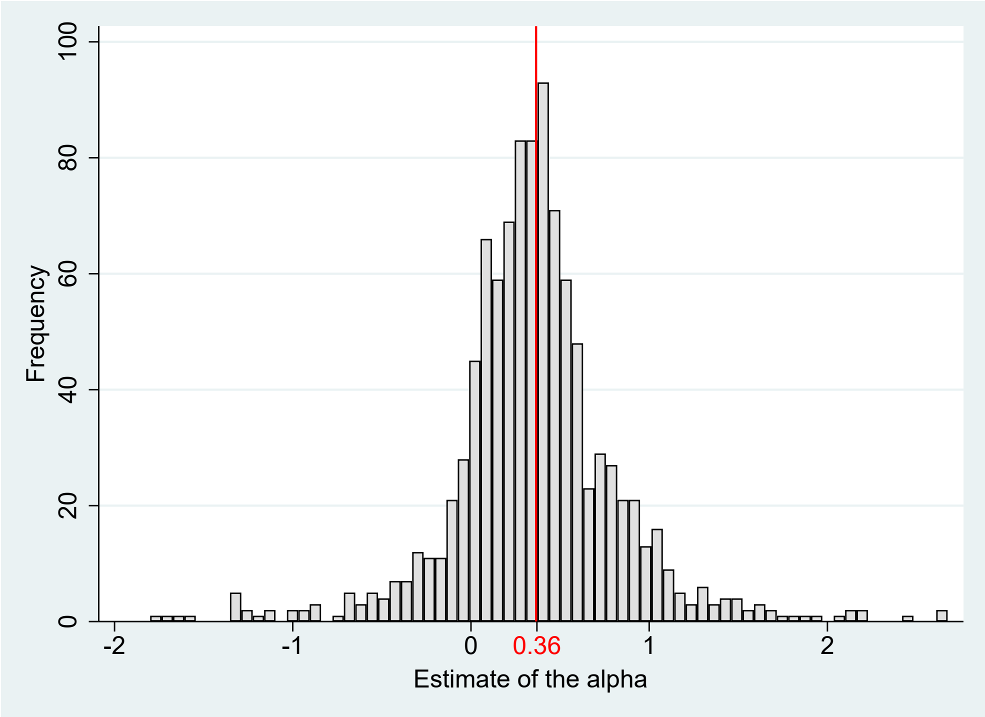
Notes: The table shows the list of 74 primary studies, from which we collect the alpha estimates that constitute our sample.

of statistical significance (1 study). We manually verify that all the coefficients with the implied t-statistic greater than 10 are referred to as highly significant in the text of primary studies. We discard 1 observation with a reported t-statistic greater than 50.

Table 1 provides a list of 74 primary studies identified by our data collection procedure. From these research articles we collected 1,019 alpha estimates that constitute the sample for our empirical analysis. The number of data points makes our study one of the largest meta-analyses in finance. The substantial number of primary studies on this topic and the number of reported alpha coefficients imply that hedge fund performance has been extensively studied in prior research and the alpha coefficients have been estimated in a variety of ways with the use of various data samples. It thus seems worthwhile to aggregate the results from diverse studies by means of a meta-analysis.

Figure 3 shows a histogram of the alpha estimates that constitute our sample. Consistent with the expectations, the distribution approaches normality. It is fairly symmetric, smooth, and free of apparent discontinuities, which indicates that our data sample exhibits the expected characteristics. The vertical red line in Figure 3 denotes the unconditional sample mean. It depicts a mean monthly alpha of 0.36%, which corresponds to an annual risk-

Figure 3: Distribution of alpha estimates



Notes: The figure depicts a histogram of our sample of 1,019 alpha estimates that we collect from 74 primary studies on hedge fund performance. The vertical red line denotes the sample mean.

adjusted return of 4.32%. This number falls within ranges of alpha estimates reported in several prominent prior studies on hedge fund performance. For example, the alpha estimates based on the Fung & Hsieh (2001) seven-factor model reported by Getmansky *et al.* (2015) range from 0.18% to 0.56%. This increases the confidence that our sample is not biased and it is representative of the population of alpha estimates that are reported in prior literature.

At the same time, Figure 3 reveals a substantial variance in the reported alpha coefficients. This suggests that even though the mean value of alpha estimates that we collect from the primary studies falls within the commonly proposed range, the individual reported estimates are quite heterogeneous. Many estimates reported in prior studies substantially deviate from these common values. This suggests that it is worthwhile to aggregate these estimates in a meta-analysis and investigate how the values vary with different hedge fund characteristics and research design choices of individual studies. We perform such an analysis in this paper.

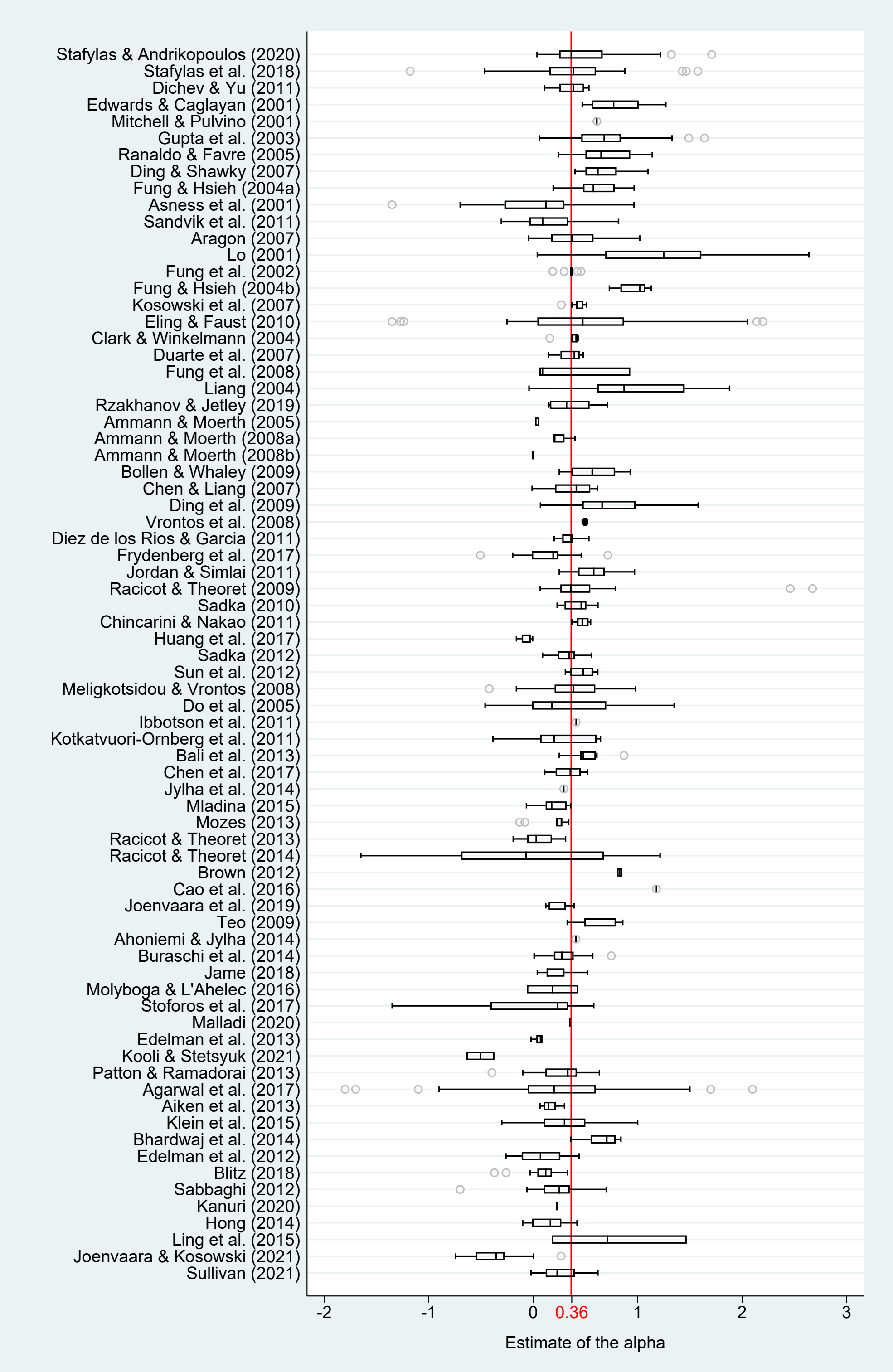
In Figure 4, we first examine how the range of reported alpha coefficients vary across the individual primary studies. For each primary study, the figure shows the median alpha estimate and their interquartile range represented by the box. The whiskers denote the minimum and the maximum values within the 1.5 times the range between the upper and lower quartiles. Figure 4 shows considerable variation in the reported alpha coefficients both within and across studies. While the interquartile ranges for some studies are fairly narrow, other studies exhibit interquartile ranges that exceed 1 percentage point of monthly returns, which corresponds to an annual return of 12%. Furthermore, interquartile ranges of some studies do not cross the vertical line representing the unconditional sample mean of 0.36%, which implies that the alpha coefficients reported in these studies substantially deviate from the values typical in the entire pool of research on hedge fund performance.

In Figure 4, the 74 primary studies are sorted by the median age of the underlying data, with the oldest samples at the top and the newer samples at the bottom of the figure. This figure thus provides the first preliminary evidence suggesting that hedge fund performance declined over time. The interquartile ranges of many of the studies using older samples exceed the unconditional sample mean, while for the more recent studies, the interquartile ranges tend to be below it. We explore the tendency of primary studies based on newer data sets to report lower alphas further in the following analysis.

Figure 5 visualizes the distribution of alpha estimates generated by hedge funds covering various geographic areas. Most of the hedge funds we study are global funds. Thus, unsurprisingly, the median alpha estimate for global funds virtually coincides with the unconditional sample mean. Furthermore, alphas generated by the global funds have a relatively narrow interquartile range that is below 0.5%. This implies that most global funds in our sample generate abnormal annual returns between 0.2% and 0.6%. Similarly, funds that concentrate on the U.S. and Canada have a median return very close to the full sample mean and a fairly narrow interquartile range. Figure 5 also provides some indication that Australian, Indian, Japanese, and Latin American funds tend to generate somewhat lower alphas than their global counterparts. In contrast, Chinese, Korean, East European, Middle-Eastern, and North African funds, on average, generate somewhat higher alphas. However, most of these findings are based on a rather small number of observations. Furthermore, these descriptive statistics do not control for hedge funds' fundamental characteristics and differences in research design choices that may vary systematically across the primary studies. Thus, these findings should be considered preliminary. We delay drawing stronger conclusions about these characteristics till Section 4, where we perform a comprehensive analysis that investigates the combined effect of these characteristics.

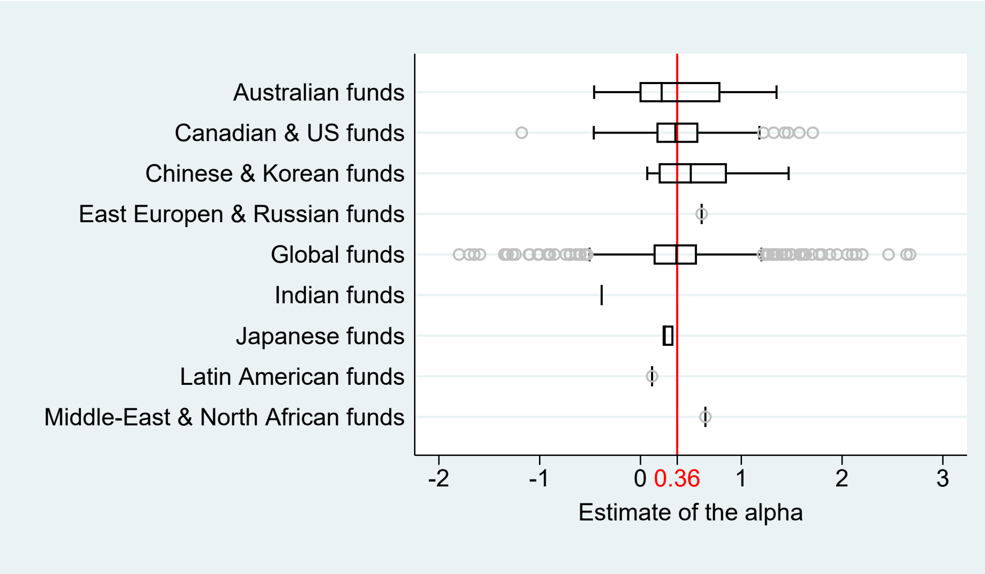
We consider several measures related to hedge fund fundamental characteristics and research design choices in the primary studies that may be relevant for explaining the cross-

Figure 4: Reported alphas differ both across and within studies



Notes: The figure depicts the distribution of the alpha estimates in the individual primary studies sorted by the age of the underlying data. The length of each box represents the interquartile range (percentile 25, percentile 75). The vertical line inside the box depicts the median value. The whiskers represent the highest and lowest data points within 1.5 times the range between the upper and lower quartiles. The vertical line denotes sample mean. For ease of exposition, outliers are excluded from the figure but included in all statistical tests.

Figure 5: Reported alphas differ across and within regions



Notes: The figure depicts the distribution of the alpha estimates across various geographic scopes covered by hedge funds. The length of each box represents the interquartile range (percentile 25, percentile 75). The vertical line inside the box depicts the median value. The whiskers represent the highest and lowest data points within 1.5 times the range between the upper and lower quartiles. The vertical line denotes sample mean. For ease of exposition, outliers are excluded from the figure but included in all statistical tests.

sectional variation in the value generated by hedge funds. Table A1 provides the definition and descriptive statistics for the explanatory variables that we use in our regression analysis. Since the determinants of hedge fund performance are not *a priori* known, we consider several "candidate" variables, and we examine how effective various combinations of these variables are in explaining the heterogeneity in the alphas reported in primary studies. For each variable Table A1 includes the definition, the unweighted mean value (Mean), the standard deviation (SD), and the mean weighted by the inverse of the number of estimates reported per study (WM), which gives all of the 74 primary studies equal weight. Many of our independent variables are indicators, and so the mean values represent the proportion of alpha estimates for which a given variable is coded as 1.

Consistent with our earlier findings, Table A1 shows that the mean value of the alpha estimates in our sample is 0.362. The mean value does not substantially change when the individual observations are weighted by the inverse of the number of estimates reported per study (WM = 0.365). The distribution of alpha estimates is fairly dispersed, with the standard deviation of 0.477. To adjust for a potential publication selection bias, we collect from the primary studies the alpha estimates' standard error (SE). Since prior literature shows that estimates based on instrumental variables (IV) tend to be less precise than coefficients estimated using different techniques Brodeur *et al.* (2020b), we interact SE with an indicator variable equal to 1 for alpha coefficients estimated using IV.

Table 2 shows summary statistics for groups of alpha estimates determined by our conditioning variables. In the left panel, the individual alpha estimates are weighted equally. In the right panel, the alphas are weighted by the inverse of the number of estimates reported in a given study, which gives each of the 74 primary studies (rather than each of the 1,019 alphas estimates) equal weight in computing the mean value and the 95% confidence interval.

Table 2 shows some variation in the reported alpha estimates based on how the primary study aggregates hedge fund returns. Specifically, treating all estimates in our sample equally, reported alphas for value-weighted hedge fund indices tend to be lower than those documented for individual funds. In contrast, reported alpha estimates for equally weighted hedge fund indices are, on average, somewhat higher. Since returns on value-weighted hedge fund indices are disproportionately driven by the performance of large hedge funds, this finding suggests smaller hedge funds tend to generate larger alphas than larger hedge funds. We consider this finding rather intuitive and consistent with the prediction of a rational model of active portfolio management proposed by Berk & Green (2004) that assumes a differential ability to identify profitable investment opportunities across fund managers, but decreasing returns to scale in deploying these abilities. The model suggests that for any given level of a fund manager's ability, the likelihood of generating abnormal returns decreases in the volume of resources that these managers allocate. In other words, managers of smaller hedge funds may find it easier to implement their investment strategy because suitable investment targets are easier to identify when the scope of their investment is smaller. Hence, smaller hedge funds may outperform larger funds.

Table 2 also suggests that the reported alpha estimates greatly vary with the treatment of hedge fund fees in the research design of a primary study. Most of the primary studies from which we collect our data sample report alpha estimates on a net-of-fee basis. The unweighted (weighted) mean value of these net-of-fee alphas is 0.348 (0.335). In comparison, the alpha estimates based on gross returns are more than twice as large. Specifically, the unweighted (weighted) mean gross alphas is 0.757 (0.817). This finding is consistent with prior literature that points out the substantial fees that hedge funds charge (Connor & Woo, 2004; Malkiel & Saha, 2005). These fees typically consist of a flat management fee of 1% to 2% of assets under management (AUM) and a variable performance fee usually 20% of realized returns above the risk-free rate (Fung & Hsieh, 1999; Connor & Woo, 2004; Stulz, 2007;

Table 2: Alphas in different contexts

		Unweighted			Weighted		
	No. of observations	Mean	95% conf. int.		Mean	95% conf. int.	
Aggregation of returns							
Individual funds	175	0.385	0.326	0.444	0.317	0.263	0.370
Equal-weighted funds	503	0.427	0.380	0.474	0.393	0.353	0.433
Value-weighted funds	341	0.256	0.213	0.298	0.357	0.314	0.399
Treatment of fees							
Net-of-fee returns	984	0.348	0.319	0.377	0.335	0.310	0.360
Gross returns	35	0.757	0.534	0.980	0.817	0.655	0.979
Data structure							
Cross-section data	855	0.355	0.322	0.388	0.379	0.349	0.409
Longitudal data	164	0.401	0.345	0.456	0.324	0.271	0.377
Source database							
Database: default	537	0.343	0.309	0.376	0.301	0.272	0.330
Database: CST	256	0.218	0.166	0.271	0.273	0.229	0.316
Database: CISDM	178	0.434	0.354	0.514	0.386	0.319	0.452
Database: hand-collected	22	0.411	0.263	0.559	0.576	0.356	0.796
Database: other	167	0.409	0.311	0.507	0.460	0.373	0.548
Market coverage							
Developed markets	140	0.388	0.315	0.461	0.462	0.393	0.530
World markets	879	0.358	0.326	0.390	0.350	0.322	0.378
Market conditions							
Bull market	39	0.272	0.199	0.346	0.277	0.206	0.347
Bear market	39	0.103	-0.006	0.211	0.097	-0.007	0.201
Hedge fund strategy							
Strategy: all funds	243	0.303	0.255	0.351	0.298	0.258	0.339
Strategy: equity hedge	229	0.352	0.286	0.418	0.360	0.296	0.424
Strategy: event driven	113	0.474	0.378	0.570	0.586	0.496	0.676
Strategy: relative value	94	0.294	0.215	0.373	0.401	0.329	0.473
Strategy: global	156	0.451	0.354	0.549	0.431	0.341	0.520
Strategy: fund of funds	67	0.298	0.208	0.389	0.243	0.156	0.331
Strategy: multi	40	0.347	0.198	0.496	0.345	0.209	0.481
Strategy: other	77	0.383	0.288	0.477	0.385	0.309	0.462
Risk model							
1-factor model	167	0.461	0.393	0.530	0.420	0.358	0.482
3-factor model	71	0.463	0.344	0.581	0.446	0.347	0.545
4-factor model	205	0.247	0.183	0.311	0.313	0.250	0.376
7-factor model	298	0.289	0.237	0.342	0.297	0.254	0.340
Modeling model uncertainty	142	0.313	0.240	0.385	0.392	0.325	0.459
Asset-based model	80	0.324	0.255	0.392	0.250	0.185	0.314
Other model	56	0.933	0.799	1.067	0.906	0.773	1.039
Treatment of biases							
Survivorship treated	587	0.330	0.289	0.371	0.321	0.286	0.357
Backfilling treated	307	0.264	0.205	0.322	0.315	0.265	0.365
No bias treated	414	0.412	0.369	0.455	0.450	0.411	0.489
Some bias treated	605	0.329	0.289	0.368	0.318	0.284	0.352
Estimation technique							
IV method	46	0.463	0.340	0.586	0.435	0.302	0.568
non-IV method	973	0.358	0.327	0.388	0.364	0.337	0.390
All estimates	1,019	0.362	0.333	0.392	0.365	0.339	0.391

Notes: The table reports summary statistics for the different subsets of alpha estimates reported the literature. The definition of the the individual variables is available in Table A1. In the left panel, the individual alpha estimates are weighted equally. In the right panel, the alphas are weighted by the inverse of the number of estimates reported in a given study. Each panel shows the mean value and the 95% confidence interval.

Kouwenberg & Ziemba, 2007; Getmansky *et al.*, 2015). The performance fee tends to be paid only after reaching the so-called "high water mark", i.e., the minimum level of absolute performance over the entire investment lifetime (Asness *et al.*, 2001; Goetzmann *et al.*, 2003; Lim *et al.*, 2016; Stulz, 2007), that is to say, only after recovering any previously incurred losses. However, managers of unsuccessful hedge funds may opt to close the fund down, which renders any "high water mark" provision irrelevant (Stulz, 2007). Our results show that unweighted net-of-fee returns account for 46 percent of gross returns while the weighted proportion is around 41 percent. The implied performance fee is slightly higher than 50 percent of gross returns, which is close to the estimation that the effective performance fees approach 64 percent of the aggregate gross profits in Ben-David *et al.* (2020).

Table 2 also shows that, on average, the magnitude of reported alpha estimates is not dramatically affected by the structure of the data used for the empirical tests in the primary studies. Both the cross-sectional and longitudinal data yield similar alpha estimates (0.355 and 0.401 on an unweighted basis and 0.379 and 0.324 on a weighted basis). The alpha estimates based on longitudinal data exhibit some difference between the simple unweighted and the weighted mean, which implies that the unweighted mean is affected by several studies that report high alphas.

Given the voluntary nature of reporting information on hedge funds, we consider it likely that prior empirical results might be affected by the choice of the database used by the researchers to obtain hedge fund performance data. Table A1 indicates that many of the primary studies are based on data from a single database. The mean number of databases that our alpha coefficients are based on is 1.366. This suggests only a limited overlap between data samples in various studies, and it underscores the benefit of aggregating and integrating prior empirical results on hedge fund performance based on these diverse samples.

Table 2 also reveals some differences in reported alpha estimates resulting from the use of databases used as a source of hedge fund performance data in individual primary studies. Most alphas in our sample are based on four commonly used databases: (1) Thomson/Refinitiv Lipper Hedge Fund (TASS), (2) Hedge Fund Research (HFR), (3) BarclayHedge, and (4) EurekaHedge database. TASS is a popular database in hedge fund research as it provides data starting from 1990, and it is available to many academics through their institutional data sources and libraries (e.g., Princeton University Library, Wharton Research Data Service of the University of Pennsylvania). HFR was established in 1992. It provides a detailed hedge fund strategy classification that is used in many studies that analyze the performance of various subsets of hedge funds. Prior empirical research also uses the multiple industry and regional hedge fund performance indices that are provided by HFR. BarclayHedge was founded in 1985. Returns on alternative investments and information on hedge fund performance are among the key data types provided in the database. Eureka-Hedge was established more recently in 2001, but it offers wider coverage of live hedge funds than the competing data providers. Hence, it is frequently used in empirical studies covering international hedge funds. More than half of our hedge fund alpha estimates (specifically 537) use one of the four main databases as a data source. Due to their popularity in prior empirical research, we classify into one category all alpha estimates that are based on the data sourced from these four main databases.

Furthermore, about one quarter of the alpha estimates in our sample (specifically, 256) are based on the data from the Dow Jones Credit Suisse Hedge Fund Index (formerly known as the Credit Suisse/Tremont Hedge Fund Index) (CST) database. Less than a fifth of alphas (specifically, 178) are based on the Morningstar Center for International Securities and Derivatives Markets database (CISDM), which is affiliated with the Isenberg School of Management, and it is also accessible through Wharton Research Data Service by many academic researchers. It provides data after 1994 but it is updated only twice a year. Our Data set also comprises 22 alpha estimates based on hand collected data End additional 167 estimates based on other than aforementioned databases.

Table 2 shows that alpha estimates based on the four most popular databases in hedge fund research are very close the the unconditional sample mean of 0.36 discussed above. The unweighted mean of alphas based on these four databases is equal to 0.343. When we weigh the alpha coefficients in our sample by the inverse of the number of estimates reported in a given primary study, we observe a slightly lower mean value of 0.301. Relative to the alphas based on the four most popular databases, estimates based on CST are somewhat lower (0.218 on an unweighted basis, and 0.273 on a weighted basis). In contrast, alphas based on CISDM, on other databases, and also those based on hand-collected data tend to be higher. These findings suggest that, except CISDM, alpha estimates based on less frequently used databases tend to be higher.

Table A1 also shows that 86% of alpha estimates are based on hedge funds that do not restrict the geographic scope of their investment, whereas 14% are based on funds focused on the developed markets as classified by the International Monetary Fund (IMF). Table 2 shows slightly better performance for funds that invest in developed markets as classified by the International Monetary Fund (IMF) relative to those that do not explicitly restrict their scope to a specific geographical location. This result may be considered surprising given that more developed markets may contain fewer mispriced assets and offer fewer opportunities to earn abnormal returns. Our regression results in Section 4 show that this difference is not statistically significant in a multivariate setting.

We also observe in Table 2 that alpha estimates based on "bear" (i.e., declining) markets are lower (mean values of 0.103 and 0.097 on the unweighted and weighted basis, respectively) than studies that concentrate on "bull" (i.e., rising) (mean values of 0.272 and 0.277 on the unweighted and weighted basis respectively). Thus, despite their name, hedge funds do not seem to hold investment positions that make their returns immune to general stock market movements (i.e., to be market-neutral).

Table 2 also exhibits some differences in the alphas generated by various hedge fund strategies. Our data set comprises 243 alpha estimates based on the data of all funds. The mean values in the most frequent category of alphas are slightly below the unconditional mean of 0.36 (mean values of 0.303 and 0.298 on the unweighted and weighted basis, respectively). Equity hedge funds constitute the largest category of specialized hedge funds. We collect 229 alpha estimates for this type of funds. The mean alphas in this category are very close to the unconditional mean of 0.36 (mean values of 0.352 and 0.360 on the unweighted and weighted basis, respectively). This suggests that equity the performance of equity hedge funds corresponds to the overall performance of all hedge fund categories.

In comparison, we observe that event-driven hedge fund strategies, on average, generate higher alphas (mean values of 0.474 and 0.586 on the unweighted and weighted basis, respectively), followed by global strategies (mean values of 0.451 and 0.431 on the unweighted and weighted basis, respectively). In contrast, reported alpha estimates based on the funds of funds tend to be lower (mean values of 0.298 and 0.243 on the unweighted and weighted basis, respectively). This finding may be driven by the additional layer of fees that are charged by the funds of funds or by the lower effect of the backfilling and survivorship biases that may inflate some of the alpha estimates based on the individual funds.

Table 2 also suggests that the choice of the risk model used in primary studies to adjust for the normal rate of returns may be consequential for the documented alphas. Fung & Hsieh (2001, 2004b) and Fung *et al.* (2008) observe that hedge funds typically exhibit risk exposures that are not typical for other asset classes, such as common equities and fixed-income securities. They propose a seven-factor model that reflects risk factors that are intended to capture risk dimensions that are relevant to common hedge fund investment strategies. The authors argue that the multiplicity of these risk dimensions makes the seven-factor model suitable for measuring abnormal returns across a wide range of hedge fund strategies. Being designed specifically for measuring hedge fund performance, the seven-factor model has been extensively used in prior empirical research. Table A1 shows that 29% of alpha estimates in our sample are based on the seven-factor model (e.g., Fung & Hsieh, 2004b; Buraschi *et al.*, 2014b; Fung *et al.*, 2008; Kosowski *et al.*, 2007). Table 2 shows that the mean values of these alpha estimates are slightly below the unconditional mean of 0.36 (mean values of 0.289 and 0.297 on the unweighted and weighted basis, respectively).

Prior hedge fund research also frequently reports alpha estimates based on several other asset pricing models that are commonly used to measure abnormal returns. The Jensen (1968) alpha based on the Capital Asset Pricing Model (CAPM) (Sharpe, 1966; Lintner, 1965; Mossin, 1966; Black, 1972) uses the equity market excess return ($R_m - R_f$) as the sole risk factor. Conceptually, the intercept term alpha represents the abnormal return to a well-diversified investor. On the one hand, this approach is simple, well-founded in financial theory, and universally applicable. On the other hand, the assumptions this approach is based on may not be suitable for measuring the performance of hedge funds that engage in complex and dynamic investment strategies that are likely to exhibit various forms of exposure to systematic risk. In this respect, the three-factor, and the four-factor models capture additional risk dimensions that may not be easy to conceptualize in a financial modeling framework, but that may still be relevant to investors due to financial market imperfections and microstructure considerations (e.g., limited liquidity of traded assets).

Table A1 shows that 20% of alphas are based on the four-factor model (Eling & Faust, 2010a; Stoforos *et al.*, 2017; Fung & Hsieh, 2003), 7% are based on the three-factor model (Dichev & Yu, 2011; Ding & Shawky, 2007), and 16% are based on the 1-factor model (Ranaldo & Favre, 2005; Ding & Shawky, 2007; Gupta *et al.*, 2003b). Table 2 shows that, relative to the seven-factor model, the alpha coefficients estimated with the use of pricing models using fewer risk factors are typically higher. The difference is particularly pronounced for the one-factor (mean values of 0.461 and 0.420 on the unweighted and weighted basis, respectively) and three-factor models (mean values of 0.463 and 0.446 on the unweighted and weighted basis, respectively). In contrast, the alpha coefficients based on the four-factor model (mean values of 0.247 and 0.313 on the unweighted and weighted basis, respectively) are comparable to the ones based on the seven-factor model. Furthermore, we also observe rather high values for the 56 alpha coefficients reported in primary studies that use other pricing models (mean values of 0.933 and 0.906 on the unweighted and weighted basis, respectively). As the choice of the pricing model is likely related to other research design choices, we delay drawing stronger conclusions from these findings to Section 4, where we examine the effect of these conditioning factors in combination.

Prior research frequently mentions concerns that the measurement of hedge fund performance may be distorted by the survivorship and backfilling biases (Fung & Hsieh, 2000, 2002, 2004b; Fung *et al.*, 2008). Table 2, indeed, shows that the alpha estimates reported in primary studies tend to be higher when the authors do not explicitly adjust for the survivorship and backfilling bias (mean values of 0.412 and 0.450 on the unweighted and weighted basis, respectively) as compared to the alpha estimates, for which at least one of the biases is addressed (mean values of 0.329 and 0.318 on the unweighted and weighted basis, respectively). This finding suggests that the commonly voiced concerns about the impact of those biases are indeed warranted, and they may indeed have a substantial impact on the inferences about hedge fund performance.

Finally, we also observe some variation in the magnitude of reported alphas depending on the use of various estimation techniques. Brodeur *et al.* (2020a) suggests that estimates based on instrumental variable (IV) techniques often exhibit greater publication selection bias. They argue that using IV gives researchers an additional layer of discretion because the pool of potentially relevant instruments is rather broad. Thus, researchers may choose instruments that yield results that support their *a priori* predictions or that are otherwise attractive for publication. This approach may induce a greater selectivity in coefficients that eventually get published. Consistent with this proposition, Table 2 shows that alphas reported in the primary studies tend to be higher when estimated based on IV (mean values of 0.463 and 0.435 on the unweighted and weighted basis, respectively) relative to those estimated using other techniques (mean values of 0.358 and 0.364 on the unweighted and weighted basis, respectively). However, the IV-based estimates are less precise so the 95% confidence intervals are rather wide, and they include the unconditional mean of 0.36 both on the unweighted basis (0.340, 0.586) and on the weighted basis (0.302, 0.568).

We also consider the impact factor of the journal where the study is published and the number of times it is cited as additional potentially relevant explanatory variables. The impact factor of a research journal and the number of citations can both be seen as proxies of publication quality. We expect studies published in more impactful journals and those that are more frequently cited to be more influential in shaping the public perception of the value generated by hedge funds. Table A1 shows that the mean number of databases that Primary studies, from which we source our alpha estimates, are published in research journals with the average discounted recursive impact factor by Research Papers in Economics (RePEc) of 4.0, and they are on average cited 5.9 times (=exp(1.773)).

Figure 6 shows histograms for subsets of reported alpha estimates with specific characteristics related to the estimation method, sources of data, and hedge fund strategies. Panel (a) shows the greater dispersion of alpha estimates based on IV. Panel (b) depicts the dispersion of alphas based on hedge funds that concentrate on developed markets. Panel (c) shows lower alpha estimates based on value-weighted hedge fund indices. Panel (d) depicts lower alphas reported after explicitly adjusting for the survivorship and/or backfilling biases. Panels (e) and (f) show the distribution of alpha coefficients for the various asset pricing models and the various hedge fund investment strategies.

4 Results

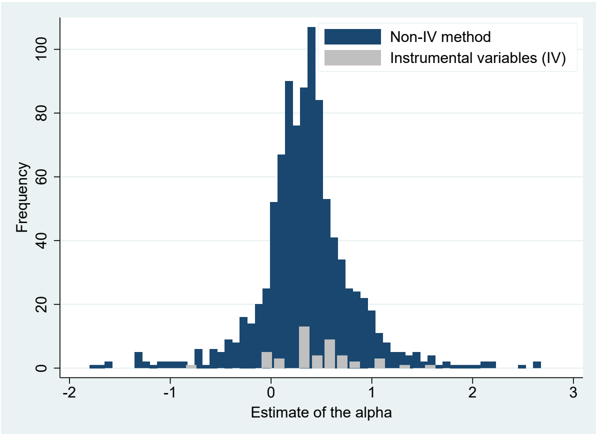
4.1 Heterogeneity Analysis

Since prior research does not provide clear guidance about the nature of hedge fund performance determinants, we treat the variables described in Table A1 as potentially relevant for explaining the heterogeneity in hedge fund performance. We examine their explanatory power using the Bayesian Model Averaging (BMA) technique. BMA considers various combinations of variables and evaluates their relevance for explaining the variation in the dependent variable. Explanatory variables that are consistently associated with the dependent variable across a multitude of regression model specifications are then identified as relevant for explaining it. By using the dilution prior, BMA allows researchers to address the model uncertainty problem and to consider a fairly large number of potentially relevant variables while avoiding multi-collinearity issues that naturally arise when numerous similar variables are included in a single regression specification.

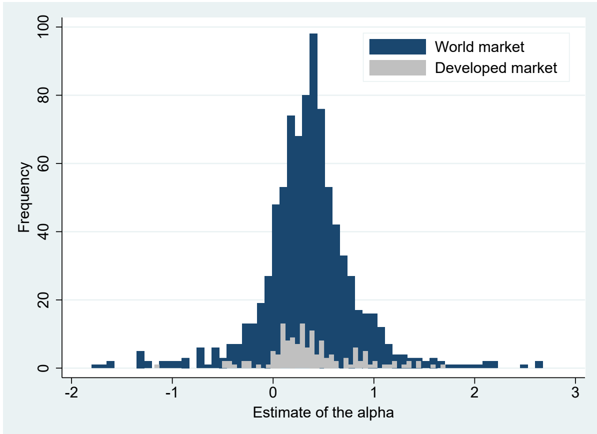
In BMA, the ability of the individual variables to explain the variation in the dependent variable is measured by their posterior inclusion probability (PIP). PIP close to 1.0 indicates that a particular variable is present in most regression models that are effective in explaining the variation in the dependent variable. In contrast, PIP close to 0.0 indicates low explanatory power of a given variable across various regression specifications. To interpret our results, we follow Jeffreys (1961) and Raftery (1995), who propose cutoff levels for PIP that can be used to evaluate how relevant a given variable is for explaining the variation in the dependent variable. They argue that PIP greater than 0.99 indicates that the variable is "decisive" for explaining the variation in the dependent variable, PIP greater than 0.95 suggests that the variable has a "strong" effect, variables with PIP greater than 0.75 can be

Figure 6: Selected patterns in the data

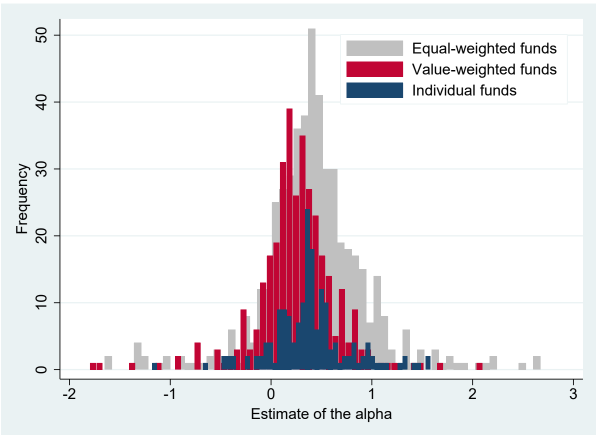
(a) Method usage



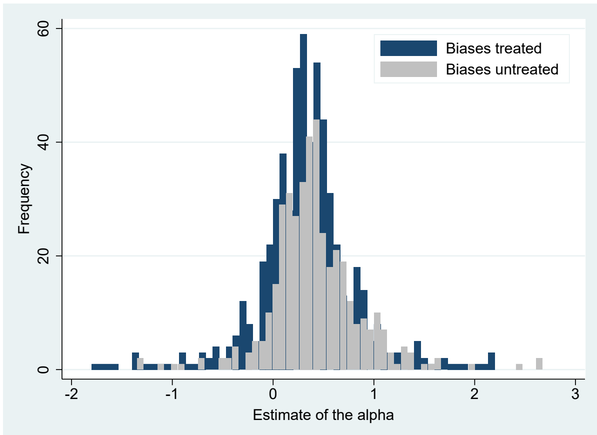
(b) Development level



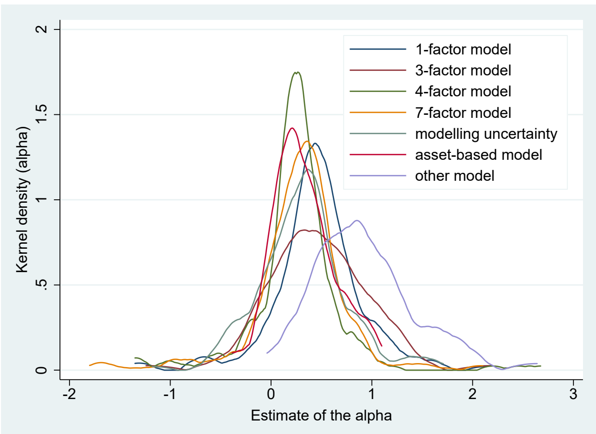
(c) Data dimension



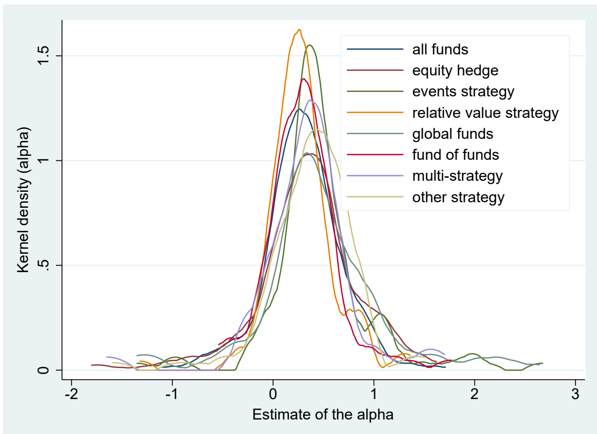
(d) Bias treatment



(e) Estimation form



(f) Hedge strategy



Notes: The figure shows histograms for subsets of reported alpha estimates with specific characteristics related to the estimation method, sources of data, and hedge fund strategies. We use the IMF definition to classify countries as developed or developing.

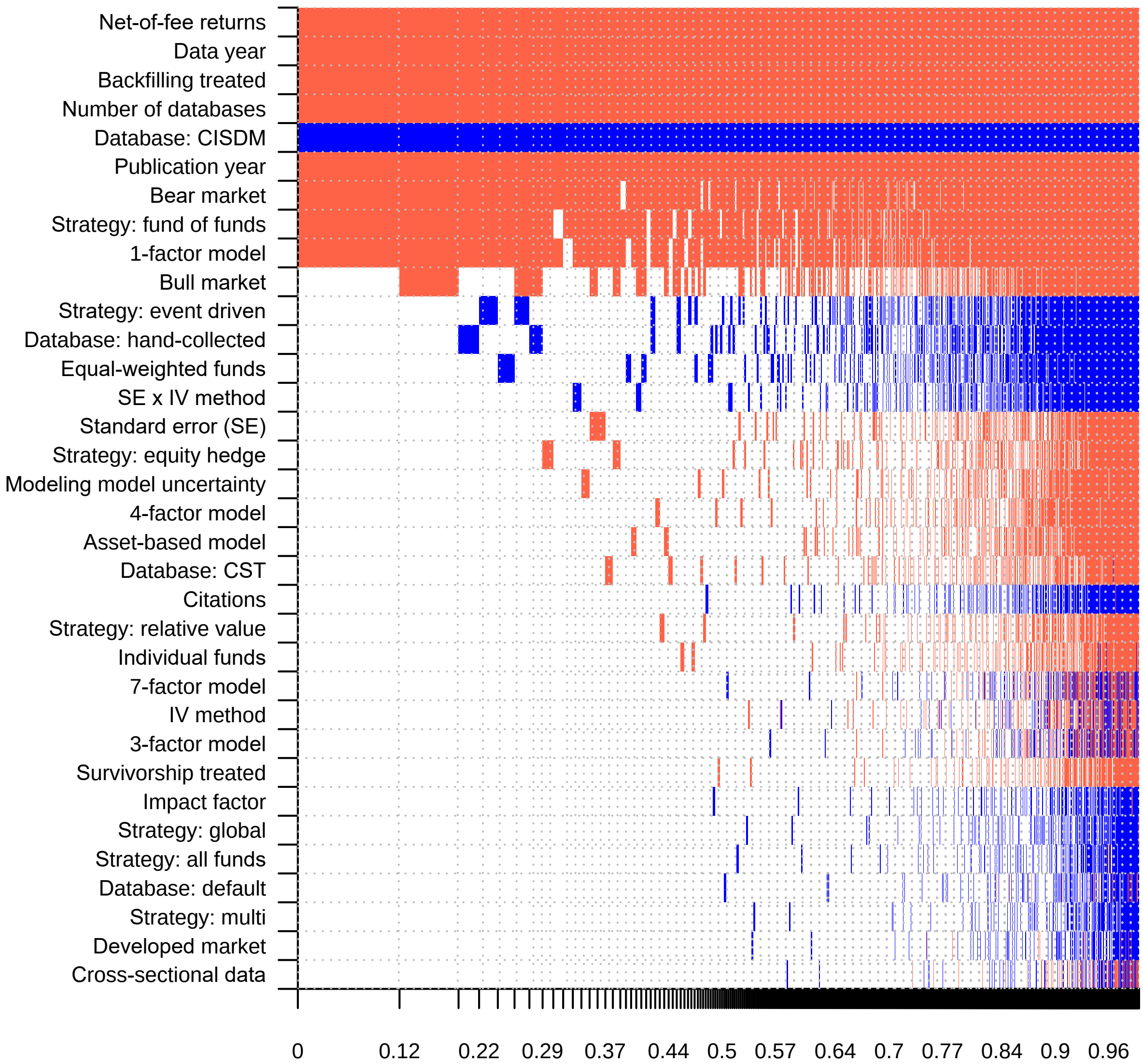
considered to have an effect on the dependent variable, and variables with PIP greater than 0.50 to have a "weak" effect. We use these cutoff levels in interpreting our empirical results.

4.2 Main Regression Results

Figure 7 provides a visualization of our results from the BMA. The columns in the figure denote alternative regression specifications that feature various combinations of explanatory variables. BMA weighs the individual regression models by their posterior model probabilities, which measure the models' goodness of fit. The posterior model probability is represented by the width of individual columns. We order the models based on their posterior probability so that the models with the best fit are represented by the widest columns in the left part of Figure 7. Similarly, explanatory variables in individual rows are sorted based on their PIP with the most relevant variables listed at the top. The nature of the association between an explanatory variable and the dependent variable in a given regression model is depicted by the color of the corresponding cell. A blue cell (equivalent to darker shading in grayscale) implies a positive impact of a given explanatory variable on hedge fund alphas in a particular regression specification and a red cell (lighter in grayscale) denotes a negative sign of the estimated coefficient. Blank cells represent variables that are not included in a given regression model.

Figure 7 features 34 potential explanatory variables that reflect differences in hedge fund types, various aspects of research design, and data samples used in primary studies, as well as their publication characteristics. Figure 7 shows that most of the considered explanatory variables exhibit a consistently positive or consistently negative association with hedge fund alphas across all model specifications. This implies that these associations are robust to the inclusion of additional explanatory variables. Figure 7 also shows that the model with the best fit (i.e., the one with the highest posterior probability based on the BMA) features only 9 of the 34 considered variables. All of these 9 explanatory variables exhibit a consistent sign in all the models that comprise them. Our model with the best fit thus suggests that the reported alpha coefficients tend to be lower when hedge fund returns are computed net of the fees hedge funds charge their investors, when the backfilling bias is treated in the primary study, and when estimated based on the 1-factor model. Furthermore, we observe that primary studies report lower alphas when the estimation is based on data from a larger number of databases, and when the CISDM database is not used as a data source. The alphas also tend to be lower for the funds of funds and in bear markets. Remarkably, there seem to be strong negative associations between the reported alpha coefficients and both

Figure 7: Model inclusion in Bayesian model averaging



Notes: This figure provides a visualization of our results from the BMA. On the vertical axis the explanatory variables are ranked according to their posterior inclusion probabilities from the highest at the top to the lowest at the bottom. The horizontal axis shows the values of cumulative posterior model probability. Blue color (darker in grayscale) denotes that the estimated parameter of a corresponding explanatory variable is positive in a given regression specification. Red color (lighter in grayscale) shows that the estimated parameter of a corresponding explanatory variable is negative. No color indicates that the corresponding explanatory variable is not included in the model. Numerical results are reported in Table 3. All variables are described in Table A1.

the data year and the year of publication. In particular, studies that use datasets with later-year midpoints, and those that are published more recently report lower alphas. We further discuss this finding below.

To quantify the magnitude and the variability of regression coefficients represented in Figure 7 by the blue or the red color, BMA expoits the characteristics of the distribution of coefficients generated by estimating various regression models. In Table 3, we report the posterior mean of the distribution of regression coefficients (P. mean), which represents the typical value of the regression coefficient across various regression specifications. Furthermore, the standard deviation of the posterior coefficient distribution (P. SD) shows how the estimated coefficients vary across various regression specifications. Table 3 also specifies PIP of individual variables, which indicates how likely each variable is to be present in the "true" explanatory model. We use the P. mean, P. SD, and PIP as the main measures to quantify the effect of the individual explanatory variables on the reported hedge fund alphas. For the sake of comparison with frequentist econometric approaches, we also report in the right panel of Table 3 the conventional ordinary least squares (OLS) estimates based on the regression model identified by the BMA as most relevant for explaining the variation in reported hedge fund alphas. For the OLS estimation, we report the regression coefficients for the individual explanatory variables (Coef.), their standard errors (SE), and the corresponding p-values.

The numerical results presented in Table 3 show that the PIP for the nine explanatory variables included in the model with the best fit range between 0.876 and 1.000, which suggests that all of these variables are important for explaining the variation in reported hedge fund alpha coefficients. Out of these nine PIPs, six are above the 0.950 cutoff that is commonly interpreted as denoting a "strong" effect of the corresponding variable. Furthermore, the PIP for the remaining three indicator variables denoting the alpha coefficients (i) estimated based on a 1-factor model, (ii) reported for funds of funds, and (iii) estimated for bear markets only are equal to 0.876, 0.905, and 0.931. This implies that all of these coefficients remain comfortably above the 0.750 cutoff proposed for the existence of a relationship between the explanatory and the dependent variables. We draw similar conclusions based on the OLS results. All of the nine variables included in the BMA model with the best fit are also significant at a better than 5% level in the OLS regression. The corresponding p-values range between 0.000 and 0.019. Thus, both the BMA and OLS estimates provide evidence in support of the relevance of these nine variables to explain the variation in hedge funds alphas. In contrast to the nine variables included in the BMA model with the best fit, the PIP of all the remaining variables is below 0.35, which indicates that they are unlikely to be relevant for explaining the variation in the alpha coefficients reported in prior empirical research. Thus, our results identify nine key characteristics that are essential for explaining the variation in reported alphas.

Six out of these nine explanatory variables are indicators that take the value of zero or one. We can thus easily compare the magnitude of the corresponding coefficients. We observe the largest coefficient for the variable denoting alpha estimates computed net of hedge fund fees. This finding is consistent with prior research that suggests that the effect

Table 3: Why do reported alphas vary?

	Bayesian model averaging			Ordinary least squares		
Variable:	P. mean	P. SD	PIP	Coef.	SE	p-value
Constant	1.851	NA	1.000	1.858	0.113	0.000
Standard error (SE)	-0.008	0.030	0.085			
SE * IV method	0.065	0.233	0.107			
Dependent variable						
Individual funds	-0.003	0.017	0.041			
Equal-weighted funds	0.010	0.026	0.144			
Net-of-fee returns	-0.439	0.075	1.000	-0.439	0.081	0.000
Data characteristics						
Cross-section data	0.000	0.010	0.013			
Data year	-0.248	0.031	1.000	-0.239	0.034	0.000
Database: default	0.000	0.006	0.016			
Database: CST	-0.004	0.020	0.060			
Database: CISDM	0.224	0.049	0.998	0.236	0.064	0.000
Database: hand-collected	0.040	0.093	0.180			
Number of databases	-0.085	0.017	0.999	-0.085	0.022	0.000
Structural variation						
Developed markets	0.001	0.008	0.014			
Bull market	-0.067	0.106	0.323			
Bear market	-0.264	0.104	0.931	-0.280	0.072	0.000
Hedge fund strategy						
Strategy: all funds	0.001	0.007	0.017			
Strategy: equity hedge	-0.006	0.021	0.085			
Strategy: event driven	0.019	0.043	0.182			
Strategy: relative value	-0.003	0.018	0.041			
Strategy: global	0.001	0.008	0.018			
Strategy: fund of funds	-0.181	0.079	0.905	-0.202	0.050	0.000
Strategy: multi	0.001	0.011	0.014			
Estimation technique						
IV method	-0.006	0.045	0.031			
1-factor model	-0.142	0.074	0.876	-0.159	0.068	0.019
3-factor model	-0.003	0.032	0.026			
4-factor model	-0.009	0.048	0.070			
7-factor model	-0.004	0.039	0.032			
Modeling model uncertainty	-0.012	0.054	0.075			
Asset-based model	-0.010	0.052	0.068			
Survivorship treated	-0.001	0.008	0.023			
Backfilling treated	-0.196	0.034	1.000	-0.198	0.062	0.001
Publication characteristics						
Publication year	-0.126	0.028	0.994	-0.138	0.056	0.013
Citations	0.001	0.007	0.046			
Impact factor	0.000	0.001	0.021			
Observations	1,019			1,019		
Studies	74			74		

Notes: The table show the main results based on BMA (left panel) and ordinary least squares (OLS) regression that includes the nine explanatory variables identified by the BMA as most relevant for explaining the variation in reported hedge fund alphas (right panel). The response variable are the hedge fund alpha estimates. P. mean represents the posterior mean of the distribution of regression coefficients. P. SD represents the posterior standard deviation of the distribution of regression coefficients. PIP denotes the posterior inclusion probability of a given variable in the "true" explanatory model. Coef. denotes the slope coefficient based on OLS. SE shows the standard error of the slope coefficient in the OLS regression model. The p-value show the probability of obtaining the result for a given explanatory variable under the assumption that the variable has no explanatory power (i.e. the null hypothesis is correct). BMA employs uniform model prior (Eicher *et al.*, 2011) and dilution prior suggested by George (2010), which accounts for collinearity. The frequentist check (OLS) includes the variables recognized by BMA to comprise the best model and is estimated using standard errors clustered at the study level. All variables are described in Table A1.

of hedge fund fees on the return generated for investors may indeed be rather substantial. Hedge funds typically charge a flat management fee of 1% to 2% of AUM and a variable performance fee, usually 20% of realized returns above the risk-free rate (Fung & Hsieh, 1999; Connor & Woo, 2004; Stulz, 2007; Kouwenberg & Ziemba, 2007; Getmansky *et al.*, 2015). The performance fee is usually paid only after reaching the so-called "high water mark," i.e., the minimum level of absolute performance over the entire investment lifetime (Asness *et al.*, 2001; Goetzmann *et al.*, 2003; Lim *et al.*, 2016; Stulz, 2007). Due to the conditional nature of some of these fees, their effective impact on the value hedge funds generate for their investors is not trivial to quantify. Less successful hedge funds are more likely terminated, and investors cannot offset gains and losses across various hedge funds. Ben-David *et al.* (2020) estimates that, on average, hedge funds appropriate in fees almost two-thirds of the excess return they generate.

Our approach offers an alternative way of estimating the effective fees paid by hedge fund investors. We exploit the composition of our sample that includes both alphas estimated using gross returns and alphas estimated net of fees. Thus, we are able to quantify the effect of hedge fund fees after controlling for all other relevant characteristics that affect the magnitude of reported alpha estimates. Our results suggest that after adjusting for all other relevant hedge fund alpha determinants, we observe that monthly alphas estimated on the net-of-fee basis are by -0.439 lower than those estimated gross of fees. We also observe that the magnitude of this coefficient is essentially identical to the one obtained based on the OLS that we report in the right panel of Table 3. These findings suggest that the combined effect of the management and performance fees is indeed large. Hedge funds seem to charge their investors more than 5.0% annually.

Considering the slope coefficients at other indicator variables we observe that the hedge fund alphas for bear markets are by -0.246 lower relative to our benchmark case. The magnitude of this coefficient is very similar to the one based on the OLS estimation of -0.280. There is a controversy in prior research literature about the relative performance of hedge funds in bull and bear markets. Our results suggest that hedge funds generate substantially lower alphas when stock market prices decline when they seem to underperform their typical performance by about -3.2% per annum. Thus, despite their name, hedge funds do not seem to hold investment positions that make their returns immune to general stock market movements (i.e., to be "market-neutral").

We also observe that the alpha coefficients reported in primary studies are related to the databases, from which the primary data are sourced. Specifically, we document that the reported alpha estimates tend to be lower when based on more source databases. We observe virtually identical coefficients corresponding to the inclusion of one additional database for obtaining the primary study sample based on the BMA and OLS (in both cases, -0.085 after rounding). Both of these coefficients are highly statistically significant. These findings suggest that using more comprehensive datasets tends to be associated with lower reported hedge fund performance estimates. Furthermore, alphas based on samples that include the CISDM as one of the source databases tend to be higher. The posterior mean coefficient based on the BMA is equal to 0.224, and it is very close to the OLS estimate of 0.236. Thus, researchers should be aware that alpha estimates based on the CISDM database tend to overstate hedge fund performance relative to studies based on the other databases.

Furthermore, we find that the alpha estimates reported in prior research tend to be lower when estimated for the funds of funds rather than for the individual hedge funds and when explicitly adjusted for the backfilling bias. The posterior mean of the coefficient at the indicator variable denoting alphas estimated for the funds of funds -0.181, which is fairly comparable to the corresponding slope coefficient based on the OLS estimation of -0.202. Similarly, alpha estimates explicitly adjusted for the backfilling bias are lower by -0.196, which is again comparable to the slope coefficient of -0.198 based on the OLS. These findings suggest that the backfilling bias and the selection biases addressed by estimating performance for funds of funds are indeed rather consequential for the reported results. Thus, the frequently voiced concerns that data biases in some prior empirical studies may affect inferences about hedge fund performance are indeed warranted.

Finally, we document strong negative associations between the magnitude of reported alpha coefficients on the one hand and the mid-year of the data sample and the publication year on the other. Increasing the data midpoint year by one, on average, reduces reported alphas by -0.248 based on BMA or by -0.239 based on OLS. In both cases, this result is strongly statistically significant, with the PIP approaching 1.0 and the p-value below 1%. In addition, studies published more recently also report lower alphas. Specifically, increasing the year of publication by one is associated with a reduction in reported alpha estimates by -0.126 based on the BMA or by -0.138 based on the OLS. The effect of the publication year is incremental to the effect of the data sample mid-year discussed above. These findings imply that studies based on newer datasets and studies published more recently tend to report substantially lower hedge fund alpha estimates. This suggests that hedge fund performance has substantially decreased over time. In subsection 4.4, we further elaborate on these findings, and we show that due to the declining time trend, the current estimate of hedge fund performance is not reliably different from zero.

We further observe that the absolute value of the posterior mean of all the other indicator variables that are not included in the model with the best fit as identified by BMA is below 0.070. This implies that their effect on hedge fund performance is less than 1% per annum. In other words, it seems that the BMA approach identified nine variables relevant for explaining variation in hedge fund alphas. The effect of other variables is likely to be fairly marginal.

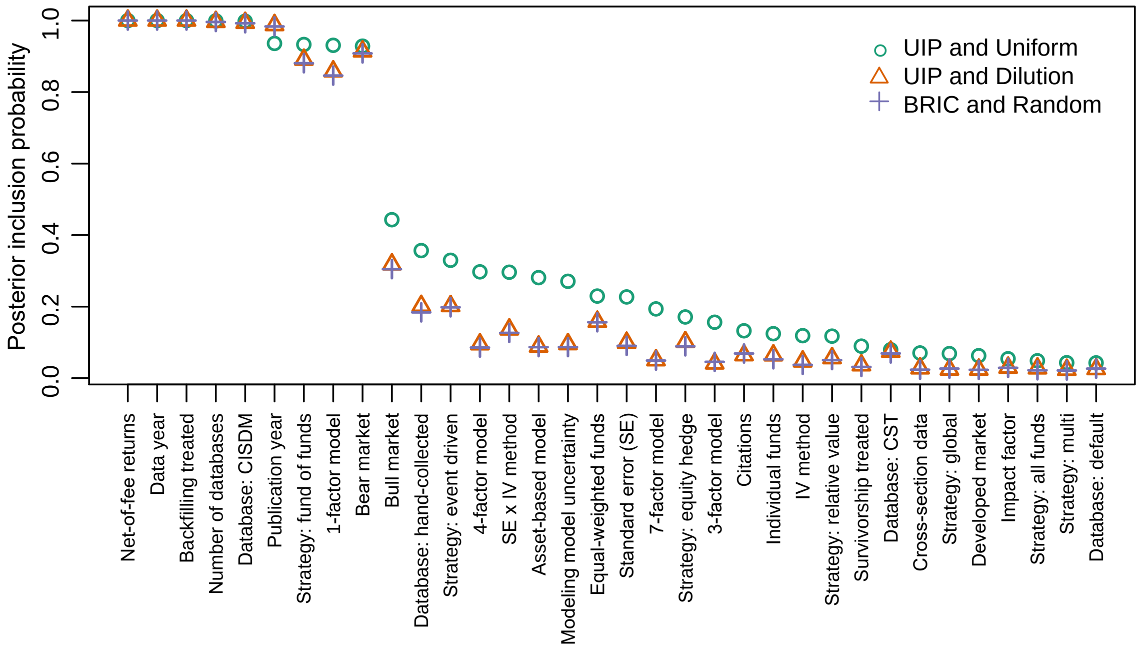
4.3 Sensitivity Analysis

Notwithstanding the BMA's advantages for analyzing research questions where the set of potential explanatory variables is not *a priori* given, the BMA method may be affected by the priors used as a point of departure for Bayesian estimation. To investigate how robust our results are to the modification of these priors, we recompute them using several different priors proposed in prior literature. We examine the extent to which the use of different priors alters our inferences about the power of the individual variables to explain the variation in the alpha coefficients reported in the primary studies on hedge fund performance.

Figure 8 depicts the results of our sensitivity analysis. Again, we order the individual explanatory variables based on their estimated relevance in our main test. Figure 8 indicates that the choice of priors in the BMA is indeed somewhat relevant for the numerical values of our results. Nevertheless, the use of different priors does not dramatically alter our main conclusions that we discuss above. For most of the explanatory variables, the estimates based on different priors are placed rather close to one another, which implies that a different choice of priors would not dramatically alter the inferences about the prominence of the nine key explanatory variables that we identify as fundamental for explaining the variation in the reported alpha coefficients.

We observe that the unit information priors (UIP) and dilution priors that are recommended by George (2010) produce virtually identical estimates as the BRIC and random that represent a g-prior proposed by Fernandez *et al.* (2001). In comparison, the UIP and uniform priors recommended by Eicher *et al.* (2011) yield slightly higher estimates for most of the variables that are not included in our BMA model with the best fit. Nevertheless, the sizable gap in relevance between the nine explanatory variables included in our model with the best fit and the remaining variables clearly stands out regardless of the set of priors we use. Thus, we conclude that our findings are fairly robust to the choice of priors in our BMA estimation.

Figure 8: Sensitivity of BMA to different priors



Notes: This figure shows the sensitivity of our results on the relevance of the individual variables for explaining the variation in the alpha coefficients reported in the primary studies to the various priors used in BMA. UIP stands for the unit information priors. UIP and Uniform represent the priors recommended by Eicher *et al.* (2011). UIP and Dilution represent the priors recommended by George (2010). BRIC and Random represent a g-prior proposed by Fernandez *et al.* (2001) for parameters with the beta-binomial model prior (Ley & Steel, 2009) for model space; this ensures that each model size has equal prior probability.

4.4 Best Practice Estimate

In subsection 4.2 we analyze the impact of variables that can potentially explain the variation in the hedge fund alpha estimates reported in the primary studies. In this section, we provide an estimate of current hedge fund performance based on the best practices of estimating alphas. Below, we motivate our choice of methodological approaches that we believe constitute the best practices in this field of research. Even though the choice of these parameters inevitably involves a subjective judgment, we closely follow arguments raised in the research discourse on the appropriate methodology and its limitations in research on hedge fund performance. Based on these arguments, we set the corresponding variables in our empirical model to values that we argue constitute the best practices for this estimation. We believe that the best practice approach likely generates the most reliable alpha estimates that are relevant for current investment decisions. Below, we discuss and motivate our choices concerning the individual variables.

First, we argue that an ideal study on hedge fund performance should be free of data and publication biases. In the results discussed above, we document a substantial impact of the backfilling bias in estimating hedge fund alphas. In our best practices model, we thus plug in one for the indicator variable that captures that the survivorship and backfilling biases are treated in the design of the primary study. Furthermore, in a companion paper, Yang *et al.* (2023) investigate the impact of the publication selection bias in hedge fund research. Following this study, we plug zero for the measure of a hedge fund alpha's standard error and also for the respective interaction term in our best practices model. This treatment ensures that our best practices estimate is free of any publication selection bias in the primary studies from which we source our dataset.

Second, we argue that from an investor's perspective, it is relevant to measure hedge fund alphas net of any management and performance fees. Fees retained by the hedge funds do not constitute realized returns that accrue to investors. Therefore, any portion of return generated by hedge funds that is retained in the form of fees should be irrelevant for computing hedge funds' effective performance from investors' perspective. Prior research argues that these fees can indeed be rather substantial (Ben-David *et al.*, 2020). Consistent with these propositions, our results also suggest a sizeable difference between the alpha coefficients estimated on the gross basis and those that are net of all fees. Hence, in our best practices model, we plug in one for the variable, indicating that the corresponding alpha is estimated on the net-of-fees basis.

Third, we expect investors to be particularly interested in the most recent estimates of hedge fund performance that likely closely reflect the investment opportunities that are currently available. The hedge fund industry has undergone substantial development over time. The number of funds and the value of resources they manage has surged over the past decades (Stulz, 2007). These days, more hedge funds compete to identify profitable investment opportunities and attract investors. The more intensive competition likely impacts the returns that hedge funds are able to generate today relative to the returns they generated in the past. Furthermore, the greater regulation of the hedge fund industry may have also limited their ability to generate superior returns to investors (Shi, 2017; Cumming *et al.*, 2020; Aragon *et al.*, 2013). We thus set both the data year and the year of publication to the maximum values these measures have in our sample.

Finally, we expect investors to value studies that are well-published and well-cited. Therefore, we plug in our sample maxima for the impact factor and the number of citations. We set the remaining variables to their sample means.

Table 4 shows our best practice estimates of alpha coefficients jointly for all hedge fund types, as well as the separate expected alphas for the individual hedge fund types. Table 4 shows that, relative to the unconditional sample mean of 0.36 discussed above, the overall best practice estimate based on all hedge fund returns is small and negative, i.e., -0.079. The corresponding 95% confidence interval is fairly wide (-0.393, 0.235), and it includes zero. Thus, judging based on the most up-to-date best practice alpha estimate, we cannot reject the null hypothesis that hedge funds currently generate no abnormal after-fee return for their investors.

The remaining rows in Table 4 report the best-practice estimates for eight main hedge fund investment strategies. Similar to the overall best-practice alpha estimate computed for the pooled sample of all hedge funds, all eight alpha estimates for the individual hedge fund types are negative, and the corresponding 95% confidence intervals all include zero. Hence, based on our evidence we are unable to document reliably positive alphas for any of the common hedge fund investment strategies. These findings suggest that after controlling for methodological imperfections and after considering the trend over time in the reported alpha estimates, no type of hedge funds generates reliably positive after-fee abnormal returns for investors.

We observe the most negative alpha estimate of -0.249 for the funds of funds. The 95% confidence interval for this approach of measuring hedge fund performance is also fairly wide (-0.590, 0.092), which prevents us from drawing stronger inferences. However, we observe that the confidence interval approaches being entirely below zero, which would indicate a reliably negative after-fee abnormal return. Estimating the alphas for the funds of funds may be viewed as one of the ways of correcting for the survivorship bias in hedge fund data. Hence, fund of funds' returns may constitute a realistic estimate of hedge fund performance plausibly achievable for investors. Furthermore, investing in the funds of funds might seem attractive for investors who want to diversify away some of the risks they take by investing across several hedge funds. Nevertheless, investing in funds of funds also entails another layer of fees. Our evidence suggests that the best-practice estimate for the fund of funds' abnormal return is indistinguishable from zero, and it approaches being significantly negative.

Table 5 shows the economic significance of key variables included in our best-practice model. The table provides insights about the relative importance of these variables for our quantification of the best best-practice estimates of hedge fund alphas. The left panel of Table 5 shows how one-standard-deviation change in a given explanatory variable effects the best-practice alpha estimate both in absolute terms and as a percentage of the best-practice estimate. In the right panel, we show the corresponding change in the best-practice alpha estimate that would result from a change in a given explanatory variable from its minimum

Table 4: Implied alphas

	Mean return	95% conf. int.	
All strategies	-0.079	-0.393	0.235
Strategy: all funds	-0.067	-0.372	0.237
Strategy: equity hedge	-0.073	-0.418	0.271
Strategy: event driven	-0.049	-0.376	0.277
Strategy: relative value	-0.071	-0.380	0.238
Strategy: global	-0.067	-0.391	0.257
Strategy: fund of funds	-0.249	-0.590	0.092
Strategy: multi	-0.067	-0.368	0.235
Strategy: other	-0.068	-0.373	0.238

Notes: The table shows the best practice alpha estimates from our BMA model for the hedge funds in general and for the individual hedge fund strategies. The mean return represents the expected alpha coefficient conditional on the inputted values of explnatory variables that we consider to represent the best practice in hedge fund performance research. We provide the motivation for our choices in the main body text. The 95% confidence intervals in parentheses are constructed using the standard errors estimated by OLS with standard errors clustered at the study level.

to the maximum value in our sample.

Consistent with our previous analysis, Table 5 shows that several explanatory variables have a substantial impact on the magnitude of the best-practice alpha estimate. We observe the largest effect for the midpoint year in the dataset used in a given primary study. Increasing the data sample midpoint year by one standard deviation reduces the monthly alpha estimate by -0.149 percentage points. Alternatively, after having controlled for all study and hedge fund characteristics, the best practice-alpha estimates based on the oldest and the most recent dataset differ by -0.802 percentage points. Furthermore, we also document a substantial effect of the year of publication. A one-standard deviation increase in the publication year is associated with a reduction in the practice-alpha estimates by -0.090 percentage points. The most recent studies in our sample report alpha estimates that are *ceteris paribus* lower by -0.384 percentage points relative to the oldest studies in our sample. These findings provide strong evidence suggesting that the abnormal returns generated by hedge funds decreased over time.

Table 5 also underscores the importance of the data sources and method choices for the magnitude of the best-practice alpha estimates. *Ceteris paribus*, increasing the number of databases used in a primary study by one tends to be associated with a reduction in the best-practice alpha estimate by -0.089 percentage points. The more comprehensive studies that pool their data from several source databases may be more effective in covering the complete universe of all existing hedge funds. Hence, their conclusions may be more representative of the entire hedge fund population. Hence, the number of source databases may be viewed

Table 5: Economic significance of key variables

	One-std.-dev. change		Maximum change	
	Effect on σ	% of best practice	Effect on σ	% of best practice
Net-of-fee returns	-0.080	101%	-0.439	557%
Data year	-0.149	189%	-0.802	1,017%
Database: CISDM	0.085	-108%	0.224	-284%
Number of databases	-0.089	112%	-0.592	750%
Bull market	-0.013	16%	-0.067	85%
Bear market	-0.051	64%	-0.264	335%
Strategy: all funds	0.000	0%	0.001	-1%
Strategy: equity hedge	-0.002	3%	-0.006	7%
Strategy: event driven	0.006	-7%	0.019	-23%
Strategy: relative value	-0.001	1%	-0.003	4%
Strategy: global	0.000	0%	0.001	-1%
Strategy: fund of funds	-0.045	57%	-0.181	229%
Strategy: multi	0.000	0%	0.001	-1%
1-factor model	-0.053	67%	-0.142	180%
Survivorship treated	0.000	1%	-0.001	1%
Backfilling treated	-0.090	114%	-0.196	248%
Publication year	-0.090	114%	-0.384	487%

Notes: The table shows the results of our analysis of the economic significance of key variables included in our best-practice model. The left panel quantifies how much one standard deviation change in a given explanatory variable affects the best-practice alpha estimate both in absolute terms and as a percentage of the best-practice estimate. The right panel shows the corresponding change in the best-practice alpha estimate resulting from changing the value of the explanatory variable from its sample minimum to its sample maximum. A detailed description of the variables is available in Table A1.

as one aspect of a study's quality. We document that more comprehensive studies tend to report lower alphas.

Furthermore, adjusting for the backfilling bias, on average, reduces the alpha estimates by -0.196 percentage points (for indicator variables, we interpret the change from the minimum value of zero to the maximum value of one). In a similar vein, computing the alphas for the funds of funds implies a reduction in the estimate by -0.181 percentage points. Finally, using a 1-factor risk model is *ceteris paribus* associated with best-practice alpha estimates that are lower by -0.142 percentage points. Since the 1-factor risk model may not be able to effectively adjust for the systematic risk that the hedge fund strategies entail, using more complex models may also be viewed as an indication of a study's quality.

Finally, Table 5 also documents a substantial effect of adjusting for hedge fund fees and of limiting the estimation on bear markets, which we discuss above. Overall, the quantification of the effect indicates that the above-discussed variables indeed have an economically substantial effect on the best-practice estimates of alpha coefficients.

5 Conclusion

We analyze the empirical evidence on hedge fund performance published in academic journals between 2001 and 2021. In recent years, the amount of capital in the economy allocated by hedge funds has surged. Their growing economic prominence, as well as the macroeconomic impact of some of their notorious failures, prompted calls for greater insight into the determinants of their performance. Measuring the value hedge funds generate for their investors is complicated by data fragmentation resulting from the voluntary nature of many hedge fund disclosures and the plurality of estimation approaches used in prior empirical research. To aggregate and synthesize this pool of diverse empirical results, we conduct a meta-analysis of 1,019 alpha coefficients from regressions of hedge fund returns on risk factors collected from 74 studies. We examine how the reported alpha estimates vary over time and across hedge fund characteristics, and we study how they are affected by research design choices in the primary studies.

We show that the value generated by hedge funds is substantially diminished by the fees they charge. Furthermore, we document a strong declining trend in the reported hedge fund alphas over time. Our best practices alpha estimates of current hedge fund performance are not reliably different from zero. Furthermore, when we classify hedge funds into common categories based on the nature of their investment strategies, we observe that the best-practice estimate of their current performance is not significantly positive for any of these categories. All of these estimates are negative. For one of the categories – the fund of funds – the 95% confidence interval approaches being fully below zero.

In addition, we identify several research design characteristics that affect the reported alphas. The published alpha estimates tend to be lower (i) when adjusted for the backfilling bias, (ii) when estimated for the fund-of-funds, (iii) when estimated based on the 1-factor model, (iv) when estimated for the declining "bear" markets, (v) when more source databases are used, and (vi) when the CISDM database is not used as a data source.

Our findings have important implications for investors who consider alternative investment strategies, for regulators who seek the optimal design of the regulatory framework, as well as for researchers who analyze hedge fund performance. Investors may benefit from a better understanding of the level of return they may expect in various hedge fund types. Our findings suggest that even though hedge funds used to generate positive value for investors in the past, on average, they do not do so anymore. This finding is also relevant for regulators as it is likely related to the intensity of competition in the hedge fund market and the impact of the regulatory requirements. The number of hedge funds has steeply increased over time, which may have intensified the competition among them and diminished abnormal returns that the early hedge funds were able to achieve. The decline in the value hedge funds generate for investors may have also been driven by the influx of resources hedge funds manage and by the decreasing returns to scale of managerial ability to identify profitable investment opportunities. Hedge fund performance may have also changed over time due to progressively tighter regulation requiring greater hedge fund transparency, which may complicate their ability to fully exploit their proprietary investment strategies. We call for more research to distinguish between these potential underlying causes, and we provide systematic evidence to researchers about how their research design choices affect the reported alpha estimates.

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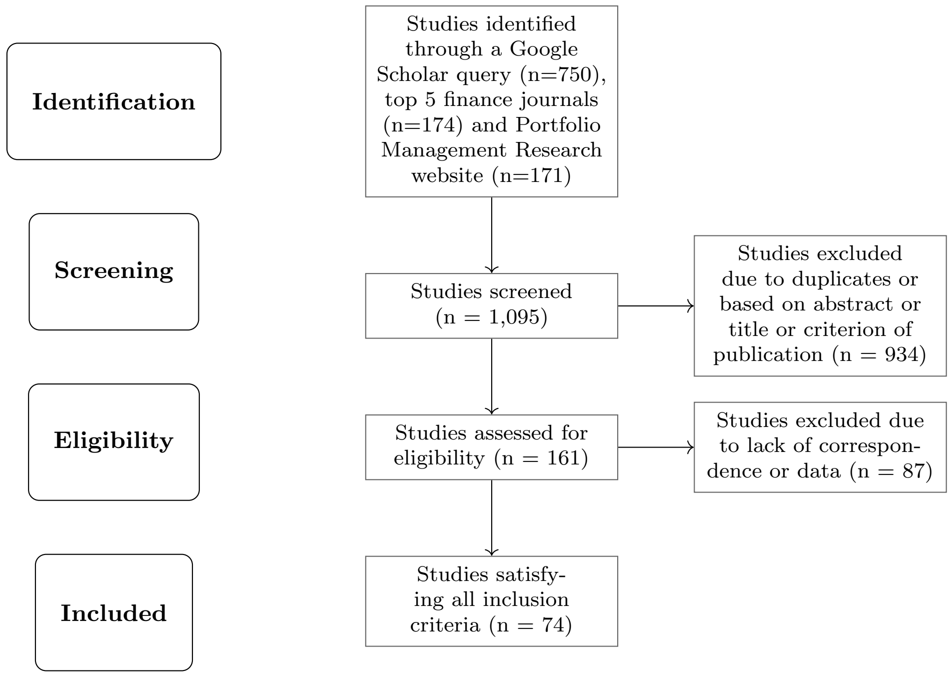
Appendix

Figure A1: PRISMA flow diagram



Notes: Our baseline search query is *("hedge fund") AND ("returns" OR "performance")* in Google Scholar and *("hedge") AND ("fund" OR "funds")* in top 5 finance journals and Portfolio Management Research website. We collect the first 750 studies returned by the search in Google Scholar and check the relevant 174 results in top 5 finance journals and 171 results on the Portfolio Management Research website. We are left with 161 studies after the screening. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) is an evidence-based set of items for reporting in systematic reviews and meta-analyses. More details on PRISMA and reporting standard of meta-analysis in general are provided by Havranek *et al.* (2020).

Table A1: Definition and descriptive statistics of explanatory variables

Variable	Description	Mean	SD	WM
Alpha	The estimate of the alpha (response variable).	0.362	0.477	0.365
Standard error (SE)	Standard error of the alpha. The variable is important for gauging publication bias.	0.251	0.285	0.240
SE * IV method	The interaction term between the standard error and IV method capturing the publication bias among IV estimates.	0.011	0.060	0.004
Dependent variable				
Individual funds	= 1 if the dependent variables is defined as returns of individual funds and 0 otherwise.	0.172	0.377	0.264
Equal-weighted funds	= 1 if the dependent variable is defined as equal-weighted returns and 0 otherwise.	0.494	0.500	0.517
Value-weighted funds	= 1 if the dependent variable is defined as value-weighted returns and 0 otherwise (reference category).	0.335	0.472	0.220
Net-of-fee returns	= 1 if the dependent variable is defined in net-of fees returns and 0 otherwise.	0.966	0.182	0.939
Gross returns	= 1 if the dependent variable is defined in gross returns including fees and 0 otherwise (reference category).	0.034	0.182	0.061
Data characteristics				
Cross-section data	= 1 if cross-sectional data are used to estimate the effect.	0.839	0.368	0.735
Longitudinal data	= 1 if longitudinal data are used to estimate the effect (reference category).	0.161	0.368	0.265
Data year	The logarithm of the mean year of the data used minus the earliest average year in our data (base = 1990).	2.405	0.603	2.485
Database: default	= 1 if the estimates are based on the data provided by either TASS, HFR, BarclayHedge, or Eureka-Hedge databases and 0 otherwise.	0.527	0.500	0.626
Database: CST	= 1 if the estimates are based on the data provided by Credit Suisse/Tremont/Dow Jones Credit Suisse database and 0 otherwise.	0.251	0.434	0.154
Database: CISDM	= 1 if the estimates are based on the data provided by CISDM database and 0 otherwise.	0.175	0.380	0.206
Database: hand-collected	= 1 if the estimates are based on the data collected by hand and 0 otherwise.	0.022	0.145	0.038
Database: other	= 1 if the estimates are based on other than aforementioned databases.	0.164	0.370	0.172
Number of databases	Total number of databases used to estimate alpha.	1.366	1.048	1.480
Structural variation				
Developed markets	= 1 if the estimates are based on the data of developed market economies (IMF classification).	0.137	0.344	0.134
World markets	= 1 if the estimates are based on the data of global markets (reference category for geographical location).	0.863	0.344	0.866
Bull market	= 1 if the estimates are relevant to bull market conditions.	0.038	0.192	0.016
Bear market	= 1 if the estimates are relevant to bear market conditions.	0.038	0.192	0.016
Hedge fund strategy				
Strategy: all funds	= 1 if the estimates are based on the data of all funds and 0 otherwise.	0.238	0.426	0.345

Continued on next page

Table A1: Definition and descriptive statistics of explanatory variables (continued)

Variable	Description	Mean	SD	WM
Strategy: equity hedge	= 1 if the estimates are based on the data of equity hedge funds and 0 otherwise.	0.225	0.418	0.186
Strategy: event driven	= 1 if the estimates are based on the data of event driven funds (merger arbitrage, distressed securitities) and 0 otherwise.	0.111	0.314	0.102
Strategy: relative value	= 1 if the estimates are based on the data of relative value strategy funds (fixed income arbitrage, convertible arbitrage) and 0 otherwise.	0.092	0.290	0.085
Strategy: global	= 1 if the estimates are based on the global hedge funds and 0 otherwise.	0.153	0.360	0.105
Strategy: fund of funds	= 1 if the estimates are based on the data of funds of hedge funds and 0 otherwise.	0.066	0.248	0.080
Strategy: multi	= 1 if the estimates are based on the data of multistrategy funds and 0 otherwise.	0.039	0.194	0.020
Strategy: other	= 1 if other strategy of hedge funds is used for estimation (reference category for the group of strategies).	0.076	0.264	0.078
Estimation technique				
IV method	= 1 if instrumental variable approach (such as GMM and 2SLS) is used for estimation.	0.045	0.208	0.017
non-IV method	= 1 if other than IV method is used for estimation (reference category for methods).	0.955	0.208	0.983
1-factor model	= 1 if one-factor model or its modifications are used to estimate the alpha.	0.164	0.370	0.139
3-factor model	= 1 if three-factor model or its modifications are used to estimate the alpha.	0.070	0.255	0.081
4-factor model	= 1 if four-factor model or its modifications are used to estimate the alpha.	0.201	0.401	0.161
7-factor model	= 1 if seven-factor model or its modifications are used to estimate the alpha.	0.292	0.455	0.363
Modeling model uncertainty	= 1 if methods dealing with model uncertainty (such as stepwise regression or model averaging) are used to estimate the alpha.	0.139	0.346	0.112
Asset-based model	= 1 if asset-based models are used to estimate the alpha.	0.079	0.269	0.095
Other model	= 1 if other (sophisticated) models are used (reference category for the group of models).	0.055	0.228	0.049
Survivorship treated	= 1 if the survisorship bias is dealt with and 0 otherwise.	0.576	0.494	0.616
Backfilling treated	= 1 if the backfilling bias is dealt with and 0 otherwise.	0.301	0.459	0.343
Publication characteristics				
Publication year	The logarithm of the year when the study appeared in Google Scholar normalized by the year of the earliest publication in our sample.	2.260	0.713	2.252
Citations	The logarithm of the number of per-year citations of the study in Google Scholar.	1.748	1.041	1.773
Impact factor	The discounted recursive RePEc impact factor of the outlet.	3.650	5.081	4.034

Notes: The table provides the definition, the (unweighted) mean value (Mean), the standard deviation (SD), and the mean weighted by the inverse of the number of estimates reported per study (WM) for the explanatory variables that we use in our regression analysis. GMM denotes the generalized method of moments, and 2SLS denotes two-stage least squares method.

Online Appendix

This Appendix is intended for online publication.

Hedge Fund Characteristics

It is commonly believed that the first hedge fund was created in 1949 by a former Fortune magazine writer Alfred Winslow Jones (Connor & Woo, 2004; Stulz, 2007). Even though the financial industry has undergone a dramatic development over the seven decades that have passed since then many of the features of this first hedge fund resemble common hedge fund characteristics today. First, A. Jones structured the fund to be exempt from the Investment Company Act of 1940, which was the main pillar of the Security and Exchange Commission (SEC) regulations of investment entities at the time (Connor & Woo, 2004). This exemption gave the fund greater flexibility in the use of investment techniques. Second, the fund made a relatively concentrated (rather than well-diversified) investment in a limited number of stocks that it considered undervalued and it hedged some of its risks by short selling other stocks. The long-short equity strategy still remains one of the most popular hedge fund strategies. It is also a strategy that gave "hedge" funds their name. Third, to build investors' confidence A. Jones co-financed a substantial portion of the fund's assets (40%) with his own money (Stulz, 2007). Fourth, A. Jones used financial leverage to increase risk and simultaneously enhance the fund's ability to earn a higher return on the base capital. Fifth, A. Jones charged the investors a performance fee of 20% of returns earned (Connor & Woo, 2004). All of these features are quite common in hedge funds even nowadays.

In the 1960s, news about the high and relatively stable returns earned by A. Jones' hedge fund inspired imitation and many new hedge funds arose. Many of these new funds modified the original investment strategy. First, due to the hedged long-short strategy, hedge funds missed out on the strong bull market of the late 1960s. That prompted many hedge funds to abandon hedging against market downturns and to pursue a leveraged long-bias strategy that keeps the fund exposed to overall market movements (Connor & Woo, 2004). In the 1980s, new global macro funds started to appear, e.g. Julian Robertson's Tiger Fund, George Soros' Quantum Fund (Connor & Woo, 2004). In contrast to the original hedge fund that aimed at limiting its exposure to overall market conditions, these funds aimed to exploit the impact of general macroeconomic conditions typically in foreign exchange markets. The global macro funds made highly leveraged bets on the appreciation or depreciation of specific currencies. When successful (e.g. the Tiger Fund's bet on U.S. dollar appreciation, the Quantum Fund's bet on U.K. pound depreciation) these strategies generated spectacular returns, which attracted further investors (Connor & Woo, 2004). However, betting against currencies also earned hedge funds a reputation as a destabilizing force that profits from financial market turmoil.

Naturally, not all hedge fund bets turned out successful. Especially, the events of the late 1990s with the dot-com equity market bubble and the Russian debt crisis uncovered many vulnerabilities in hedge fund investment strategies. Both the Tiger Fund and the Quantum Fund lost billions on bets against the new economy that they were not able to sustain. The late 1990s also witnessed perhaps the most infamous hedge fund collapse of the Long-Term Capital Management (LTCM). The fund was started in 1993 by John Meriwether (a renowned Wall Street trader) and Myron Scholes and Robert Merton (Nobel Prize-winning economists). Between 1994 and 1998 it was very successful in pursuing the fixed-income arbitrage strategy that exploits small interest rate spreads between various debt securities. Pricing discrepancies in fairly efficient bond markets tend to be relatively small. Thus, the LTCM used very high leverage to earn an acceptable return on the capital provided by investors. This leverage became unsustainable during the Russian debt crisis when debt markets exhibited temporary anomalies. Some large investors "flew to safety" and closed their positions in riskier debt securities (Connor & Woo, 2004), which prompted the LTCM's collapse. To avoid wider contagion in financial markets the Federal Reserve Bank (FED) organized a bailout. The cost of this bailout led to further discussions about the potentially destabilizing macroeconomic impact of hedge funds. It became widely acknowledged that notwithstanding their prominent role in promoting financial markets' efficiency hedge funds may also play a more detrimental role. This understanding provided a strong motivation for systematic research in hedge funds.

Despite their growth there is, in fact, no universally accepted definition of a hedge fund (Brav *et al.*, 2008). However, hedge funds share several characteristics that distinguish them from other investment facilities. First, hedge funds are structured to take advantage of exceptions from regulatory requirements and to benefit from a favorable tax treatment (Connor & Woo, 2004). The legal framework that regulates investment entities, such as the Securities Act of 1933 and the Investment Company Act of 1940, typically allows funds with a number of investors below some threshold (often 100) to be exempted from regulatory requirements that commonly apply to mutual funds (Connor & Woo, 2004; Stulz, 2007). To qualify for such exceptions hedge funds target a limited number of high-net-worth individuals and institutional investors. From the regulatory perspective, these investors may be considered sufficiently competent to make investment decisions and sufficiently wealthy to sustain potential losses. Hence, regulators may consider it unnecessary to protect these investors from potentially adverse consequences of their investment decisions (Stulz, 2007). Furthermore, hedge funds tend to be organized as limited partnerships to benefit from pass-through tax treatment where the returns are only taxed at the individual investors' level rather than at the level of the hedge fund (Connor & Woo, 2004).

Second, the exemptions from regulatory oversight allow hedge funds to implement unorthodox and often dynamic investment strategies that may exploit a wide range of diverse investment opportunities. Furthermore, hedge funds typically use limited amounts of base capital and they use substantial leverage to increase the return earned on their investment strategies. Leverage makes hedge fund investments substantially riskier than what is common for mutual funds. Nevertheless, hedge funds frequently engage in short selling and they make a complex use of financial derivatives (Aragon & Spencer Martin, 2012) to concentrate their exposure to the idiosyncratic risk components that are inherent to the information trading they perform (Brown *et al.*, 2018). Besides the investment strategies already discussed above (long-short equity, global macro, and fixed-income arbitrage) hedge funds also engage in event-driven strategies that are based on investing in anticipation of major corporate events, e.g. mergers and acquisitions (M&As), spin-offs, reorganizations, and bankruptcies (Stulz, 2007). The success of event-driven strategies crucially depends on fund managers' ability to predict the outcome and the price impact of these events and on identifying the optimal time to make the investment.

Third, hedge funds often require their investors to commit their investment for a fairly long time (Teo, 2009). The "lockup periods" may last for several years. Even after the expiration of the lockup periods investors may be obliged to notify managers several months in advance when they want to redeem their investment (Aragon, 2007). These withdrawal restrictions give managers more flexibility in investing in illiquid assets, the value of which may remain depressed for some time. Hedge funds may also exploit opportunities that arise when more conservative investment entities such as pension funds are obliged to divest distressed securities (Connor & Woo, 2004). Holding distressed securities is typically associated with higher liquidity risk. Hence, hedge funds may have substantial exposures to macroeconomic liquidity shocks (Boyson *et al.*, 2006; Sadka, 2010). The lockup period and redemption notice period thus limit the likelihood that hedge funds will be forced to quickly liquidate these assets under unfavorable conditions.

Fourth, being exempted from many regulatory requirements allows hedge funds to remain rather opaque, which helps them protect their proprietary trading strategies from imitation by competitors. Hence, investors can typically barely learn about the rough contours of investment strategies that a given fund aims to pursue. Furthermore, unlike mutual funds, most hedge funds are not obliged to periodically report audited financial statements to regulators. Nevertheless, some funds may provide information on their performance on a voluntary basis (Stulz, 2007). Hedge funds are not allowed to publicly advertise and so having their performance record included in commercial databases may help them attract investors (Fung & Hsieh, 2004b; Baquero *et al.*, 2005). This discretion was constrained by the Dodd-Frank Act of 2010 which mandates investment funds domiciled in the U.S. that manage more than $150 million in aggregate assets to register with the SEC and to provide basic periodic disclosures on asset values, returns, borrowings, strategy classifications, investor composition, and their largest counterparties (Barth *et al.*, 2020). The asset value cutoff implies that the regulation applies only to the large hedge funds that may be systemically important.

Fifth, hedge funds typically charge their investors substantial management and performance fees (Malkiel & Saha, 2005). A common arrangement consists of a flat management fee of 1% to 2% of AUM and a variable performance fee usually 20% of realized returns above the risk-free rate (Fung & Hsieh, 1999; Connor & Woo, 2004; Stulz, 2007; Kouwenberg & Ziemba, 2007; Getmansky *et al.*, 2015). The performance fee is usually paid only after reaching the so-called "high water mark", i.e. the minimum level of absolute performance over the entire investment lifetime (Asness *et al.*, 2001; Goetzmann *et al.*, 2003; Lim *et al.*, 2016; Stulz, 2007). In other words, in a given year fund managers receive the performance fee only after having recovered any losses incurred in previous years. However, effectively the performance fees constitute even a larger portion of realized returns because investors cannot offset gains and losses across funds, they tend to withdraw capital after a poor past performance, and managers sometimes terminate hedge funds after large losses, which renders the high water mark provision irrelevant. Ben-David *et al.* (2020) find that due to these three reasons the effective performance fees approach one-half of the aggregate gross profits. The high level of hedge fund managers' participation in realized returns strongly incentivizes them to perform and it allows successful managers to earn compensation similar to what they would earn in mutual funds 10 times their hedge fund size (Connor & Woo, 2004; Jobman, 2002). Furthermore, unlike in mutual funds, the performance fee in hedge funds makes the compensation structure highly asymmetric. Hedge fund managers are compensated for gains, but they are not equivalently penalized for commensurate losses. These option-like payoffs strongly motivate them to take risk. The high-water mark provisions are likely to only partially moderate these risk-taking incentives because managers of unsuccessful hedge funds may opt to close the fund down and open a new one (Stulz, 2007). Getmansky *et al.* (2015) report that only about one-half of hedge funds survive for more than five years. Hence, hedge funds are likely to take substantial risks, which should be taken into consideration when measuring their performance.

Hedge Fund Performance

A priori, it is not quite obvious whether hedge funds should be expected to outperform other types of investments. Hedge funds typically make their investments in financial markets that are rather competitive and where investors have strong incentives to quickly eliminate any mispricing. In efficient markets, any quest for mispriced assets that subsequently earn abnormal returns may be elusive. In the past, many famous hedge fund successes were followed by spectacular failures, which suggests that extraordinary performance may be temporary and driven by chance. For example, the once-lauded and abundantly financed investment strategy of the LTCM later failed and necessitated a massive bailout (Stulz, 2007). Furthermore, competition is intensive even within the hedge fund industry. Light regulation implies relatively low barriers to entry. Any profitable strategies discovered by hedge funds may invite imitation by competitors and their ability to generate abnormal returns may quickly disappear.

Furthermore, the generous and convex "option-like" compensation packages that reward success but do not commensurately penalize failure may encourage excessive risk-taking (Cao *et al.*, 2016). Hedge fund managers may thus take aggressive positions that expose investors to substantial risks. Stulz (2007) argues that hedge fund risk profiles may resemble those of firms selling earthquake insurance. They may exhibit stable profitability for a long time but incur catastrophic losses at rare events when a disaster strikes. The LTCM's arbitrage strategy was ex-post likened to "*picking up pennies in front of a steamroller*" (Stulz, 2007). Since most hedge funds are not obliged to systematically report their performance some of these failures may be kept off the radar. If successful hedge funds are more likely to be included in the private databases and become better known to investors than the failed ones (Posthuma & Van der Sluis, 2003), investors' view of overall hedge fund performance may be distorted.

In addition, the light regulatory oversight and limited reporting requirements may impair managerial accountability and complicate monitoring by investors. Information on the portfolio composition and periodic performance may not be independently audited and so its reliability may be in question. Hedge fund managers may thus be able to camouflage inferior performance for some time, which may prevent investors from taking timely corrective action. When investors are kept in the dark they may find it difficult to base their investment decisions on a pragmatic economic calculus. Rather, they may fall prey to hedge fund managers' personal charm and keep trusting them for longer than appropriate. The Bernard L. Madoff Investment Securities investors mention the founder's personality as one of the reasons why they remained confident in the fund for so long.[3]

Finally, hedge funds charge very substantial management and performance fees. Thus, it is also conceivable that hedge funds actually beat the benchmark but the return they generate is not sufficient to cover these high fees. Paying these fees may thus leave the investors worse off than they would be by simply tracking the market index at a modest cost.

On the other hand, the flexibility resulting from the regulatory status puts hedge funds in a strong position to exploit opportunities that others cannot. It allows them to adopt a wide range of rather unorthodox investment styles that cannot be pursued by more tightly regulated mutual funds and pension funds. The light regulation allows hedge funds to remain secretive about the nature of their strategies, their holdings, and annual performance, which may allow them to protect their proprietary trading strategies and keep exploiting them longer than conventional mutual funds could. Hedge funds can thus act as investment strategy innovators and benefit from their first-mover advantage. They can also benefit from being a counterparty to transactions when more conventional investment entities are obliged due to regulation to divest distressed assets. Hedge funds may also benefit from introducing competition into previously oligopolistic market segments such as fixed-income arbitrage that used to be the domain of investment banks (Connor & Woo, 2004; Schneeweis, 1998).

Furthermore, investors typically agree to forgo some of the diversification benefits, which allows hedge funds to keep asset holdings relatively concentrated and to specialize in a fairly narrowly defined niche. Investment concentration may allow hedge funds to realize some gains from their high degree of investment specialization. The lack of aspiration to hold well-diversified portfolios may also give hedge funds an opportunity to act more aggressively in acquiring substantial stakes in firms and to become "activist", i.e. they can actively use their ownership rights to alter how the companies are run. Hedge fund activism can make the companies more valuable by rectifying some of the agency conflicts between the owners

[3]Source: https://www.nbcnews.com/business/business-news/madoff-exploited-weak-oversight-did-regulators-learn-their-lesson-n1264094.

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