

FOMO in equity markets?

Concentration risk in (sustainable) investing

Andreas Brøgger
Joren Koëter
Mathijs van Dijk

Colophon

Industry papers are papers for pension sector professionals. They are published on the Netspar website after approval by the Netspar Editorial Board (EB). The EB checks the papers for both academic quality and accessibility by non-academic professionals. Industry papers are presented for discussion at Netspar events. Representatives from partners in the academic, pension, and insurance sectors are invited to these events.

Netspar Industry Paper 2026-06, Mei 2026

Acknowledgements

We are grateful to Hank Bessembinder, David Blitz, Marco Ceccarelli (discussant), Erik Hulsegge, Paul Mensink, Roger Otten, Maarten Roth, Dirk Schoenmaker, Willem Schramade, Paul Smeets, Rogier Swierstra, Laurens Swinkels, Marta Szymanowska, Patrick Tuijp, Martijn van den Hoorn, Maurice Versaavel, Bas Werker, Jan-Willem Wijckmans, and seminar participants at Erasmus University Rotterdam, University of St Andrews Business School, a Netspar after-lunch webinar, a CFA Society Netherlands seminar, a Robeco Asset Management seminar, an ICPM webinar, the 2025 Netspar annual conference, and the 2025 Netspar International Pension Workshop for their useful comments. We acknowledge financial support from the VBA reserves of CFA Society Netherlands and from Netspar through a Topicality Grant (TP2024.01).

Editorial Board

Chair: Andries de Grip, Maastricht University

Members:

Joyce Augustus-Vonken, APG
Mark-Jan Boes, Vrije Universiteit Amsterdam
Damiaan Chen, De Nederlandsche Bank
Bart Dees, Nationale-Nederlanden
Arjen Hussem, PGGM
Kristy Jansen, University of Southern California
Sven Klijnhout, Achmea
Raymond Montizaan, Universiteit Maastricht
Alwin Oerlemans, APG
Jan Maarten van Riemsdijk, PGGM
Mariëtte Sanderse, PMT
Peter Schotman, Universiteit Maastricht
Erik Schouten, Ministerie van Financiën | Belastingdienst
Anja De Waegenare (TIU)
Ivor Witte, a.s.r.

Design Maan

Lay-out Bladvulling

Editor Frans Kooymans

Industry Papers are publications by Netspar. No reproduction of any part of this publication may take place without permission of the authors.

Table of contents

Abstract	4
Nederlandse samenvatting	5
1. Introduction	6
2. Data and methods	14
3. Results	23
4. Conclusions	41
References	43
Appendix	45

Affiliations

Andreas Brøgger – Rotterdam School of Management, Erasmus University

Joren Koëter – Rotterdam School of Management, Erasmus University

Mathijs van Dijk – Rotterdam School of Management, Erasmus University

Abstract

This paper revisits the financial consequences of imperfectly diversified portfolios – in light of the trend towards concentrated (sustainable) portfolios among some institutional investors. Arguments for a more concentrated portfolio range from the desire to invest more sustainably and/or to engage more intensively with companies, to “know what you own” and improved risk management. We study the financial consequences of more concentrated equity portfolios based on backtests of different types of portfolios in a large dataset of stocks from 47 countries over the period 1985–2023.

Our main findings are twofold. First, contrary to Statman (1987), we find that a portfolio consisting of 30 to 40 stocks is not sufficient for full diversification. Second, we identify a second dimension of concentration risk, which we call FOMO (fear of missing out). When forming concentrated portfolios, the selection of stocks becomes very important for portfolio performance, and investors may regret their portfolio choice ex post when other choices would have yielded better performance. We find similar diversification and FOMO effects for portfolios constructed based on ESG screens, exclusion of sin industries, and portfolio weight optimization.

Our analyses suggest three possible strategies to “accelerate” diversification for small portfolios: smart stock selection based on correlations and volatility, limiting the portfolio weight of individual stocks, and maintaining the sector composition of the market as a whole. Even then, however, 30–40 stocks are insufficient for full diversification. Conceptually, FOMO, by contrast, can only be mitigated by predicting which stocks will perform best in the future—and the literature shows that this is extremely difficult. Regardless of the specific investment strategy, it therefore remains important to take FOMO into account when considering a concentrated portfolio. For investors in concentrated portfolios, it is relevant to consider which alternative portfolio choices they would view as realistic.

There are also non-financial arguments in favor of concentrated portfolios, and our analysis has several limitations. Nevertheless, our study highlights the importance of two financial consequences of concentrated portfolios (incomplete diversification and FOMO) that should be considered alongside other arguments when choosing a concentrated portfolio.

Nederlandse samenvatting

Er is een levendig debat over de voor- en nadelen van geconcentreerde aandelenportefeuilles, zowel onder Nederlandse als buitenlandse pensioenfondsen en verzekeraars. Een gebruikelijke beleggingsstrategie is het aanhouden van duizenden aandelen in een wereldwijde portefeuille. Recent lijkt een trend te zijn ontstaan richting portefeuilles met slechts enkele honderden aandelen, of zelfs minder dan honderd. Argumenten voor deze keuze variëren van de wens om duurzamer te beleggen en/of intensievere engagement met bedrijven te voeren tot “know what you own” en betere risicobeheersing. Wij bestuderen de financiële consequenties van meer geconcentreerde aandelenportefeuilles op basis van backtests van verschillende soorten portefeuilles in een grote dataset van aandelen uit 47 landen over de periode 1985-2023.

Onze belangrijkste bevindingen zijn tweeledig. Ten eerste vinden we, in tegenstelling tot Statman (1987), dat 30-40 aandelen onvoldoende zijn voor volledige diversificatie. Ten tweede identificeren wij een nieuwe, tweede dimensie van concentratierisico, die wij FOMO (fear of missing out) noemen. Bij het samenstellen van geconcentreerde portefeuilles is de aandelenselectie van groot belang en kunnen beleggers achteraf spijt hebben van hun keuze wanneer andere keuzes tot een beter beleggingsresultaat zouden hebben geleid. Onze analyses laten zien dat dit FOMO-risico van belang is: zelfs bij portefeuilles met honderden aandelen kan de keuze van de specifieke aandelen in de portefeuille veel rendement schelen.

Onze analyses suggereren drie mogelijke strategieën om diversificatie te “versnellen” voor kleine portefeuilles: het slim kiezen van aandelen op basis van correlaties en volatiliteit, het beperken van het gewicht van individuele aandelen en het behouden van de sectorcompositie van de markt als geheel. Maar zelfs dan zijn 30-40 aandelen onvoldoende voor volledige diversificatie. Conceptueel gezien kan FOMO daarentegen alleen beperkt worden door te voorspellen welke aandelen in de toekomst het beste zullen presteren – en we weten uit de literatuur dat dit zeer lastig is. Onafhankelijk van de specifieke beleggingsstrategie blijft het daarom van belang om FOMO in aanmerking te nemen bij het overwegen van een geconcentreerde portefeuille. Voor beleggers in geconcentreerde portefeuilles is het relevant om te bedenken welke andere portefeuillekeuzes zij als realistisch alternatief zouden zien.

Er zijn ook niet-financiële argumenten voor geconcentreerde portefeuilles en onze analyse kent diverse beperkingen. Maar onze studie wijst op het belang van twee financiële consequenties van geconcentreerde portefeuilles (onvolledige diversificatie en FOMO) die samen met andere argumenten in ogenschouw zouden moeten worden genomen bij de keuze voor een geconcentreerde portefeuille.

1. Introduction

In the past several decades, asset owners such as pension funds and insurance companies have predominantly followed investment strategies that closely track broad market indices. The resulting equity portfolios often consist of thousands of individual stocks stemming from many different countries and economic sectors. More recently, a trend has arisen among some institutional investors to hold more concentrated portfolios that contain only several hundreds of stocks (Schoenmaker and Schramade, 2019) – and occasionally even fewer than 100 stocks (Investment & Pensions Europe, 2024; Market Screener, 2025).

Several developments have contributed to this trend. First, the increasing focus on Environmental, Social, and Governance (ESG) and other forms of sustainable investing has led investors to pursue exclusion strategies that exclude individual firms (e.g., based on poor ESG performance), economic sectors (e.g., the fossil fuels sector), and/or countries (e.g., countries with human rights violations). Second, institutional investors concerned about reputation risks increasingly feel compelled (by stakeholders or regulators) to “know what they own” – which is challenging for portfolios with many stocks. Related, ESG risk management can be a motivation for more concentrated portfolios since measuring and monitoring complex ESG risks such as climate risks (which new regulations, including the European Union’s Corporate Sustainability Due Diligence Directive require to be assessed across the entire supply chain) may not be feasible for many stocks. Third, impact investing that involves active investor engagement with firms may be difficult for large portfolios.

In this paper, we address the question whether such investment strategies involving portfolios with fewer stocks lead to material *concentration risk*. At least since Markowitz, (1952), it is well-understood that it is important to have a sufficient number of (imperfectly correlated) stocks in investment portfolios to diversify idiosyncratic risk. An often-cited empirical paper in the literature on diversification is Statman (1987), who concludes that it takes only 30–40 stocks to fully diversify idiosyncratic risk.¹ However, there are good reasons to revisit this conclusion. First, many studies in this literature are relatively old. Second, most studies take a U.S. perspective only. Third, these studies are generally based

1 Other studies find different numbers of stocks required for complete diversification, e.g.: 8–10 stocks in Evans and Archer (1968); 15 stocks in Solnik (1974), and over 73 stocks in Alexeev and Tapon (2014). Statman (2002) finds that more than 120 stocks are needed for full diversification. Bender and Sun (2023) conclude that 100–200 stocks are needed to keep portfolio tracking error below 1%. Zaimovic, Omanovic, and Arnaut-Berilo (2021) review 150 studies on this topic and conclude that (i) there is no single answer to the question how many stocks are needed for diversification, (ii) the size of a well-diversified portfolio is now larger than in the past, and (iii) the size of a well-diversified portfolio is smaller in emerging markets. To illustrate how pervasive the notion is that around 30 stocks are sufficient for diversification, we asked ChatGPT on December 23, 2025: “How many stocks does it take for an equity portfolio to be fully diversified?” The answer was: “There is no single number, but most research finds that about 20–30 stocks are enough to achieve most of the benefits of diversification, and 30–50 stocks gets you very close to “fully diversified” for practical purposes”.

on random draws from the universe of stocks, while ESG investing clearly tilts the investment universe. Fourth, stock market concentration has increased over time, which suggests that idiosyncratic risk may have become harder to diversify in more recent periods (Gabaix, 2011; Emery and Koëter 2024; Jiang, Vayanos, and Zheng, 2025). Our first main goal is thus to revisit the question of how many stocks are needed for diversification, based on a large recent global sample of stocks and taking into account ESG screens.

Our second main goal is motivated by Bessembinder (2018) and Bessembinder, Chen, Choi, and Wei (2023), who find that most stocks underperform the risk-free rate and that just 2-4% of stocks account for the entire (U.S. as well as global) equity premium. To illustrate how dominant a few stocks are in delivering the equity premium, Bessembinder (2018) documents that merely 5 stocks (Exxon Mobile, Apple, Microsoft, General Electric, IBM) out of 35,000 U.S. stocks over 1926-2016 account for 10% of total wealth creation on the U.S. stock market over this 90-year period. This dominance is echoed by the performance of the “Magnificent 7” (Alphabet, Amazon, Apple, Meta Platforms, Microsoft, NVIDIA, Tesla) over the past decade. The implication of this pronounced skewness in the distribution of long-term returns across stocks could be that portfolios containing fewer stocks are more likely to miss out on these top-performing stocks – and thus on part of the realized equity premium. As a result, concentrated portfolios could not only exhibit a *greater volatility* (when they are less than perfectly diversified), but also possibly a *lower return* (when they exclude the top-performing stocks). To the best of our knowledge, this potentially important implication of concentrated portfolios has not been examined thus far.

Our analysis is based on a variety of backtests on the financial performance of portfolios holding different numbers of stocks. Building on Jensen, Kelly, and Pedersen (2023), we create a comprehensive global dataset of stock returns and characteristics for 87,266 unique stocks from 47 countries (around 25,000 stocks on average each year) over the period January 1985 - December 2023 (468 months). We obtain ESG rating data from five different rating providers: FTSE, ISS, MSCI, Refinitiv, and S&P Global. Since the investable universe for most institutional investors is considerably smaller than our full sample of stocks, we create a “pseudo MSCI ACWI sample” that stays close to one of the most widely used global equity benchmarks for institutional investors worldwide: the MSCI All Country World Index.

We simulate investment strategies with different degrees of concentration by randomly drawing N stocks (where $N = 10, 50, 100, 250, 500, 750, 1000, 1500$) into portfolios each month, from both the full sample with all stocks and from the pseudo MSCI ACWI sample. We repeat this random draw 10,000 times for each N . In our baseline analyses, we draw stocks with equal probability and then create value-weighted portfolios in which the weight of each stock that is drawn into the portfolio is proportional to its market capitalization.

We examine the historical financial performance of the portfolios for each N across the 10,000 draws (mean and 95% confidence band around the mean) for the following performance metrics: volatility, average return, Sharpe ratio, downside risk (2.5th percentile of the portfolio's time-series return distribution), and tracking error relative to the value-weighted market index including all stocks in our sample or relative to the pseudo MSCI ACWI index.

There are several limitations to our backtests. First, our findings could in part be driven by "chance patterns" in our historical dataset that may not show up going forward. This is a particular concern for our analyses based on ESG data, which span a relatively short sample period. Related, some investors argue that concentrated portfolios allow for better management of ESG risks such as climate risks (e.g., averting "stranded assets"; Caldecott et al., 2021), which may only be observed to a limited extent in past data. We address this concern in part by examining the robustness of our conclusions to different variations of the baseline analyses.

Second, our aim is to examine the severity of concentration risk in equity portfolios actually held by institutional investors. But, as empirical researchers, it is virtually impossible to replicate actual investment strategies, given all the degrees of freedom in real-life portfolio choice. Again, we address this concern in part by considering various ways to construct investment portfolios. We also acknowledge that actual investment strategies are not based on random draws of stocks. That said, there is a lot of discretion in determining both the selection of stocks and their weight in an investment portfolio, and we believe that the randomness in our analysis is a useful way to illustrate the wide variation in investment decisions possible when composing concentrated portfolios in real life. We note that our analyses focus on equity portfolios only. Diversification across asset classes could lead to different conclusions.

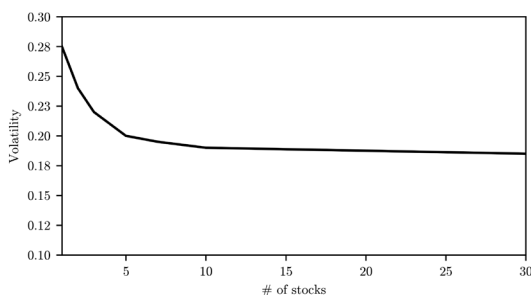
Before running our backtests, we examine some basic features of our global sample of stocks. The equity premium (return on a value-weighted index of all stocks in our sample in excess of the risk-free rate) over our almost 40-year sample period from 1985 to 2023 is 6.9% per annum, with an annual volatility of 15.5%, a Sharpe ratio of 0.44, and a drawdown (2.5th percentile) of -9.2%. These numbers are very similar for our value-weighted pseudo MSCI ACWI index. We confirm findings from the literature on well-known stock market anomalies (among others, size, value, profitability, investment) and on the absence of a relation between stock returns and ESG ratings (Alves, Krüger, and van Dijk, 2025) in our sample.

We then turn to revisiting the diversification analysis of Statman (1987), which is still often cited by practitioners and academics alike as evidence that it takes only 30-40 stocks to fully diversify idiosyncratic risk. For example, the *Investments* textbook by Bodie, Kane, and Marcus (2023), which is used at business schools around the world, features a figure that replicates the Statman (1987) result based on NYSE data over 2008-2017, see Panel A

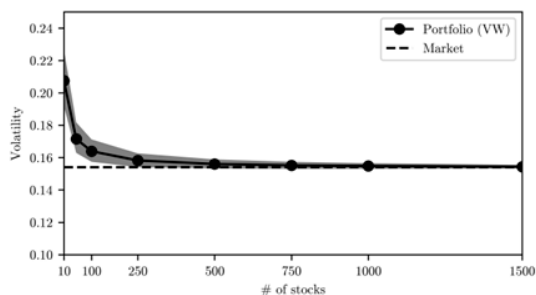
Figure i. Replication of Statman’s (1987) diversification result

Panel A (Panel A of Figure 2 at the end of this paper) shows a mimicked version of the Bodie, Kane, and Marcus (2023, p. 203) graph of portfolio volatility vs. # stocks in the portfolio, which is based on NYSE data over 2008-2017. Panel B (Panel B of Figure 3) shows a graph of portfolio volatility (mean volatility in black dots/line and 95% confidence band in gray; market volatility as dashed line) vs. # stocks in the portfolio, based on our MSCI ACWI sample over 1985-2023 (10,000 draws; equal drawing probability; value-weighted portfolios).

Panel A: Statman replication



Panel B: Our global sample



of Figure i. The graph shows that portfolio volatility declines very rapidly as the number of stocks in the portfolio is increased, with most diversification of idiosyncratic risk already achieved at $N = 10$ and no discernable further reduction in portfolio volatility observable beyond $N = 25$.

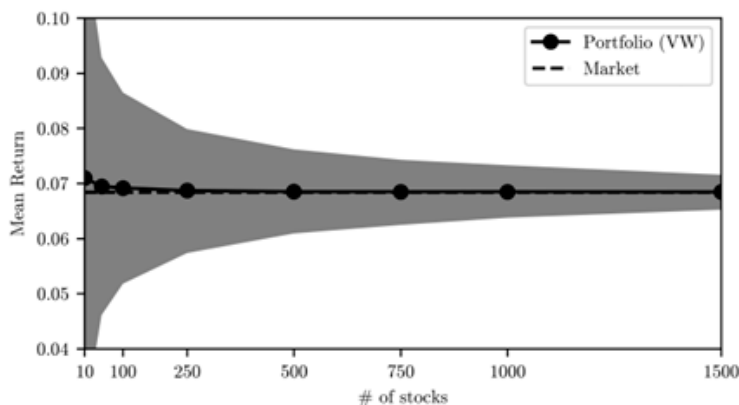
Panel B of Figure i shows the result of our backtest for our global pseudo MSCI ACWI sample over 1985-2023. The black dots (connected by straight black lines) show the mean portfolio volatility in our backtest for $N = 10, \dots, 1500$. The gray area around the black line reflects the confidence band based on the 2.5th and 97.5th percentiles of the volatility distribution across the 10,000 draws for each N . The dashed horizontal line represents the market volatility (value-weighted MSCI ACWI). The gray area illustrates that the rate of convergence of portfolio volatility to market volatility naturally depends on the specific portfolio draws – although the confidence bands are rather narrow here.

The overall pattern in Panel B of Figure i is similar to that in Panel A in the sense that portfolio volatility is reduced when N is increased, and that the reduction gets smaller when N gets greater. However, the rate of convergence to market volatility is considerably slower than suggested by Panel A. There are still notable gains from diversification from increasing N to over 100 stocks, and – although the gains from diversification become smaller for greater N – only at around $N = 750$ and beyond does it become hard to visually distinguish the mean portfolio volatility from the market volatility. Our first main result is thus that it takes considerably more than 30-40 stocks to fully diversify idiosyncratic risk in a global sample.

We next turn to our analysis of how concentrated portfolios may affect the return profile of investment strategies, since in concentrated portfolios stock selection is likely to be very important for portfolio performance, and investors may regret their choice of stocks ex post when other portfolio choices would have generated better performance. We demonstrate

Figure ii. FOMO risk in global stock portfolios

This figure (Panel B of Figure 5 at the end of this paper) shows a graph of portfolio return (mean return in black dots/line and 95% confidence band in gray; market return as dashed line) vs. # stocks in the portfolio based on our MSCI ACWI sample over 1985-2023 (10,000 draws; equal drawing probability; value-weighted portfolios).



this FOMO (Fear Of Missing Out) effect by plotting the returns (in excess of the risk-free rate) of portfolios for different N , see Figure ii. The mean portfolio return is close to the value-weighted MSCI ACWI return (dashed horizontal line), regardless of N . But the 95% confidence band (in gray) around the mean return is very wide. At $N = 100$, the 2.5th percentile of the return distribution across the 10,000 draws is slightly above 5% per annum, whereas the 97.5th percentile is around 8.6% per annum. The return difference between a “lucky pick” of 100 stocks and an “unlucky pick” of 100 stocks thus amounts to around 3.5% per annum, which could lead to huge differences in compound returns over long investment horizons (even greater differences obtain with 99% confidence bands). Our second main result is thus that concentrated portfolios are associated with potentially large FOMO risk.

Figure ii shows that FOMO risk decreases only relatively slowly when N gets larger - notably slower than volatility in Panel B of Figure i. The spread in stock returns between the 2.5th and 97.5th percentile of the return distribution across draws in Figure ii equals almost 2% per annum for $N = 500$ and still around 1% for $N = 1000$. Even return differences of 1% per annum can add up to large wealth differences over long horizons; compounding a constant 7% return over 30 years yields a final wealth of €7.61 for every €1 invested, while compounding a constant 6% return yields only €5.74 for every €1 invested (difference of one third).

Our FOMO analyses are motivated by the findings by Bessembinder (2018) and Bessembinder et al. (2023) that a very small percentage of stocks account for the equity premium. We first redo their analysis in our sample. Consistent with their results, we find that only 41% of the 87,266 stocks in our global sample positively contribute to wealth creation over 1985-2023. The top-performing 2.1% of all stocks account for all wealth creation for investors over our sample period, while just 162 stocks (0.19% of all stocks) account for 50% of all wealth creation, and merely 30 stocks (best-performing 0.03% of all global

stocks) account for 25% of global stock market wealth creation over a 40-year period.² This extreme skewness in the distribution of long-term returns across individual stocks could render investors in concentrated portfolios exposed to the risk of missing out on the small fraction of top performing stocks – and thus on part of the equity premium. That said, we use the term “FOMO” to describe the cross-sectional dispersion in mean returns (or Sharpe ratios) of different portfolios for a given N . Although the result that a very small fraction of stocks account for the equity premium is an important motivation for examining this cross-sectional dispersion, our current results do not yet establish a direct link between the FOMO effect and the findings regarding the small fraction of top performing stocks – an issue that we intend to study in follow-up analyses.

To consider alternative investment approaches, we also use different specifications for both drawing probability and portfolio weights. For the portfolio weight of the stocks drawn into a portfolio, we also use equal weights (to mimic $1/N$ strategies as in DeMiguel, Garlappi, and Uppal, 2009) and optimal weights in a portfolio optimization sense (based on minimum variance, maximum Sharpe ratio, and Black-Litterman approaches). We also use drawing probabilities proportional to a stock’s optimal weight (minimum variance, maximum Sharpe ratio, and Black-Litterman approaches). We further consider portfolios of which 20% of stocks are randomly replaced each year (instead of the 100% monthly rebalancing in our baseline analysis) and portfolios that impose a maximum weight for individual stocks. We also rerun our backtests in such a way that the industry composition of the portfolios resembles that of the MSCI ACWI. The bottom line of these further tests is that our findings on diversification and FOMO are maintained under these alternative specifications. There are three exceptions: it appears that the convergence of portfolio volatility to market volatility is somewhat quicker when portfolio weights are optimized (especially in a minimum variance sense), when imposing a maximum weight for individual stocks, or when maintaining the industry composition of the market as a whole. However, even in these specifications, 30-40 stocks are not enough to fully diversify idiosyncratic risk, and there are still strong FOMO effects that persist for large N .

We present two specific analyses to examine the risk and return characteristics of concentrated portfolios constructed based on ESG considerations. In the first ESG analysis, we let the drawing probability be proportional to a stock’s ESG rating – to mimic ESG screens that tilt portfolios towards stocks with better ESG ratings. In the second ESG analysis, we redo our baseline analyses while dropping sin stocks (Hong and Kacperczyk, 2009). We find very similar diversification and FOMO effects in these analyses, which suggests that

2 The finding that the top-performing 2.1% of stocks account for all wealth creation (while 41% of stocks contribute positively to wealth creation) implies that the net aggregate wealth creation of the remaining 97.9% stocks is zero.

there is nothing special about small sustainable portfolios relative to small portfolios in general.

Overall, our paper presents two key results that we believe are novel to the literature and relevant for real-life investors. The first key result is that the often-cited finding by Statman (1987) that 30-40 stocks are sufficient for full diversification does not apply in our global sample of stocks over almost 40 years: considerably more stocks are needed for full diversification. The second key result is what we call FOMO risk: the possibility that investors ex post regret their selection of stocks for concentrated portfolios when other portfolios exhibited better performance. This risk can be viewed as a novel, second dimension of risk (next to volatility) that investors should assess when considering concentrated equity portfolios. We are not aware of other papers on this FOMO risk dimension of concentrated portfolios, which – given the magnitudes in our backtests – is arguably even more important than insufficiently diversified idiosyncratic risk.

We further show that these key results obtain in various different specifications and that there do not seem to be straightforward methods to alleviate concerns around imperfectly diversified idiosyncratic risk as well as FOMO. Our analyses do indicate that classical portfolio optimization techniques (minimum variance, maximum Sharpe ratio) are at least somewhat helpful in “speeding up” diversification as N increases as well as in boosting Sharpe ratios, but these techniques still leave substantial FOMO risk in portfolio choice.

Although we acknowledge that our study has several important limitations and that there may be non-pecuniary motivations to pursue concentrated portfolios, our results indicate that overly concentrated portfolios may have non-negligible financial consequences. This conclusion is also relevant outside of the context of the recent trend towards concentrated (sustainable) portfolios, since many retail and institutional investors hold concentrated portfolios (Campbell, 2006; Goetzmann and Kumar, 2008; Kojien and Yogo, 2019). To illustrate, Dyakov, Jiang, and Verbeek (2020) document that the median number of stocks in the portfolio of 13,807 international equity mutual funds over 2001-2014 is just 86.

Our study documents important FOMO effects in the context of concentrated portfolios. More generally, one could consider *any* of the choices made in constructing investment portfolios (e.g., how many and which stocks to include, their portfolio weights, rebalancing frequency, trading strategy) to result in FOMO risk: the possibility of “regret” (Lin, Huang, and Zeelenberg, 2006; Bourgeois-Gironde, 2010; Goossens, 2022) about not having made different choices ex ante. In that sense, the total magnitude of FOMO risk has to be evaluated relative to *all other* portfolio choices that could have been made and thus cannot be “reduced” by choosing, for example, a particular weighting scheme. Alternatively, FOMO could be considered from an investor’s perspective: the relevant degree of FOMO risk depends on each specific investor’s perspective on what other portfolio choices could have been made (e.g., in light of mandates) and/or were feasible. Our study is further related to

recent work on “non-standard errors” in finance research (Menkveld et al., 2024; Soebhag et al., 2024) illustrating that different design choices can lead to widely different outcomes. More research is needed to fully understand the nature and extent of FOMO in portfolio choice.

2. Data and methods

2.1 Data

We use an exhaustive global dataset of monthly stock returns and stock-level characteristics from January 1985 through December 2023, based on the Jensen-Kelly-Pedersen WRDS integration (Jensen, Kelly, and Pedersen, 2023), which combines CRSP and Compustat global return data. Monthly excess stock returns in this database are measured relative to the 30-day U.S. Treasury bill rate from CRSP. The database also gives us the stock-level variables size, beta, book-to-market, profitability, investment, quality, short-term reversal (last month's return), momentum, and idiosyncratic volatility. We obtain ESG rating data from five different rating providers: FTSE, ISS, MSCI, Refinitiv, and S&P Global. We refer to Table 1 for a description of variable definitions.

To ensure data quality, we manually correct identified obvious market capitalization errors for one individual Brazilian firm. For the remaining observations, we apply standard filters, removing observations with missing returns or market capitalizations and winsorizing monthly excess returns at the 0.1% and 99.9% percentiles within each period, to mitigate the influence of remaining outliers.

Our final sample contains a total of 87,266 unique firms across 47 countries, with an average of 24,988 firms per month. For a subset of our analyses, we construct a "pseudo MSCI ACWI sample" (which we will refer to as the MSCI ACWI sample) to simulate the constituents of a widely tracked global equity index: the MSCI All Country World Index. We are not able to use the actual constituents of this index and instead use the largest 2,500 stocks based on their market capitalization each month. According to recent public information on the composition of the MSCI ACWI, our "pseudo MSCI ACWI" sample is close to the actual MSCI ACWI in terms of number of stocks as well as country and sector composition. In April 2025, MSCI ACWI consisted of 2,558 constituents from 23 developed and 24 emerging markets. Our pseudo MSCI ACWI sample consists of 2,500 stocks each month from the same 47 countries and, at the end of our sample period, exhibits country and sector weights that are very similar to the actual MSCI ACWI at this point in time.³

2.2 Sample statistics

Table 1 shows summary statistics of all stock-level variables used in our analyses. To get a sense of the features of our historical sample, Table 2 shows the equity premium, volatility, Sharpe ratio, and drawdown (2.5th percentile of the time-series return distribution) of market indices that we construct based on different (sub)samples. The value-weighted equity premium based on all stocks (relative to the 1-month U.S. T-bill rate) is 6.9% per

³ See: <https://www.msci.com/documents/10199/8d97d244-4685-4200-a24c-3e2942e3adeb>.

Table 1. Summary statistics of stock returns and characteristics

This table presents summary statistics for stock-level variables in our global sample over 1985-2023 (all stocks in Panel A and pseudo MSCI ACWI sample in Panel B). *Return* is the monthly stock return measured in dollars in excess of the 30-day T-bill rate. *Size* is the market capitalization measured in millions of U.S. dollars. *Beta* is the CAPM beta estimated over months $t-60$ through $t-1$. *B/M* is the ratio of the book value of equity to market equity. *Profitability* is gross profits over total assets. *Investment* is the annual growth rate in total assets. *Momentum* is the cumulative stock return over months $t-12$ through $t-1$. *Quality* is the z-score computed across a broad set of characteristics related to profitability, growth and safety. *Idio vol* is the idiosyncratic volatility over the past 21 days based on the Fama-French 3-factor model. *ESG provider* is the Z-score of the ESG rating of five different ESG rating providers (FTSE, ISS, MSCI, Refinitiv, S&P) computed within global industries (GICS sectors), *ESG* is the mean Z-score across the different ESG rating providers. The table reports the number of observations, cross-sectional mean, standard deviation, 25th percentile, median, and 75th percentile for each variable.

Panel A: All stocks						
	#obs.	mean	std	25%	50%	75%
<i>Return</i>	11,694,235	0.82%	17.55%	-7.08%	-0.37%	6.59%
<i>Size</i>	11,694,235	1,556	12,731	27	113	531
<i>Beta</i>	8,815,430	1.04	0.61	0.67	0.99	1.34
<i>B/M</i>	9,899,024	1.10	1.90	0.35	0.68	1.23
<i>Profitability</i>	8,827,103	0.28	0.34	0.10	0.21	0.38
<i>Investment</i>	9,751,190	0.35	4.62	-0.05	0.05	0.20
<i>Momentum</i>	10,730,106	0.14	0.80	-0.24	0.01	0.30
<i>Quality</i>	7,330,018	0.00	1.00	-0.86	0.00	0.87
<i>Idio vol</i>	8,786,308	2.78%	2.52%	1.35%	2.09%	3.34%
<i>ESG FTSE</i>	267,331	0.00	1.00	-0.78	-0.01	0.78
<i>ESG ISS</i>	349,339	0.00	1.00	-0.76	-0.22	0.62
<i>ESG MSCI</i>	835,315	0.00	1.00	-0.66	-0.03	0.65
<i>ESG Refinitiv</i>	797,362	0.00	1.00	-0.80	-0.08	0.75
<i>ESG S&P</i>	669,376	0.01	1.00	-0.72	-0.34	0.47
<i>ESG</i>	1,235,467	-0.05	0.81	-0.62	-0.11	0.45
Panel B: ACWI						
	#obs.	mean	std	25%	50%	75%
<i>Return</i>	1,170,000	0.61%	10.76%	-4.95%	0.45%	5.94%
<i>Size</i>	1,170,000	12,584	38,485	2,042	5,037	11,021
<i>Beta</i>	1,009,356	1.02	0.48	0.72	0.99	1.26
<i>B/M</i>	1,055,721	0.56	0.54	0.25	0.45	0.74
<i>Profitability</i>	917,341	0.30	0.29	0.13	0.24	0.40
<i>Investment</i>	1,037,034	0.22	2.64	0.00	0.08	0.20
<i>Momentum</i>	1,119,732	0.21	0.58	-0.07	0.12	0.35
<i>Quality</i>	868,076	0.33	0.89	-0.36	0.42	1.10
<i>Idio vol</i>	1,047,673	1.58%	0.97%	0.96%	1.35%	1.92%
<i>ESG FTSE</i>	149,271	0.16	0.98	-0.58	0.20	0.92
<i>ESG ISS</i>	182,026	0.01	0.98	-0.74	-0.19	0.62
<i>ESG MSCI</i>	383,421	0.04	1.01	-0.64	0.01	0.71
<i>ESG Refinitiv</i>	374,699	0.14	1.02	-0.68	0.11	0.94
<i>ESG S&P</i>	363,912	0.10	1.03	-0.68	-0.25	0.75
<i>ESG</i>	466,798	0.05	0.74	-0.46	0.01	0.53

Table 2. Summary statistics of the global equity premium for different samples

This table presents summary statistics for the equity premium in our global dataset of stocks, defined as the excess return of a value-weighted portfolio of the universe considered (although two rows of the table report the equity premium based on an equally-weighted portfolio). *All stocks (1985-2023)* is the universe of all stocks in our global sample over 1985-2023. *All stocks EW (1985-2023)* is the equally-weighted index based on the universe of all stocks in our global sample over 1985-2023. *ACWI (1985-2023)* is the pseudo MSCI ACWI sample over 1985-2023. *ACWI EW (1985-2023)* is the equally-weighted index based on the pseudo MSCI ACWI sample over 1985-2023. *ACWI ex. JPN (1985-2023)* is the pseudo MSCI ACWI sample excluding Japan over 1985-2023. *ACWI ex. MAG7 (1985-2023)* is the pseudo MSCI ACWI sample excluding the Magnificent 7 over 1985-2023. *ACWI ex. small decile (1985-2023)* is the pseudo MSCI ACWI sample excluding the 10% smallest stocks each month over 1985-2023. *ACWI (2014-2023)* is the pseudo MSCI ACWI sample over 2014-2023. *ACWI ex. MAG7 (2014-2023)* is the pseudo MSCI ACWI sample excluding the Magnificent 7 over 2014-2023. *ACWI (2003-2021)* is the pseudo MSCI ACWI sample over 2003-2021, which is the period for which we have sufficient ESG coverage. *ACWI ex. Bottom 10% ESG (2003-2021)* is the pseudo MSCI ACWI sample excluding stocks with an ESG rating in the bottom 10% each month over 2003-2021. *ACWI ex. Top 10% ESG (2003-2021)* is the pseudo MSCI ACWI sample excluding stocks with an ESG rating in the top 10% each month over 2003-2021. The table reports the time-series mean, standard deviation (volatility), Sharpe ratio, and drawdown corresponding to the 2.5% percentile of the return distribution.

	mean	volatility	Sharpe ratio	drawdown
<i>All stocks (1985-2023)</i>	6.9%	15.5%	0.44	-9.2%
<i>All stocks EW (1985-2023)</i>	9.9%	17.0%	0.58	-9.3%
<i>ACWI (1985-2023)</i>	6.8%	15.4%	0.44	-9.2%
<i>ACWI EW (1985-2023)</i>	7.3%	16.0%	0.46	-9.2%
<i>ACWI ex. JPN (1985-2023)</i>	7.6%	15.4%	0.49	-9.3%
<i>ACWI ex. MAG7 (1985-2023)</i>	6.5%	15.3%	0.42	-9.3%
<i>ACWI ex. small decile (1985-2023)</i>	6.8%	15.4%	0.44	-9.2%
<i>ACWI (2014-2023)</i>	7.2%	14.1%	0.51	-7.5%
<i>ACWI ex. MAG7 (2014-2023)</i>	6.0%	13.9%	0.43	-7.5%
<i>ACWI (2003-2021)</i>	9.6%	15.1%	0.64	-9.2%
<i>ACWI ex. Bottom 10% ESG (2003-2021)</i>	9.5%	15.2%	0.63	-9.0%
<i>ACWI ex. Top 10% ESG (2003-2021)</i>	9.5%	15.1%	0.63	-9.2%

annum over 1985-2023, with an annual volatility of 15.5%, a Sharpe ratio of 0.44, and a drawdown of -9.2%. These numbers are almost identical for the value-weighted pseudo MSCI ACWI index, which shows an equity premium of 6.8%, volatility of 15.4%, Sharpe of 0.44, and drawdown of -9.2%. Table 2 also shows that the equally-weighted equity premium is higher than the value-weighted equity premium, especially for all stocks but also for the pseudo MSCI ACWI sample. This finding suggests a non-negligible size effect in our samples, where small firms on average have higher returns than large firms.

Dropping Japan from the global sample boosts the equity premium from 6.9% to 7.6%, as seen in Table 2. Conversely, the equity premium is lower when we exclude the Magnificent 7 (6.5% vs. 6.8%), especially over the last ten years of our sample period (6.0% vs. 7.2%) – illustrating the potentially large influence of a small number of stocks. On the contrary, there is little indication that the equity premium over our sample period is different when we exclude the 10% smallest stocks (smallest decile; the size premium mentioned above thus does not stem from the smallest size decile), or the top or bottom 10% of stocks based

Table 3. Summary statistics of stock market concentration for different samples

This table presents summary statistics (time-series mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum) for several measures of the concentration of the value-weighted stock market index based on different samples (all stocks in Panel A, pseudo MSCI ACWI sample in Panel B). *Effective N* is defined as $\frac{1}{HHI_t}$, where $HHI_t = \sum_{i=1}^N w_{i,t}^2$ and $w_{i,t}$ denotes the market capitalization based weight of stock i in month t within the market index based on the respective sample; this Herfindahl Index corresponds to the number of stocks invested as if forming an equally-weighted portfolio. A lower *Effective N* indicates a more concentrated stock market. *Top 10* (25, 100) is the cumulative weight of the top 10 (25, 100) stocks within the value-weighted index based on the sample involved.

Measure	mean	std	min	q ²⁵	median	q ⁷⁵	max
Panel A: All stocks							
<i>Effective N</i>	735	250	242	501	763	970	1149
<i>Top 10</i>	7.6%	2.4%	4.6%	5.6%	6.8%	9.0%	14.0%
<i>Top 25</i>	13.4%	3.0%	9.4%	10.7%	12.4%	16.2%	21.0%
<i>Top 100</i>	28.2%	4.4%	22.1%	24.2%	27.1%	31.3%	40.5%
Panel B: MSCI ACWI							
<i>Effective N</i>	500	145	195	378	545	628	719
<i>Top 10</i>	9.0%	2.7%	5.9%	7.0%	8.0%	10.5%	17.2%
<i>Top 25</i>	16.0%	3.2%	11.9%	13.4%	14.9%	18.6%	24.7%
<i>Top 100</i>	33.7%	4.0%	28.3%	30.5%	32.0%	37.3%	42.1%

on their composite ESG rating across the five ESG ratings. We note that our ESG data are limited to 2003-2021.

In Table 3, we present some summary statistics of different measures of stock market concentration within a value-weighted market index based on the sample of all stocks (Panel A) and based on the MSCI ACWI sample (Panel B). *Effective N* corresponds to the number of stocks invested as if the portfolio were equally-weighted, based on a Herfindahl index of the weights within a value-weighted market index. A lower *Effective N* indicates a more concentrated stock market. The numbers reported for the Top 10/25/100 stocks are the cumulative market cap weights of the largest 10/25/100 stocks in the respective value-weighted index. The mean *Effective N* for the market index based on all stocks is 735 stocks, but this number varies considerably over our sample period, from a minimum of 242 to a maximum of 1,149. The mean cumulative weight of the top 10/25/100 stocks in the value-weighted market index of all stocks is 7.6%, 13.4%, and 28.2%, respectively. However, at times, the largest stocks constitute a much greater fraction of the value-weighted stock market index, with maximum weights of 14.0%, 21.0%, and 40.5%, respectively. The corresponding concentration measures in Panel B of Table 3 for the MSCI ACWI sample are naturally larger, since the value-weighted index based on the largest 2,500 stocks only is, by definition, more concentrated than the value-weighted index of all stocks. The considerable time-variation in stock market concentration is illustrated in Figure 1, which shows how *Effective N* (based on all stocks and based on the MSCI ACWI sample) varies over our sample period. The figure indicates that over 1985-2023, there were three periods of comparably high stock market concentration: the late 1980s, the early 2000s, and the 2020s.

Figure 1: Effective number of stocks in value-weighted stock market index

This figure plots the effective number of stocks (*Effective N*) of the value-weighted stock market index, based on different samples (all stocks and MSCI ACWI) over 1985-2023. *Effective N* is defined as $\frac{1}{HHI_t}$, where $HHI_t = \sum_{i=1}^N w_{i,t}^2$ and $w_{i,t}$ denotes the market capitalization based weight of stock i in month t within the market index based on the respective sample; this Herfindahl Index corresponds to the number of stocks invested as if forming an equally-weighted portfolio. A lower *Effective N* indicates a more concentrated stock market.

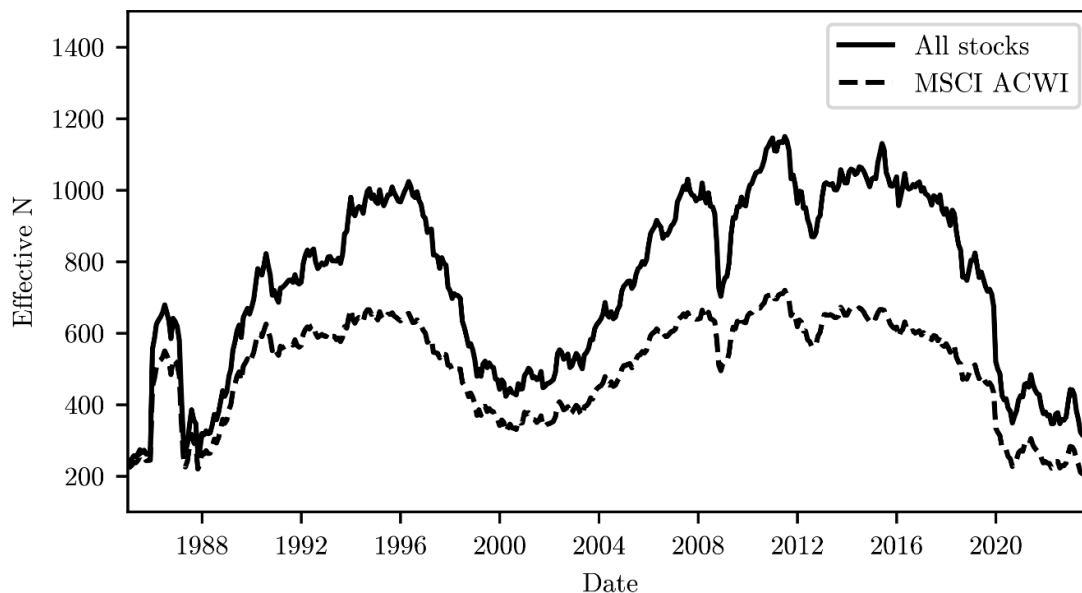


Table 4 shows the results (regression coefficients with t -statistics in parentheses; all stocks in Panel A and MSCI ACWI sample in Panel B) of a standard analysis of stock market anomalies for our sample, based on monthly cross-sectional Fama-MacBeth regressions of stock returns on a number of stock characteristics. Columns (1), (2), and (3) show regression results including different sets of stock characteristics for our global sample over 1985-2023, while columns (4) and (5) show the results of regressions that include the composite ESG rating for the sample for which the ESG data are available over the shorter period 2003-2021.

Consistent with the literature on stock market anomalies, Panel A of Table 4 shows that stock returns in our sample of all stocks are negatively related to, again, firm size (market equity), but also to investment, last-month returns, and idiosyncratic volatility, while they are positively related to value (book-to-market ratio), momentum, and quality. In line with Alves, Krüger, and van Dijk (2025), we find no significant relation between stock returns and a firm's ESG rating. This is relevant since it suggests that the returns of portfolios that we construct based on ESG ratings may not be materially affected by historical patterns in our data involving a link between returns and ESG. The results for the MSCI ACWI sample in Panel B are very similar, although with a weaker size effect (not surprisingly since it is well-known that the size effect is driven by very small stocks not included in this sample) and a weaker profitability effect.

Table 4. Fama-Macbeth regressions of global stock returns on stock-level variables

This table reports the estimation results (coefficient and t-statistic in parentheses) for Fama-Macbeth regressions of stock returns on various firm-level variables in our global sample over 1985-2023 (all stocks in Panel A and pseudo MSCI ACWI sample in Panel B). We refer to Table 1 for variable definitions. Regressions (5) and (6) include the ESG rating and are thus based on the shorter sample period 2003-2021. All independent variables (except for *Return t-1* and ESG) are winsorized at the 1% and 99% percentiles. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *. The bottom two rows of each panel report the number of observations and the sample period.

Panel A: All stocks					
	(1)	(2)	(3)	(5)	(6)
<i>Beta</i>	0.023 (0.18)	0.057 (0.44)	0.077 (0.70)		0.079 (0.47)
<i>ln(Size)</i>	-0.101*** (-3.34)	-0.085*** (-2.73)	-0.137*** (-5.45)		-0.117*** (-4.21)
<i>B/M</i>	0.328*** (6.71)	0.367*** (7.70)	0.392*** (8.40)		0.126 (1.57)
<i>Profitability</i>		0.710*** (6.10)	0.346*** (2.78)		0.316* (1.70)
<i>Investment</i>		-0.265*** (-4.26)	-0.312*** (-5.12)		-0.074 (-0.77)
<i>Return t-1</i>			-0.022*** (-6.60)		-0.011* (-1.89)
<i>Momentum</i>			0.743*** (6.22)		0.429 (1.60)
<i>Quality</i>			0.242*** (9.50)		0.115** (2.29)
<i>Idio vol</i>			-12.364*** (-4.32)		-10.363* (-1.93)
<i>ESG</i>				-0.021 (-0.56)	0.012 (0.32)
#obs.	7,864,836	6,741,456	4,909,835	1,246,449	911,955
Sample period	1985-2023	1985-2023	1985-2023	2003-2021	2003-2021

Panel B: ACWI					
	(1)	(2)	(3)	(5)	(6)
<i>Beta</i>	0.071 (0.41)	0.114 (0.65)	0.031 (0.21)		0.054 (0.29)
<i>ln(Size)</i>	0.018 (0.62)	0.033 (1.08)	-0.003 (-0.10)		-0.072** (-2.42)
<i>B/M</i>	0.256* (1.88)	0.353** (2.40)	0.483*** (5.17)		0.192* (1.66)
<i>Profitability</i>		0.667*** (4.24)	0.484*** (3.11)		0.379* (1.87)
<i>Investment</i>		-0.174 (-1.47)	-0.165* (-1.76)		-0.068 (-0.60)
<i>Return t-1</i>			-0.018*** (-3.61)		-0.012* (-1.69)
<i>Momentum</i>			0.664*** (3.73)		0.323 (1.17)
<i>Quality</i>			0.117*** (3.39)		0.093** (1.97)
<i>Idio vol</i>			-15.151*** (-2.84)		-8.307 (-1.17)
<i>ESG</i>				0.028 (0.51)	0.033 (0.78)
#obs.	958,730	816,002	713,728	468,479	362,831
Period	1985-2023	1985-2023	1985-2023	2003-2021	2003-2021

2.3 Portfolio construction

Our primary analysis examines how the financial performance of investment portfolios changes with the number of stocks in the portfolio. We conduct backtests to identify diversification benefits across different portfolio construction methods. In our backtests based on a global sample of stocks over 1985-2023, we simulate investment strategies with different degrees of concentration by randomly drawing N stocks (where $N = 10, 50, 100, 250, 500, 750, 1000, 1500$) into portfolios each month. We carry out separate backtests based on the full sample with all stocks and based on the pseudo MSCI ACWI sample. We repeat these monthly random draws 10,000 times for each N (for some more computationally involved analyses, we use 1,000 draws). After drawing the stocks into the portfolio, we examine three primary stock weighting schemes:

- *Equally-weighted portfolios*, where each stock that is drawn has an identical weight.
- *Value-weighted portfolios*, where stocks are weighted proportionally to their market capitalization.
- *Optimally weighted portfolios* using modern portfolio theory, including minimum variance, tangency (i.e., maximum Sharpe ratio), the Bayesian Black and Litterman (1992) approach, and mixed approaches (discussed in more detail in Section 2.4 below). The optimal weights are computed for each draw with a computational complexity increasing in N , which means that we are able to use only 1,000 random draws for this weighting scheme.

For the backtests where we compute optimally weighted portfolios, we use a factor model to estimate both correlations across stocks as well as each stock's return signal. The correlations and return signals are recomputed every month using the previous 60 months (minimum of 48 months) of data, which limits the sample of stocks for which we can carry out this analysis. We obtain data on the global five-factor model of Fama and French (2017) for developed markets from the website of Ken French. Since especially correlations may partly be driven by region, we replace the global market factor in that model with the regional market factors for four regions (Europe, Japan, Asia Pacific ex Japan, and North America) from the same website. We thus rely on an 8-factor model with four regional market factors and the global size, value, profitability, and investment factors.

In addition to varying weighting schemes, we also vary the approach for selecting stocks into portfolios for each N (i.e., the drawing probability):

- *Uniform random selection*, where each stock has equal probability of inclusion.
- *Optimal selection*, where the drawing probability is proportional to a stock's theoretically optimal portfolio weight within the full sample of stocks.
- *ESG-based selection*, where the drawing probability is proportional to a stock's composite ESG rating; the drawing probability is based on a stock's relative Z-score

computed based on the cross-sectional ESG rating distribution. Z-scores are capped at 3 and -3, such that 3 (-3) corresponds to a drawing probability that is twice (half) the uniform drawing probability. In case we do not observe an ESG rating for a certain firm, we set the Z-score equal to -3, which corresponds to having a very low ESG rating.

We further rerun our baseline backtests in such a way that the industry composition of the portfolios resembles that of the MSCI ACWI. To maintain the industry composition (based on SIC Divisions) of the MSCI ACWI for each industry, we first select a number of stocks that is proportional to the market weight of that industry (i.e., approximately $N \cdot w_I$, where w_I is the market weight of industry I in the MSCI ACWI) and then form an industry portfolio of those stocks by value-weighting within the industry. Subsequently, we value-weight the industry portfolios with the market weight of each industry to construct the overall portfolio.⁴

2.4 Optimal portfolios

For optimal portfolio construction, we estimate stock covariances using a factor model approach. We decompose stock return variances into systematic and idiosyncratic components using estimated factor betas and residual variances. For each month t , we use a 60-month rolling window ending in month $t-1$ (requiring at least 48 observations) to estimate:

- *correlations and volatilities* (historical pairwise Pearson correlations and historical annualized standard deviations).
- *Stock-level factor loadings* (betas with respect to the factors obtained from multivariate time-series regressions for each stock).
- *Stock-level volatilities* (historical annualized standard deviations).

We implement the Woodbury matrix identity to efficiently compute the inverse covariance matrix Σ^{-1} :

$$\Sigma^{-1} = (A + BCB')^{-1} = A^{-1} - A^{-1}B(C^{-1} + B'A^{-1}B)^{-1}B'A^{-1} \quad (1)$$

where A is a diagonal matrix of idiosyncratic variances, B contains the factor loadings (betas), and C is the factor covariance matrix. The first step in Equation (1) is to show that we can write the covariance matrix as the sum of a stock's idiosyncratic variance A and its systematic variance BCB' . The second step is the Woodbury matrix identity itself, which shows that we can rewrite the matrix inversion problem as a sum of sub-matrix inversions. This is helpful, because the inversion of the diagonal matrix of idiosyncratic risk and low-dimensional factor matrix make each sub-matrix inversion much simpler. This is especially helpful when the number of stocks N far exceeds the number of factors F , as what used to be a problem of order $O(N^3)$ becomes $O(F^3)$, with $F \ll N$.

⁴ In this analysis, we focus on SIC divisions rather than GICS sectors, because the coverage for the GICS sectors only starts toward the end of the 1990s.

Using the inverted covariance matrix, we compute the various optimal portfolio weights of interest. In the following, w_x denotes a vector of stock weights of type $x \in \{min, tan, bl, mix\}$. $\mathbf{1}$ denotes a vector of ones, s is the return signal, which we take to be the sum of a stock's factor t -statistics⁵, and w_m is the stock's weight in the market portfolio:

$$\text{Minimum variance weights: } w_{min} = \Sigma^{-1}\mathbf{1} / (\mathbf{1}'\Sigma^{-1}\mathbf{1}) \quad (2)$$

$$\text{Tangency portfolio weights: } w_{tan} = \Sigma^{-1}s / (\mathbf{1}'\Sigma^{-1}s) \quad (3)$$

$$\text{Black-Litterman weights: } w_{bl} = \Sigma^{-1}w_m / (\mathbf{1}'\Sigma^{-1}w_m) \quad (4)$$

We also consider "mixed weights" based on the tangency and Black-Litterman weights:

$$\text{Mixed weights: } w_{mix} = (1 - \kappa) w_{bl} + \kappa w_{tan}, \quad (5)$$

with $\kappa = 0.5$. Lastly, to ensure that these optimal weights are implementable, we impose no shorting constraints (non-negative weights) and concentration limits (maximum weight for individual stocks equal to $2/N$, where N is the number of stocks in the portfolio). These weight caps have the added benefit of avoiding portfolio implementation errors due to extreme portfolio concentrations arising from parameter uncertainty and limited sample size.⁶

2.5 Financial performance metrics

For each portfolio construction approach, we compute the following financial performance metrics for each portfolio:

- *Return*: annualized average monthly return in excess of the risk-free rate.
- *Volatility*: annualized standard deviation of returns.
- *Sharpe ratio*: ratio of average excess return to volatility (*Return/Volatility*).
- *Drawdown*: 2.5th percentile of the portfolio's time-series return distribution.
- *Tracking error*: annualized standard deviation of the return difference between the portfolio and a value-weighted market index (based on all stocks or based on the MSCI ACWI sample, depending on the context).

For each portfolio size and construction methodology (a backtest), we calculate the cross-simulation mean, 2.5th percentile, and 97.5th percentile of each financial performance metric across the 10,000 draws to understand the central tendency and dispersion of outcomes across draws for each N . A key novel performance metric proposed in this paper is the cross-simulation dispersion in performance outcomes when an investor invests in fewer stocks than the index. We illustrate this FOMO risk with the 95% confidence band around the mean performance metric.

5 This approach is similar in spirit to Brandt, Santa-Clara, and Velikov (2009), where we use betas and normalize with the standard error instead of using characteristics and normalizing with the standard deviation. In practice, this means that we reduce the weights for high beta stocks for which we have less observations relative to similarly high beta stocks with more observations.

6 Lassance, Vanderveken, and Vrins (2024) make the point that reducing parameter uncertainty may be a relevant argument for holding concentrated portfolios.

3. Results

In this section, we discuss our baseline results on the diversification of idiosyncratic risk (Section 3.1) and the FOMO effect (Section 3.2) as well as the diversification and FOMO results for optimal portfolios (Section 3.3), for portfolios constructed based on ESG criteria (Section 3.4), and the results of several robustness tests (Section 3.5).

3.1 Diversification

As a starting point for our analysis, we revisit the seminal analysis of the “speed of diversification” by Statman (1987), who concludes that it takes only 30-40 stocks to fully diversify idiosyncratic risk. This study remains highly influential, as illustrated by the replication of its main result in the widely used *Investments* textbook by Bodie, Kane, and Marcus (2023) on their page 203: a simple graph showing the relation between the volatility of a portfolio and the number of stocks in the portfolio. For copyright reasons, we cannot include this figure in this paper, but Panel A of Figure 2 mimics this figure based on visual inspection. The figure indicates a portfolio volatility of around 28% (per annum) for $N = 1$. Portfolio volatility declines rapidly as N become greater, to around 20% for $N = 5$ and to roughly 19% for

Figure 2: Replication of Statman’s (1987) diversification result

This figure shows a mimicked/replicated version of the Bodie-Kane-Marcus (BKM, 2023, p. 203) replication of Statman’s (1987) diversification result in a graph of portfolio volatility vs. # stocks in the portfolio, which BKM mention is based on data for all stocks listed on the NYSE stock exchange during 2008-2017 (BKM sample). Panel A shows the mimicked graph from BKM, Panel B shows our own replication of this result when constructing equally-weighted (EW) portfolios of N stocks in the equivalent of the BKM sample within our dataset, and Panel C shows our replication result when constructing value-weighted (VW) portfolios of N stocks in the BKM sample.

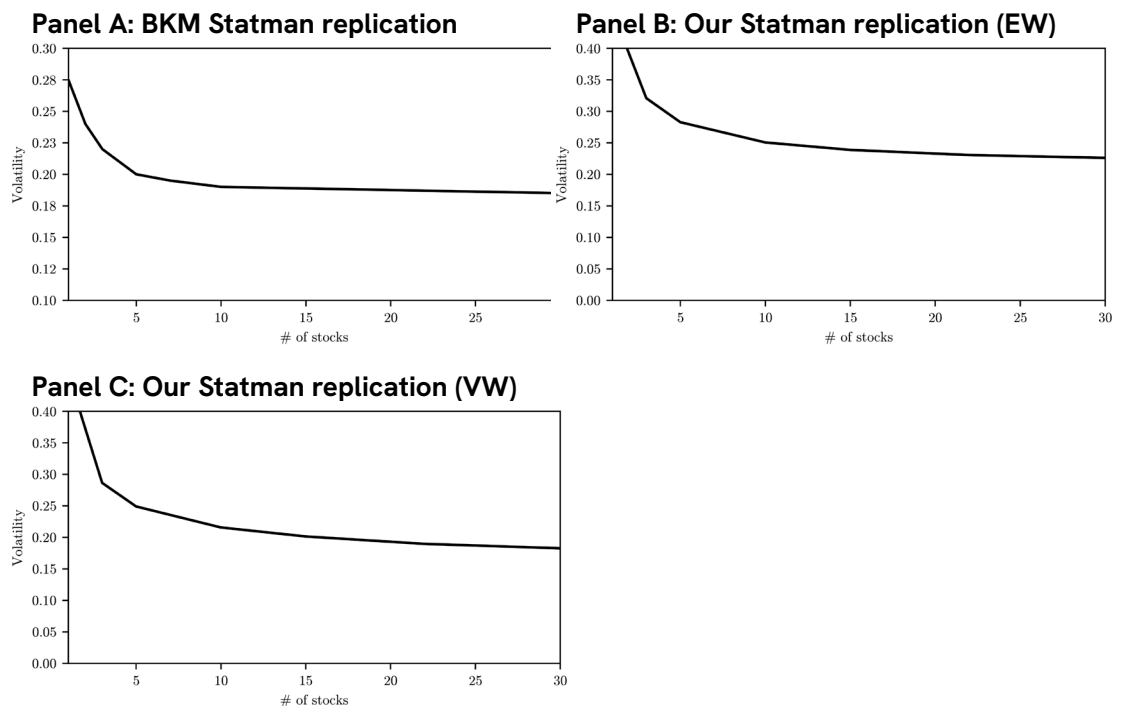
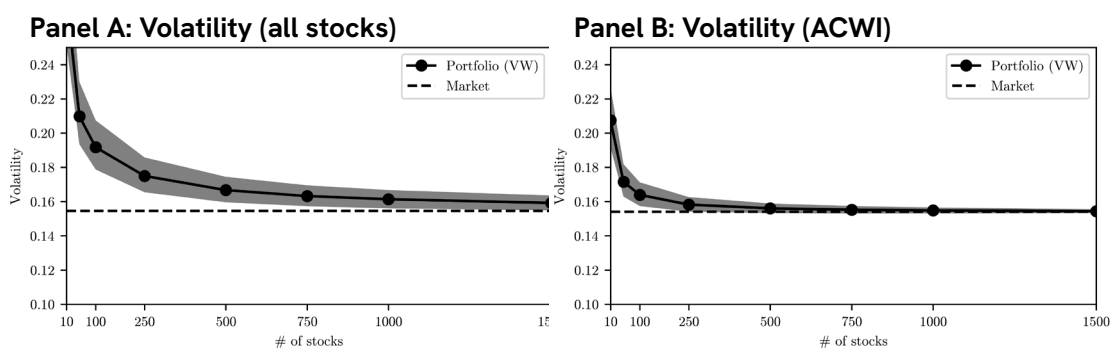


Figure 3: Portfolio volatility vs. number of stocks in our global sample

This figure shows the relation between portfolio volatility and the number of stocks N in the portfolio in our global sample. Panel A shows the portfolio volatility for all stocks in our global sample over 1985-2023. Panel B shows the portfolio volatility for stocks in the MSCI ACWI sample over 1985-2023. The graphs are constructed based on backtests with 10,000 random draws for each N . For each draw for each N , at the beginning of each month, we first draw N stocks from the respective sample with equal probability. We let N vary between 10 and 1,500. Second, we value-weight these N stocks to form our portfolio. We repeat this process for each month in the sample period. We then compute the time-series portfolio performance measures (volatility in this figure, and mean return, Sharpe ratio, drawdown, and tracking error in subsequent figures) and plot the results of the mean performance measure across all 10,000 draws for each N in black dots and lines and the 95% confidence band around the mean (that is, based on the 2.5th and 97.5th percentiles of the volatility distribution across the 10,000 draws for each N) as a gray area, where the number of stocks N is on the horizontal axis. The equivalent performance measure (in this figure: volatility) for the value-weighted market index formed on the respective sample is shown as a dashed horizontal line. See Section 2.1 for a more detailed description of our variable definitions and dataset construction.



$N = 10$. For greater N , it is difficult to observe a further reduction in volatility, and the figure suggests that diversification of idiosyncratic risk is complete from around $N = 25$.

The figure caption on page 203 of Bodie, Kane, and Marcus (2023) is succinct, but it mentions that the replication of the Statman (1987) result is based on NYSE data over 2008-2017. Using NYSE stocks in our own sample for this period, we do our own replication of this figure. Panel B of Figure 2 shows the result when portfolios are equally-weighted and Panel C when portfolios are value-weighted (the weighting scheme is not specified in the Bodie-Kane-Marcus figure caption). As is clear from these panels, we are not able to perfectly replicate this graph, but the overall patterns are similar: portfolio volatility declines rapidly with N , and diversification seems virtually complete at $N = 30$. There are some slight differences across Panels A and B in the sense that the convergence seems somewhat quicker for equally-weighted portfolios (possibly because these portfolios are not dominated by a few large stocks), but the convergence is towards a lower volatility level for value-weighted portfolios (possibly because smaller stocks with greater volatility have lower weights in these portfolios).

In Figure 3, we show similar graphs as in Figure 2 but then based on our own global sample of stocks over 1985-2023 (all stocks in Panel A and the MSCI ACWI sample in Panel B). In these baseline analyses, we use equal drawing probabilities for each stock and value-weighted portfolios, since value-weighted portfolios seem a more realistic representation of

actual investment strategies by institutional investors than equally-weighted portfolios. An important extra element in Figure 3 relative to Figure 2 is that we include the 95% confidence band (in gray) around the mean portfolio volatility across all 10,000 draws for each N . The confidence bands in these and subsequent graphs illustrate how the performance metric of interest (in this case portfolio volatility) varies as the stocks included in the portfolio for a given N are varied across the 10,000 draws. We also include a horizontal dashed line representing the volatility of the value-weighted market portfolio (based on all stocks in Panel A and on the MSCI ACWI sample in Panel B).

The difference between Figure 3 and Figure 2 is quite striking. Although the graphs in Figure 3 also reflect the power of diversification in the sense that portfolio volatility declines with greater N , the rate of convergence of portfolio volatility to market volatility is considerably slower for our global sample in Figure 3. It is clear from the graphs that 30 or 40 stocks are insufficient to fully diversify idiosyncratic risk. In Panel A (all stocks), there are still considerable diversification benefits from increasing N to more than 250 or even 500 stocks. In fact, even at $N = 1000$, the mean portfolio volatility is still visibly above the horizontal line as portfolio volatility is above market volatility - reflecting undiversified risk. Convergence to market volatility is somewhat quicker in Panel B (MSCI ACWI sample), likely because this sample excludes many small stocks with large (idiosyncratic) volatilities. But still, diversification remains visibly effective beyond $N = 100$ and even $N = 200$, and only at around $N = 750$ has the mean portfolio volatility virtually fully converged to market volatility ("complete diversification").⁷ The gray confidence bands in both graphs indicate that the rate of convergence depends on the specific portfolios drawn at each N , but not to a great extent. In short, the first main result of our paper is that it takes considerably more than 30-40 stocks for full diversification in a global sample.⁸

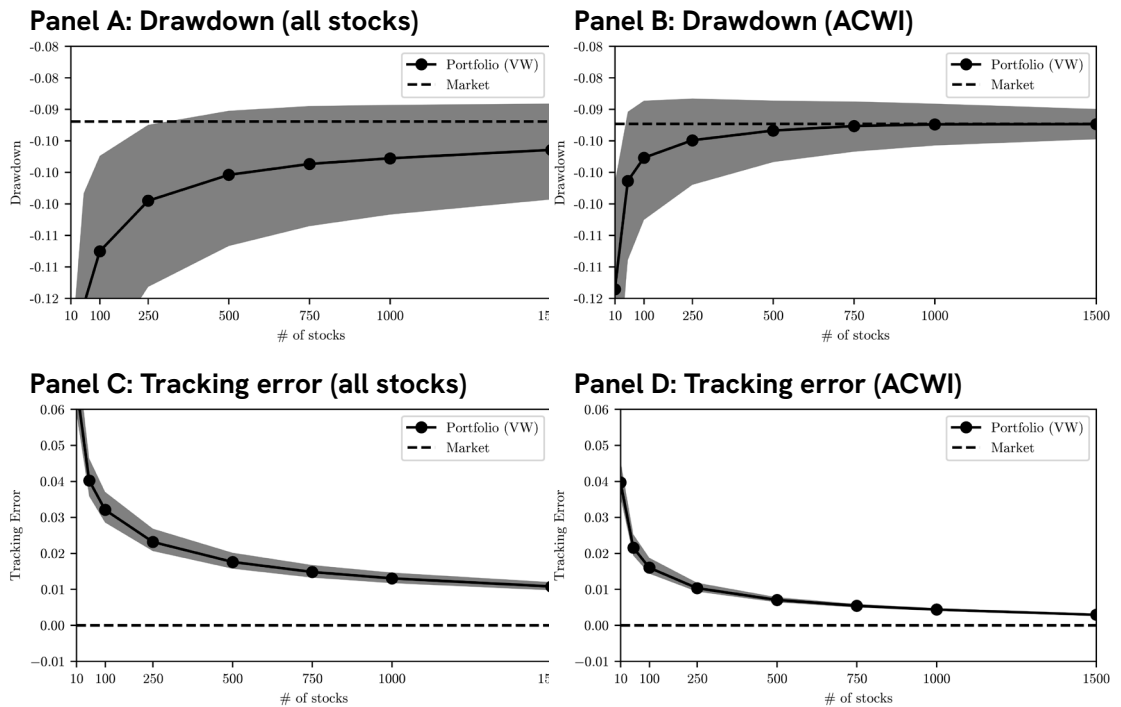
As alternative portfolio risk measures that are often used in practice, we also examine the downside risk (drawdown, defined as the 2.5th percentile of the portfolio's time-series return distribution) and tracking error of the random portfolios with size N . Figure 4 shows very similar graphs as in Figure 3 but then for drawdown (based on all stocks in Panel A and the MSCI ACWI sample in Panel B) as well as for tracking error (all stocks in Panel C and MSCI ACWI in Panel D), again including 95% confidence bands in gray. For the drawdown,

7 We note that we use the term "complete diversification" somewhat loosely in the sense of full convergence of portfolio volatility to the value-weighted market volatility, and based on visual inspection of the graphs showing the relation of portfolio volatility with the number of stocks N . However, the "best diversified" portfolio is arguably not the value-weighted market portfolio but the minimum variance portfolio - an issue we return to in Section 3.3 on optimal portfolios.

8 We do not investigate in detail exactly why our results differ from those of Statman and Bodie-Kane-Marcus, but a likely explanation stems from our global sample vs. their sample of NYSE stocks only. In line with this point, we note that the market volatility in our MSCI ACWI sample (15.4%, see Table 2 and Panel B of Figure 3) is considerably lower than in their NYSE sample (around 19%, see Panels A and C of Figure 2), highlighting the benefits of diversification across international stock markets - which may require more stocks.

Figure 4: Portfolio drawdown and tracking error vs. number of stocks

This figure shows the relation between portfolio drawdown as well as portfolio tracking error and the number of stocks N in the portfolio in our global sample. Panels A and B show the portfolio drawdown, and Panels C and D show the portfolio tracking error (relative to the value-weighted portfolio of the sample from which the stocks are drawn). Panels A and C show results for the sample of all stocks, and Panels B and D show results for the MSCI ACWI sample. Black dots and lines show the means of the portfolio drawdown and the portfolio tracking error, respectively; the gray area indicates the 95% confidence band around the mean; and the dashed horizontal line shows the drawdown and tracking error (the latter is zero by definition) of the value-weighted market index based on the sample involved. We refer to Figure 3 and Section 2.3 for a more detailed description of the backtests and data.



we observe that small portfolios ($N = 10$) have a drawdown of around -12% in both samples, gradually converging to the market drawdown of -9.2% for larger N . Although the convergence of portfolio tracking error displays a similar pattern as the convergence of portfolio volatility in Figure 3, there are some notable differences. First, the convergence to the market drawdown is (even) slower than the convergence to market volatility, especially for the sample of all stocks in Panel A of Figure 4. Second, the gray confidence bands around the mean portfolio drawdown are much wider than the confidence bands around the mean portfolio volatility in Figure 3 (for both Panels A and B, but more so for Panel A), indicating that there is a greater dispersion in portfolio drawdown across the 10,000 draws than there is in portfolio volatility.

In Panel D of Figure 4 (MSCI ACWI sample), we observe a very large tracking error for small N (2% for $N = 50$), and it slowly decreases as N gets larger, reaching 1% at around $N = 100$ and 0.5% at around $N = 1000$. The tracking error is greater and converges more slowly (it is still 1% at $N = 1500$) for the sample of all stocks in Panel C. Not surprisingly, investors

to whom it is important to closely track a broad market index thus require a substantial number of stocks to keep the tracking error in check.

3.2 FOMO

The results in Section 3.1 indicate that insufficient diversification is a non-negligible risk when considering concentrated portfolios, and that global equity portfolios need to contain considerably more stocks than previously thought. In this section, we introduce a novel, second dimension of concentration risk that investors should consider when reducing the number of stocks in their portfolio: FOMO (fear of missing out). The study of this risk dimension was inspired by the work of Bessembinder (2018) and Bessembinder, Chen, Choi, and Wei (2023), showing that the majority of stocks underperform the risk-free rate and that a very small fraction of stocks account for the entire equity premium: in these studies, 4.3% of stocks in a U.S. sample over 1926-2016 and 2.4% of stocks in a global sample over 1990-2020.

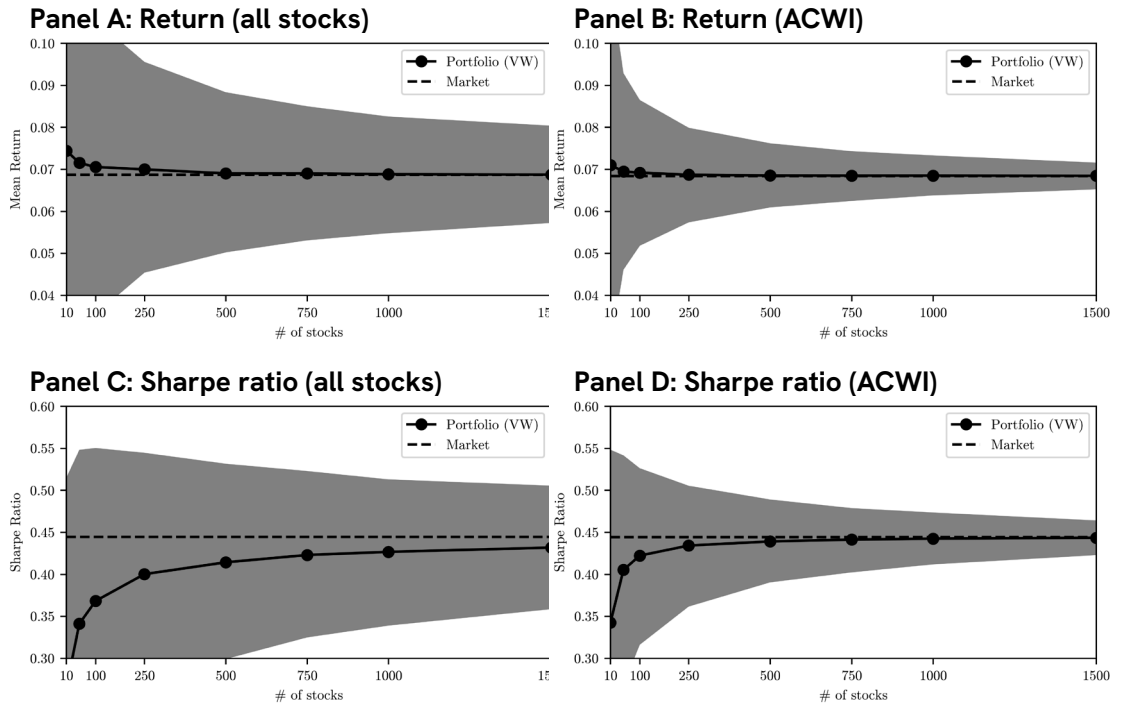
We first revisit these results in our own global sample over 1985-2023. For each stock, we compute its wealth creation over our sample period. As Bessembinder et al. (2023, p. 36) put it, wealth creation is defined as “the premium, in terms of end-of-sample [dollar] wealth, earned by the shareholders who exposed themselves to the risk of investing in company stock, as compared to the wealth they would have attained if they had invested in one-month Treasury bills.” We then rank stocks based on their wealth creation and examine what fraction of stocks accounts for a certain fraction of aggregate wealth creation of the global stock market over our sample period.

Our results are in line with those of the global analysis of Bessembinder et al. (2023). Only 41% of the 87,266 stocks in our sample positively contribute to wealth creation over our almost 40-year sample period. The stock with the single greatest contribution is Apple, accounting for 3.8% of global wealth creation, followed by Microsoft (3.2%), Amazon (1.5%), NVIDIA (1.2%), Alphabet (0.9%), and Exxon Mobile (0.86%). The top-performing 30 stocks (0.03% of all stocks) account for no less than 25% of global stock market wealth creation over these 40 years. The top-performing 162 stocks (0.19% of all stocks) account for 50% of all wealth creation, and the top-performing 1,871 stocks (2.1% of all stocks) account for all global wealth creation for investors over our sample period.⁹ These findings underscore that the ex post financial performance (return, Sharpe ratio) of concentrated portfolios may significantly depend on the degree to which they include the stocks that have shown

⁹ In unreported tests, we redo this analysis for the MSCI ACWI sample only and find that the 18 top-performing stocks (0.14% of all stocks) account for 25% of global stock market wealth creation over 1985-2023, the 82 top-performing stocks (0.62% of all stocks) account for 50% of all wealth creation, and the top-performing 595 stocks (4.5% of all stocks) account for all global wealth creation for investors over our sample period.

Figure 5: FOMO – Portfolio return and Sharpe ratio vs. number of stocks

This figure shows our main Fear of Missing Out (FOMO) results: the relation between portfolio return as well as portfolio Sharpe ratio and the number of stocks N in the portfolio in our global sample. Panels A and B show the portfolio return, while Panels C and D show the portfolio Sharpe ratio. Panels A and C show results for the sample of all stocks, and Panels B and D show results for the MSCI ACWI sample. Black dots and lines show the means of the portfolio return and the portfolio Sharpe ratio, respectively; the gray area indicates the 95% confidence band around the mean; and the dashed horizontal line shows the return and Sharpe ratio of the value-weighted market index based on the sample involved. We refer to Figure 3 and Section 2.3 for a more detailed description of the backtests and data.



the best performance over the period that the portfolio was held, possibly giving rise to substantial FOMO effects.

We investigate and quantify this FOMO risk in Figure 5. The figure shows the relation between portfolio returns (based on all stocks in Panel A and the MSCI ACWI sample in Panel B) as well as portfolio Sharpe ratios (all stocks in Panel C and MSCI ACWI in Panel D) with the number of portfolio stocks N . Panels A and B show little relation between the mean portfolio return and N . Mean portfolio returns across the 10,000 draws largely coincide with the market return (horizontal dashed line).¹⁰

The salient finding in Panels A and B of Figure 5 is the broad confidence band (gray area in the graphs) around the mean portfolio return for each N . The mean portfolio return of a portfolio with N stocks varies widely across the 10,000 draws. In other words, the ex

¹⁰ For small N , mean returns are slightly above market returns because of a size effect (see also Table 4). When drawing few stocks, the average weight (across draws) of large stocks in a portfolio is lower than their weight in the market portfolio. To illustrate, consider $N = 1$: in that case, the average weight (across draws) of each stock in the portfolio equals one over the total number of stocks, and thus the mean portfolio return with $N = 1$ across draws equals the mean return of the equally-weighted market portfolio. Over our sample period, the mean return of the equally-weighted portfolio is higher than the mean return of the value-weighted portfolio (see Table 2).

post return of a concentrated portfolio critically depends on which particular stocks are selected. These FOMO effects are very large indeed. For the sample of all stocks (Panel A), the 95% confidence band around average returns exceeds ten percentage points for very small N (exceeding the y-axis scale). For large N , the FOMO effect (height of the grey confidence band) is reduced, but only relatively slowly. A “lucky draw” of 1,500 stocks (97.5th percentile of the return distribution across stocks) shows an average return of more than 8% per annum vs. an average return below 6% per annum for an “unlucky draw” of 1,500 stocks (2.5th percentile). This difference in returns, depending on which particular stocks are included in a portfolio amounts to huge differences in final wealth over long horizons. Moreover, these FOMO effects would be even more extreme when considering a 99% confidence band.

For the MSCI ACWI sample (Panel B), the confidence band is smaller for every N compared to the full sample. This indicates that, within the MSCI ACWI universe, FOMO risk is somewhat less severe than in the sample of all stocks. This is not surprising since, by definition, there is more variation in performance across around 25,000 stocks than across a subsample of 2,500 stocks. That said, it is *not* the case that FOMO risk per se is reduced when reducing the universe from which stocks can be drawn in the portfolio. After all, an investor in, say, $N = 100$ stocks from the MSCI ACWI sample may still regret not having picked a much better performing portfolio of 100 stocks out of the bigger sample of all stocks.

Furthermore, even in Panel B of Figure 5 (which is relevant in particular for investors who really consider the MSCI ACWI to be their investable universe and would not consider investing in any stocks beyond this universe), FOMO risk is substantial by any reasonable standard. For $N = 100$, a lucky draw (97.5th percentile) yields a portfolio with a mean of around 8.6% per annum, whereas an unlucky draw (2.5th percentile) results in a return of slightly over 5% per annum. For $N = 500$, the spread in stock returns between the 2.5th and the 97.5th percentiles is almost 2% per annum, and the spread is still around 1% for $N = 1000$. It goes without saying that even return differences of 1% per annum result in large wealth differences over long horizons. As a simple illustration, compounding a constant 7% return over 30 years yields a final wealth of €7.61 for every €1 invested, while compounding a constant 6% return yields only €5.74 for every €1 invested – a difference of almost 200 percentage points.

When plotting Sharpe ratios in Panels C and D of Figure 5, we observe that the mean portfolio Sharpe ratio converges to the market Sharpe ratio at a similar rate as the mean portfolio volatility converges to the mean market volatility (since there is essentially immediate convergence for mean returns). The large FOMO effects in portfolio returns (Panels A and B) translate into similarly large FOMO effects (confidence bands) in the Sharpe ratio. To illustrate, at $N = 750$, the 2.5th and 97.5th percentiles of the distribution of Sharpe ratios

Table i. Summary of relation between N and returns, volatility, Sharpe ratio

This table summarizes the results of our baseline analysis of the relation between the number of stocks N and the portfolio return (Panel A), volatility (Panel B), and Sharpe ratio (Panel C) for the MSCI ACWI sample, based on the graphs in Panel B of Figure 3 and Panels B and D of Figure 5. For each of these three performance metrics, we present the mean across 10,000 draws as well as the 2.5th and 97.5th percentiles.

	10	50	100	250	500	750	1000	1500
Panel A: Return								
q ^{2.5}	2.73%	4.61%	5.18%	5.74%	6.09%	6.25%	6.38%	6.52%
Mean	7.10%	6.95%	6.92%	6.87%	6.85%	6.85%	6.85%	6.85%
q ^{97.5}	11.42%	9.29%	8.65%	7.99%	7.62%	7.43%	7.33%	7.16%
Panel B: Volatility								
q ^{2.5}	19.17%	16.29%	15.74%	15.40%	15.32%	15.30%	15.31%	15.32%
Mean	20.75%	17.15%	16.39%	15.82%	15.60%	15.52%	15.48%	15.44%
q ^{97.5}	22.68%	18.18%	17.12%	16.26%	15.89%	15.74%	15.65%	15.55%
Panel C: Sharpe ratio								
q ^{2.5}	13.26%	26.78%	31.61%	36.15%	39.04%	40.22%	41.18%	42.28%
Mean	34.25%	40.52%	42.22%	43.42%	43.91%	44.13%	44.25%	44.34%
q ^{97.5}	54.83%	54.16%	52.63%	50.54%	48.90%	47.88%	47.36%	46.42%

across the 10,000 draws are around 0.40 and 0.48, respectively, for the MSCI ACWI sample (Panel D).

We conclude that FOMO risk (which we illustrate by the height of the gray confidence band for each N) gives rise to substantial uncertainty about future portfolio performance, possibly because it is unknown ex ante whether a portfolio contains the “next Magnificent 7” – which a large literature on the performance of professional investors shows is very hard to predict. We view this as a hitherto unstudied dimension of risk of concentrated portfolios (next to the risk stemming from imperfect diversification of idiosyncratic volatility). Based on the magnitudes discussed in this section, it seems that FOMO risk is at least as economically important as imperfect diversification, and it persists for considerably larger N .

We summarize the main results of our analyses of the relation between N and portfolio return, volatility, and Sharpe ratio for the MSCI ACWI sample in Table i.

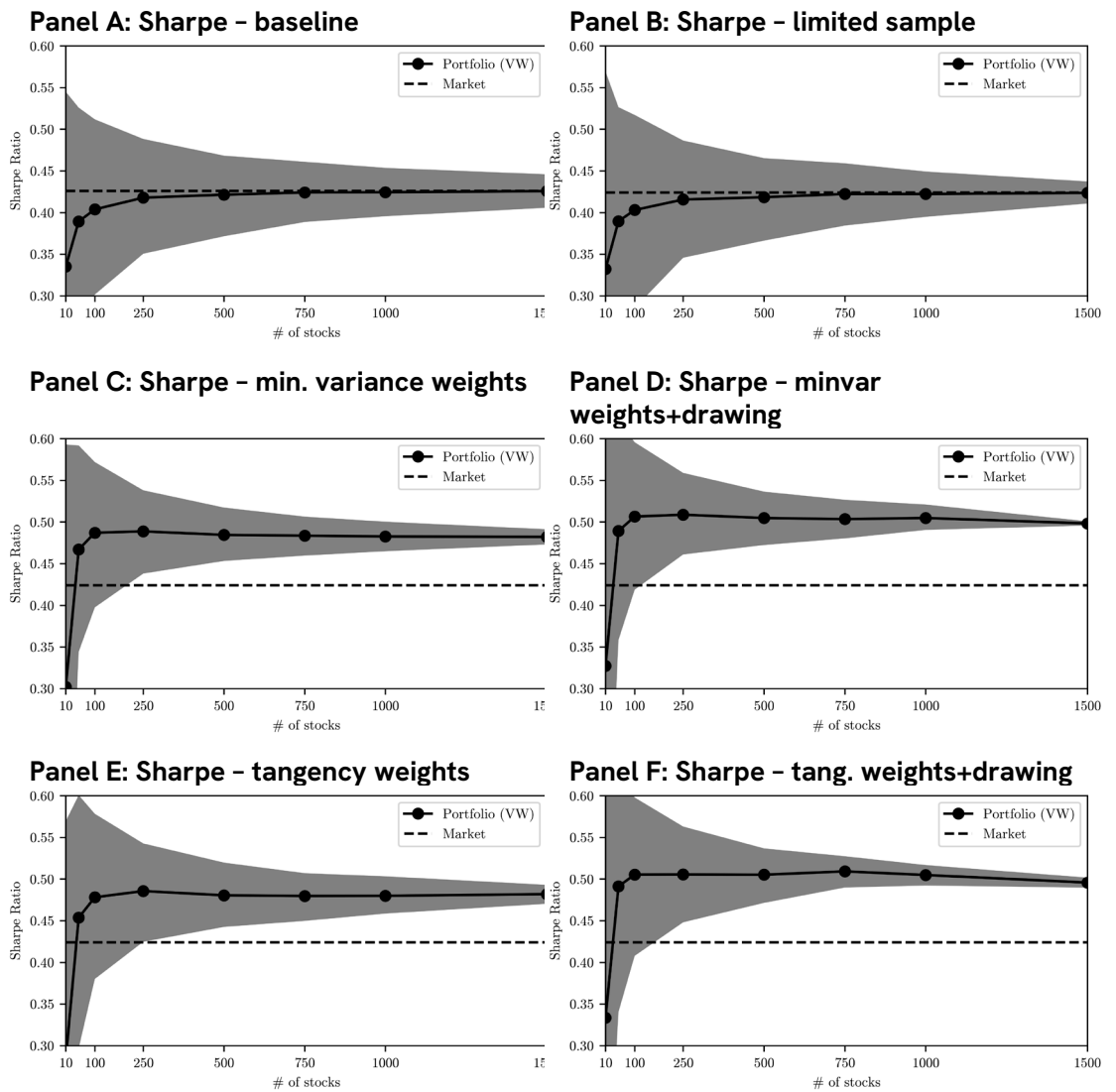
3.3 Diversification and FOMO effects for “optimal” portfolios

In this section, we examine whether our conclusions depend on the chosen specifications in the portfolio construction within our backtests. As discussed in Section 2.3, next to our baseline specification in Figures 2-4 with equal drawing probabilities and value-weighted portfolios, we also consider alternative weighting schemes as well as alternative drawing probabilities. In this section, we focus in particular on “optimal” portfolios.

In Figure 6, we examine whether the speed of diversification and FOMO effects are affected by letting the drawing probability of individual stocks into the portfolio and/or the weights of the selected stocks within the portfolio be equal to measures of “optimal” portfolio allocation, using variations of Markowitz’s (1952) modern portfolio theory. As

Figure 6: Optimal portfolios – Sharpe ratio vs. number of stocks

This figure shows our main results for optimal portfolios: the relation between portfolio Sharpe ratio and the number of stocks N in the portfolio in our global sample, where the portfolios are “optimized” using modern portfolio theory in the sense of assigning optimal weights to the stocks in the portfolio and/or making the drawing probability of stocks into the portfolio dependent on optimal weights. Panel A shows the portfolio Sharpe ratio for the baseline backtest (equal drawing probability, value-weighted portfolios) for the MSCI ACWI sample (reproduced from Panel D of Figure 5). Panel B shows the portfolio Sharpe ratio for the baseline backtest, but limited to the subsample of MSCI ACWI stocks for which we can estimate the factor model that we use in our optimal portfolio allocation. Panel C shows the portfolio Sharpe ratio with optimal minimum variance portfolio weights. Panel D shows the portfolio Sharpe ratio with optimal minimum variance drawing probability and optimal minimum variance portfolio weights. Panel E shows the portfolio Sharpe ratio with optimal tangency portfolio weights. Panel F shows the portfolio Sharpe ratio with optimal tangency drawing probability and optimal tangency portfolio weights. Black dots and lines show the means of the portfolio Sharpe ratio; the gray area indicates the 95% confidence band around the mean; and the dashed horizontal line shows the Sharpe ratio of the value-weighted market index based on the sample involved. We refer to Figure 3 and Sections 2.3 and 2.4 for a more detailed description of the backtests and data.



discussed in more detail in Section 2.4, we consider three key measures of optimal allocation: minimum-variance, tangency (maximum Sharpe ratio), and Black-Litterman. In this figure, we gauge both diversification and FOMO effects with the evolution of the mean Sharpe ratio of the portfolios for different N , as well as with the height of the gray confidence band around this mean.

For comparison purposes, in Panel A of Figure 6, we reproduce the Sharpe ratio graph of our baseline specification for the MSCI ACWI sample (taken from Panel D of Figure 5). The graph in Panel B also shows the Sharpe ratio based on our baseline specification, but now, for the subsample of MSCI ACWI stocks for which we can estimate the factor model that we use in our optimal portfolio allocation (see Section 2.4). This graph looks very similar to the one in Panel B. In Panel C, we plot the Sharpe ratio when we maintain the equal drawing probability for portfolio selection, but use the minimum variance weights within the portfolios. Three differences with Panel B stand out. First, using portfolio weights that minimize portfolio volatility based on ex ante information notably boosts the mean Sharpe ratio from around 0.43 to around 0.49 for large N , which is an economically substantial effect. Second, using minimum variance portfolio weights increases the speed of diversification to some degree. Contrary to Panel B, Panel C shows no discernable further diversification benefits beyond $N = 250$.¹¹

The third notable difference between the graphs in Panels B and C of Figure 6 is that the height of the confidence bands is somewhat smaller in Panel C. This finding may suggest that FOMO effects are smaller when using minimum variance weights. However, we note that FOMO effects in Panel C are still very large and persist for large N . To illustrate, for $N = 1000$, the 2.5th and 97.5th percentiles of the distribution of Sharpe ratios across the 1,000 draws are around 0.46 and 0.50, respectively, thus indicating that the financial performance of the selected portfolio still to a non-negligible extent depends on the specific 1,000 stocks selected into the portfolio.

More philosophically, in a sense FOMO effects *cannot* be decreased by changing the way portfolios are constructed in our backtests. Truly reducing FOMO effects can only be done by limiting the probability of missing out on the top-performing stocks; in other words, through some predictive power of which stocks will be the top performing stocks going forward. But the large literature on active investing and market efficiency suggests that this is very hard to do. The wider confidence bands around the mean portfolio in the baseline specification in Panel B still apply to investors choosing minimum variance weights as in

11 There are two caveats to this conclusion. First, the Sharpe ratio for small N is “contaminated” to some degree by the mean portfolio return being above the market return; see Panel B of Figure 5 and footnote 4. Second, due to the smaller number of draws in Figure 6 (1,000 vs. 10,000 in Figure 5), the mean Sharpe ratio may be subject to slightly greater estimation uncertainty. In other words, Panel C-F of Figure 6 may somewhat overestimate the speed of diversification.

panel C. After all, the value-weighted portfolios depicted in Panel B are still potentially valid alternative portfolios that could have been chosen instead of minimum variance portfolios. And if such value-weighted portfolios ex post turn out to have better financial performance than minimum variance portfolios (for example, because the ex post top-performing stocks have a greater weight in such portfolios), investors could still experience regret (Lin et al., 2006; Bourgeois-Gironde, 2010; Goossens, 2022) about not having chosen these portfolios. And, ex ante, investors may thus face FOMO relative to other portfolio selection specifications: the fear of missing out on financial performance as a result of either not selecting the top-performing stocks and/or of underweighting the top-performing stocks that are selected into the portfolio.

Taken to its logical extreme, this argumentation implies that “true” FOMO may need to be expressed relative to the very best portfolio that could have been chosen ex post. Such a portfolio would consist for 100% of the single best performing stock in each individual month and would have a titanic return ex post. Of course, no investor would take such a hypothetical portfolio as a reasonable benchmark for assessing own portfolio performance ex post. In other words, a realistic assessment of the degree of FOMO depends on the investment strategies (both selection and weighting of stocks in the portfolio) that the investor considers to be viable alternatives to the actual portfolio chosen. For professional investors (such as pension funds, insurance companies, and mutual funds), the degree of FOMO may depend on the set of portfolios that their participants / clients would consider as viable alternatives and thus relevant benchmarks. These observations also imply that FOMO may exist for very large portfolios, since investors still have a great deal of discretion in determining the weights of individual stocks within their portfolio. Quantifying FOMO may thus be subject to debate, but the key conceptual point in this paper that reducing the number of stocks significantly increases FOMO risk seems to transcend the particular portfolio specifications presented in this paper.

With these arguments in mind, we turn to the other specifications in Figure 6 based on optimal portfolios. In Panel D, we not only let the weights but also the drawing probability depend on minimum variance optimization. The patterns in the Sharpe ratio and confidence band are very similar to Panel C, with the mean Sharpe ratio being slightly higher still when also optimizing the selection of stocks in a minimum variance sense. In Panel E, we show the Sharpe ratio with equal drawing probability and weights based on the estimated tangency (maximum Sharpe ratio) portfolio using the factor model. Panel F depicts the Sharpe ratio when both the drawing probability and the weights depend on tangency optimization. Remarkably, these graphs are very similar to those in Panels C and D, respectively. The implication is that minimum variance optimization helps to boost the Sharpe ratio and speed up diversification, but additionally optimizing based on expected returns (tangency optimization) does little to further enhance the Sharpe ratio or diversification (consistent

with a large body of literature showing that predicting stock returns is very hard). Similarly, tangency optimizing drawing and portfolio weights helps to boost the Sharpe ratio relative to the value-weighted baseline portfolios in Panel B, but additionally optimizing the selection of stocks into the portfolio only results in a relatively limited further increase in the Sharpe ratio.

In Figure A1 in the Appendix, we examine the relation between the portfolio Sharpe ratio and the number of stocks N when the optimal portfolios are based on the Black-Litterman (1992) approach that is discussed in more detail in Section 2.4. In Panel A of Figure 5, we again reproduce the Sharpe ratio graph of our baseline specification for the MSCI ACWI sample (taken from Panel D of Figure 5). Panel B shows the Sharpe ratio with Black-Litterman portfolio weights and Panel C shows the Sharpe ratio when portfolio weights are the average of Black-Litterman weights and tangency weights. The results are by and large similar to those in Figure 6; portfolio optimization boosts the Sharpe ratio (although Black-Litterman seems less effective than minimum variance or tangency approaches), the speed of diversification is somewhat greater, and FOMO risk is still economically substantial.

In sum, when constructing optimal portfolio, the key aspect for boosting the Sharpe ratio is to optimize the weights of the stocks selected into the portfolio based on their correlations and volatilities. Additionally trying to improve the stock selection and/or getting closer to the tangency portfolio seems to be a second-order concern. Having said that, FOMO is a relevant concern in constructing portfolios regardless of the optimization approach.

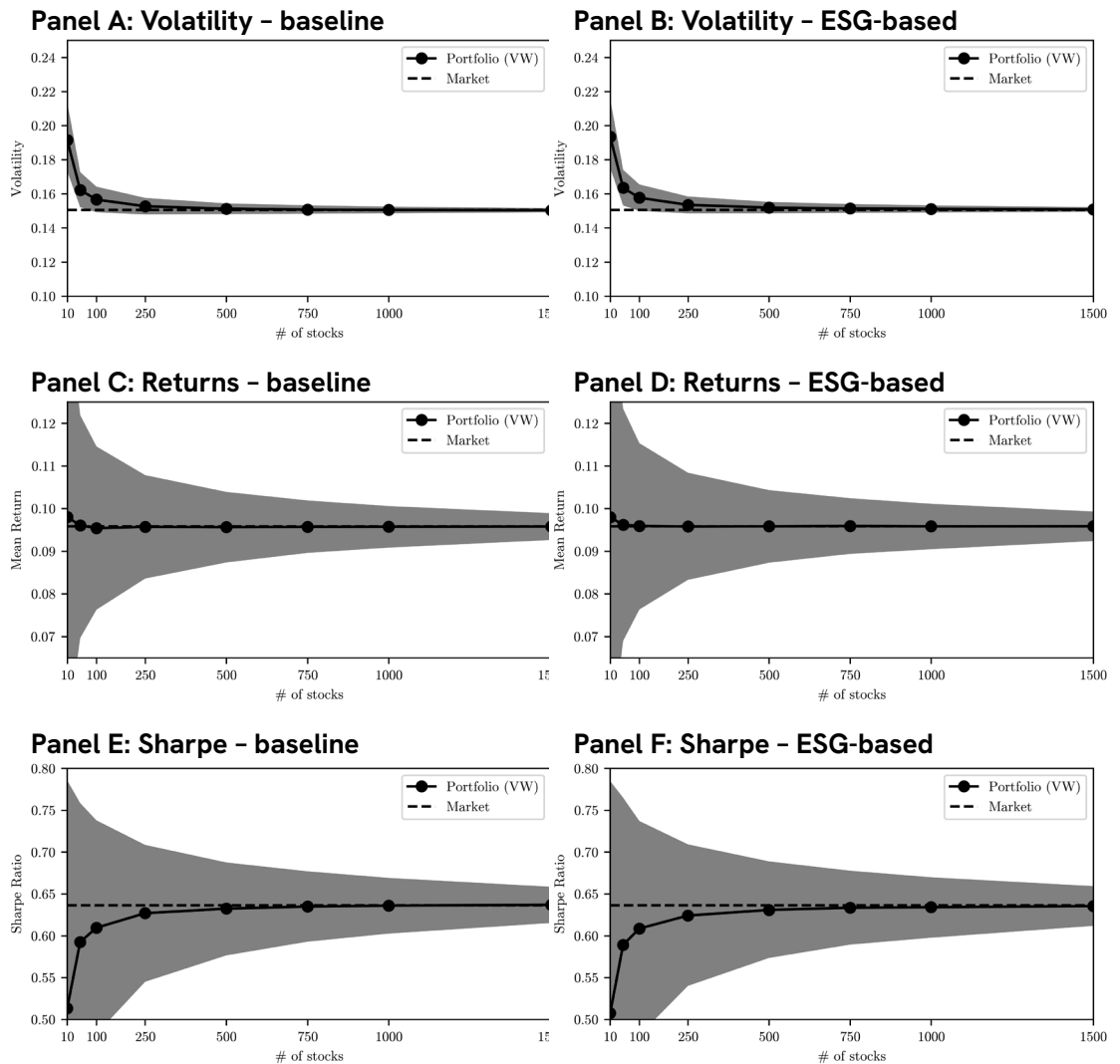
3.4 Diversification and FOMO effects in ESG investing

Our analyses thus far do not address the context that was one of the motivations for our study: the trend among some institutional investors towards more concentrated portfolios motivated by ESG and other forms of sustainable investing goals. In this section, we consider diversification and FOMO effects in light of two common approaches to incorporating such goals into portfolio choice: (i) tilting portfolios towards stocks with higher ESG ratings and (ii) dropping “sin stocks” (Hong and Kacperczyk, 2009) from the universe of investable stocks.

Figure 7 shows the relation between portfolio performance (volatility, return, and Sharpe ratio) and the number of stocks N in the portfolio when the drawing probability depends on the ESG rating of a stock – as discussed in detail in Section 2.3. For comparison purposes, Panels A, C, and E (the left column) of Figure 7 show the portfolio volatility, return, and Sharpe ratio, respectively, for the baseline backtest (equal drawing probability, value-weighted portfolios; reproduced from Panel B of Figure 3 and Panels B and D of Figure 5), respectively. Panels B, D, and F (the right column) show the same portfolio performance measures for the backtest with ESG-based drawing probability and value-weighted portfo-

Figure 7: ESG portfolios – Volatility, return, and Sharpe ratio vs. number of stocks

This figure shows our main results for ESG portfolios: the relation between portfolio volatility, return, Sharpe ratio, and the number of stocks N in the portfolio in our global sample, where the probability of drawing stocks into the portfolio depend on the stock's composite ESG rating. All graphs in this figure are based on the MSCI ACWI sample. For each stock in an industry (GICS sector), we compute the Z-score of the ESG rating by each rating agency, by demeaning with the industry mean and scaling by the standard deviation of ESG ratings within that industry. We then average the Z-score across rating agencies for this stock, cap the Z-score at -3 and 3, and assign a drawing probability that is twice (half) the uniform drawing probability for the stock with the highest (lowest) Z-score, with linear interpolation. For stocks without any ESG rating, we assign a drawing probability that is half the uniform drawing probability (equivalent of a very low ESG rating). Panel A shows the portfolio volatility for the baseline backtest (equal drawing probability, value-weighted portfolios; reproduced from Panel B of Figure 3). Panel B shows the portfolio volatility for the backtest with ESG-based drawing probability and value-weighted portfolios. Panel C shows the portfolio return for the baseline backtest (reproduced from Panel B of Figure 5). Panel D shows the portfolio return for the backtest with ESG-based drawing probability and value-weighted portfolios. Panel E shows the portfolio Sharpe ratio for the baseline backtest (reproduced from Panel D of Figure 5). Panel F shows the portfolio Sharpe ratio for the backtest with ESG-based drawing probability and value-weighted portfolios. Black dots and lines show the means of portfolio volatility, return, and Sharpe ratio, respectively; the gray area indicates the 95% confidence band around the mean; and the dashed horizontal line shows the volatility, return, and Sharpe ratio of the value-weighted market index based on the sample involved. We refer to Figure 3 and Section 2.3 for a more detailed description of the backtests and data.



lios. The results of Figure 7 are clear-cut: each of the three graphs (volatility, return, Sharpe ratio), based on the portfolios tilted towards stocks with higher ESG ratings (through the drawing probability), is very similar to the graphs from our baseline backtests. In other words, the speed of diversification as well as FOMO effects are not affected by this specification of ESG investing.

Figure 8 shows the relation between portfolio performance (volatility, return, and Sharpe ratio) and the number of stocks N in the portfolio when portfolios are selected from the investment universe that excludes sin stocks – defined as stocks in sin industries (following Blitz and Swinkels, 2023: smoke, beer, guns, coal, oil, utilities, transportation, mines, gold, soda, and meals following the 49 industries from the data library of Ken French). As in Figure 7, Panels A, C, and E (left column) of Figure 8 show the portfolio volatility, return, and Sharpe ratio, respectively, for the baseline backtest. Panels B, D, and F (right column) show the same portfolio performance measures for the backtest, based on portfolios that only contain stocks drawn from “sinless” industries. Here, there are more differences between the baseline backtests and this specification of sustainable investing. First, in our sample, portfolio volatility (Panel B) is higher across the board when excluding sin stocks, suggesting that sin stocks exhibit lower volatility and/or lower correlations over our sample period. Second, portfolio returns (Panel D) tend to be slightly higher when excluding sin stocks, consistent with recent evidence that questions the finding that sin stocks tend to have greater returns (Blitz and Fabozzi, 2017). Third, the portfolio Sharpe ratio (Panel F) tends to be lower when excluding sin stocks, indicating that the considerably higher volatility in Panel B outweighs the small return benefit in Panel D. That said, our overall conclusions on the speed of diversification and the degree of FOMO risk do not materially change in this analysis of dropping sin industries. The confidence bands around the mean Sharpe ratio in Panel F are as wide as in Panel E. And the Sharpe ratio converges to a lower level in Panel F compared to Panel E (to a tailor-made benchmark excluding sin stocks if you will), but at a similar speed.

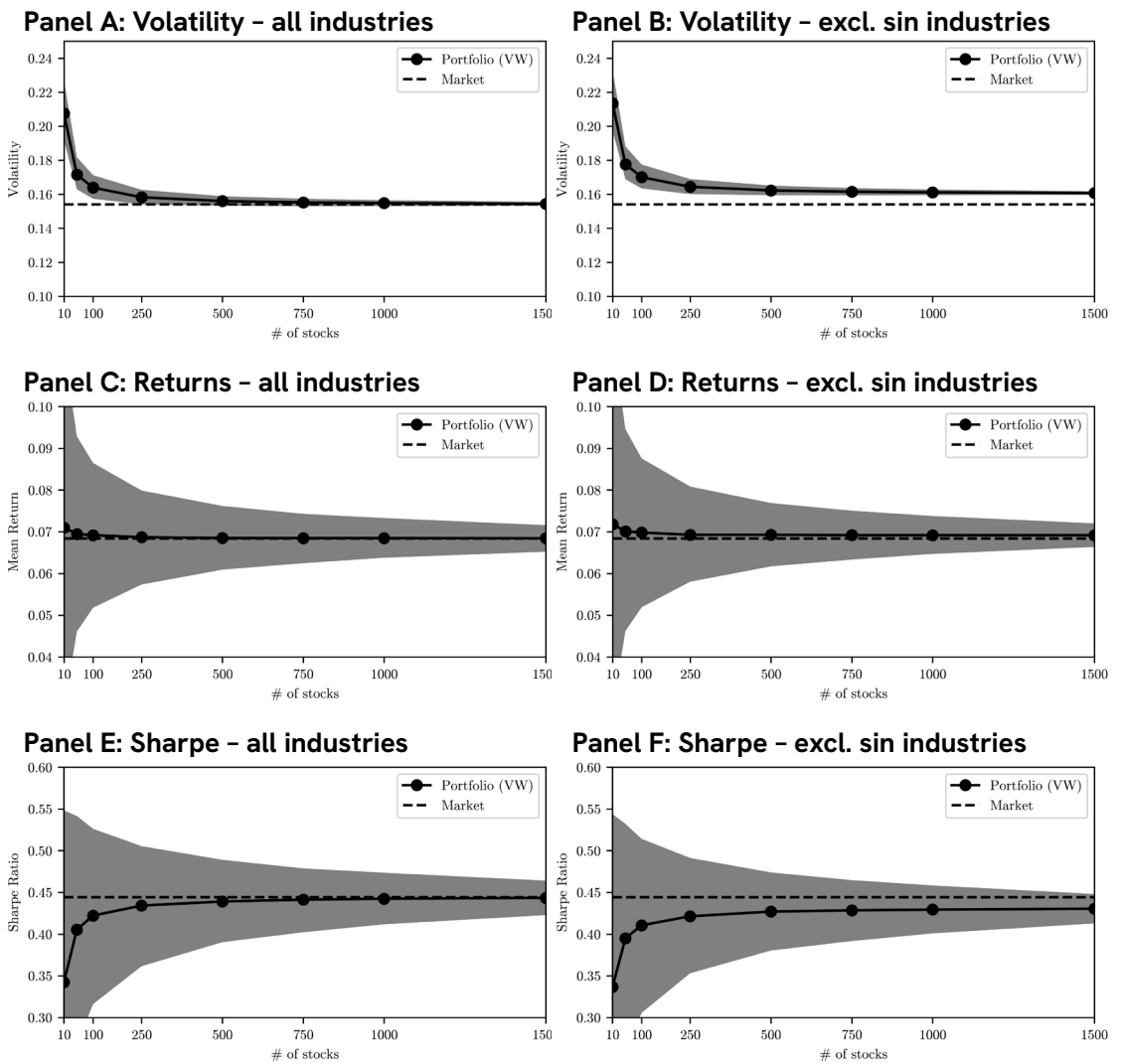
Taken together, the results in this section provide little indication that two common approaches to ESG investing (examined in Figures 6 and 7) affect our findings on diversification and FOMO. In other words, there is nothing particular about these forms of investing that systematically affects the speed of diversification or the dispersion in returns across different portfolios of size N constructed with these approaches.

3.5 Diversification and FOMO effects in robustness tests

In this section, we examine whether our main findings are robust to variations in a number of design choices that we make in our backtests discussed so far. The Appendix includes three figures that show the relation between portfolio volatility, return, and Sharpe ratio with the number of stocks N when (i) portfolios are rebalanced 20% annually instead of 100%

Figure 8: Sinless portfolios - Volatility, return, and Sharpe ratio vs. number of stocks

This figure shows our results for portfolios that exclude sin industries: the relation between portfolio volatility, return, Sharpe ratio and the number of stocks N in the portfolio in the MSCI ACWI sample, where the sample from which stocks are drawn excludes sin industries – defined as (following Blitz and Swinkels, 2023) smoke, beer, guns, coal, oil, utilities, transportation, mines, gold, soda, and meals, following the 49 industries from the data library of Kenneth French). Panel A shows the portfolio volatility for the baseline backtest (equal drawing probability, value-weighted portfolios; reproduced from Panel B of Figure 3) for all industries. Panel B shows the portfolio volatility for the baseline backtest for the sample excluding sin industries. Panel C shows the portfolio return for the baseline backtest for all industries (reproduced from Panel B of Figure 5). Panel D shows the portfolio return for the baseline backtest for the sample excluding sin industries. Panel E shows the portfolio Sharpe ratio for the baseline backtest for all industries (reproduced from Panel D of Figure 5). Panel F shows the portfolio Sharpe ratio for the baseline backtest for the sample excluding sin industries. Black dots and lines show the means of portfolio volatility, return, and Sharpe ratio, respectively; the gray area indicates the 95% confidence band around the mean; and the dashed horizontal line shows the volatility, return, and Sharpe ratio of the value-weighted market index based on the sample involved. We refer to Figure 3 and Section 2.3 for a more detailed description of the backtests and data.



monthly, (ii) we introduce a cap on the weight of an individual stock in the portfolio, and (iii) we redesign our portfolio construction in such a way that the industry composition of the MSCI ACWI index is preserved in the portfolios.

In our baseline backtests, portfolios are 100% rebalanced each month. One objection against this design choice is that it is very unrealistic: most investors do not rebalance their portfolios that frequently and drastically. As a robustness test, we therefore redo our analysis, assuming that investors effectively rebalance 20% of their portfolio each year. In this backtest, each month a random 20%/12 of stocks is discarded from the portfolios, and a new random draw is made (with uniform drawing probability) to replace these stocks (with replacement). The resulting portfolios are more realistic in the sense that they are much more stable over time, where again the random discarding and drawing of new stocks reflects the many choices that real-life investors have when doing so. Figure A2 in the Appendix shows the result. As in Figures 6 and 7, Panels A, C, and E (left column) of Figure A2 show the portfolio volatility, return, and Sharpe ratio, respectively for the baseline backtest with 100% monthly rebalancing. Panels B, D, and F (right column) show the same portfolio performance measures for the backtest with 20% annual rebalancing. The graphs of the backtest with annual rebalancing are almost identical to those of the baseline backtest. Our intuition is that, unless there are strong patterns of autocorrelation in monthly stock returns, it does not matter for the sake of our analysis whether portfolios are redrawn 100% each month or only 20% of the portfolio is redrawn each year. And although we know since Jegadeesh (1990) that monthly stock returns have a slightly negative autocorrelation, it may not be strong enough to affect our results.

We next turn to backtests that impose a maximum portfolio weight for individual stocks. This is a common approach in the investment industry to alleviate concerns about concentration risk in individual stocks. We specify the maximum weight invested in a single stock in a randomly drawn portfolio as follows: . In case the value-weight for a particular stock exceeds w_{max} , the weight is capped at $w_{max} = \max\left(\frac{2.5}{N}, 0.025\right)$, and the remainder is allocated in a value-weighted manner across the other stocks in the portfolio (this process is continued until the weight constraint is met for all individual stocks). This specification implies that, for large portfolios, the maximum weight of an individual stock is 2.5%, and for a portfolio of 10 stocks the maximum weight is 25%. The results are in Figure A3. As in Figure A2, the graphs for portfolio volatility, return, and Sharpe ratio in the baseline backtest are reproduced in Panels A, C, and E (left column) of Figure A3, while the same performance indicators for the backtest that imposes a maximum weight are in Panels B, D, and F (right column).

For small N , imposing a maximum weight decreases portfolio volatility, as can be seen in Panel B of Figure A3. This is not surprising, since preventing that portfolios are dominated by one or a few stocks is beneficial for diversification. However, this benefit of imposing a

maximum weight dissipates for larger N and is hard to detect visually from about $N = 250$. Moreover, the overall pattern in the speed of convergence of portfolio volatility to market volatility is quite similar in panels A and B. Panel D of Figure A3 shows that the mean return in the backtest with a maximum weight is higher than in the baseline backtest until about $N = 750$. This can be explained by a size effect in our sample; over our sample period, the equally-weighted market portfolio has a higher mean return than the value-weighted market portfolio (see also Table 4 and footnote 4). Imposing a maximum weight brings the value-weighted portfolios in our backtests closer to an equally-weighted portfolio, thereby boosting returns somewhat. We note that, given the inconsistency and poor understanding of the size effect (van Dijk, 2011; Hou and van Dijk, 2019), this effect may stem from specific patterns in our sample that may not occur out of sample. We would thus be very cautious in advocating weight caps as a means of boosting portfolio returns. As a result of the effects in Panels B and D, the mean portfolio Sharpe ratio in Panel F converges more quickly to the market Sharpe ratio than in the baseline backtest in Panel E, and is even slightly elevated above the market Sharpe ratio between $N = 100$ and $N = 750$. Both Panels D and F show equally wide confidence bands as in the baseline backtest. In sum, imposing a maximum weight on individual stocks may help the speed of diversification (especially for N below 100) but leaves FOMO effects essentially unaffected.

We next turn to backtests that aim to maintain the industry composition (based on SIC divisions) of the MSCI ACWI index in the randomly drawn portfolio (see Section 2.3 for details on how we do this). In principle, this approach makes the portfolio closer to the MSCI ACWI index and should alleviate concerns that FOMO effects are driven by the possibility of being excessively (moderately) exposed to industries with extreme (high or low) volatility or returns. Maintaining industry composition is a common approach in practice to enhance diversification due to the relatively low stock correlations across different industries. The results are in Figure A4. As in Figure A3, the graphs for portfolio volatility, return, and Sharpe ratio in the baseline backtest are reproduced in Panels A, C, and E (left column) of Figure A4, while the same performance indicators for the backtest that imposes a maximum weight are in Panels B, D, and F (right column).

For small N , maintaining the industry composition decreases portfolio volatility, as can be seen concluded from Panel B of Figure A4. This is expected, since the industry composition of the drawn portfolios is now similar to the market and therefore does not over- or underweight industries with differential volatilities. This effect is quite similar to the effect of imposing weight caps in Panel B of Figure A3; again the effect dissipates for portfolio sizes above 250, while there is a marginal effect on the confidence interval of the volatility. Therefore, maintaining industry composition mainly affects the mean volatility of the portfolios for small N , whereas the overall convergence of the mean to the market volatility is similar to our benchmark. Panel D of Figure A4 shows that the mean return in the backtest

with a maximum weight is higher than in the baseline backtest until about $N = 750$. This can again be explained by a size effect in our sample (see also Table 4 and footnote 4), as the probability of overweighting a small stock increases when maintaining industry composition. Because there are several sizable industries within the MSCI ACWI index, the probability of selecting only small stocks within an industry is larger than when selecting only small stocks from the MSCI ACWI index directly. As a result of the effects in Panels B and D, the mean portfolio Sharpe ratio in Panel F converges more quickly to the market Sharpe ratio than in the baseline backtest in Panel E. Both Panels D and F show equally wide confidence bands as in the baseline backtest. In sum, maintaining industry composition in the drawn portfolios may help the speed of diversification to some degree (especially for N below 100) but leaves FOMO effects unaffected.

As a final sensitivity test, we rerun our baseline backtests for the MSCI ACWI sample but then for more limited investment universes: NYSE stocks only and the largest 1,000 stocks in terms of market capitalization each month (instead of the largest 2,500 as in our pseudo MSCI ACWI sample). Unreported results show that our main conclusions also hold in these smaller samples: it takes considerably more than 30-40 stocks to form a fully diversified portfolio, and FOMO risk is substantial, even for portfolios with hundreds of stocks. The main difference with our baseline results is that the speed of diversification is somewhat greater in these smaller samples, but full diversification in randomly drawn portfolios still requires several hundreds of stocks.

4. Conclusions

This paper examines the financial consequences of concentrated equity portfolios using backtests in a global sample of stocks from 47 countries over 1985-2023. Our main results are two-fold. First, we document that – contrary to the findings of Statman (1987) – in our global sample, 30-40 stocks are insufficient to fully diversify idiosyncratic risk. In our baseline backtest with equal drawing probability and value-weighted portfolios, it takes around 750 stocks for portfolio volatility to converge to market volatility.

Second, we uncover a thus far unstudied dimension of concentration risk, which we refer to as FOMO (fear of missing out): the possibility that investors may experience regret about the stock selection for their concentrated portfolios when other portfolios with the same number of stocks would have performed better. We illustrate this FOMO effect by the 95% confidence band around the mean portfolio return and show that the dispersion in portfolio returns for a given number of stocks greatly depends on which particular stocks are selected into the portfolio. The confidence band around the mean return is still 1% for portfolios with $N = 1000$ stocks (out of the pseudo MSCI ACWI sample) and substantially greater for smaller N . Given this substantial magnitude, we believe that FOMO risk is a very relevant consideration to take into account for equity investors with concentrated portfolios.

The cross-sectional dispersion in the performance of portfolios of stocks with a given number of stocks depending on the stock selection (which we call FOMO risk), is possibly related to the probability of missing out on the small fraction of top-performing stocks that drive the global equity premium. In line with Bessembinder et al. (2023), we document that just 2.1% of stocks in our sample account for the entire global equity premium over our almost 40-year sample period. The consequence of this pronounced skewness in returns across stocks is that (very) concentrated portfolios are not only characterized by higher volatility, but potentially also by lower returns. More research is needed to fully understand the relation between our FOMO findings and the Bessembinder et al. (2023) results.

Our paper provides some pointers on how investors could increase the speed of diversification for small N . Our analysis of optimal portfolios indicates that wisely selecting stocks into concentrated portfolios (based on their correlations and volatilities) can help to reduce volatility. Similarly, imposing maximum weights for individual stocks or maintaining industry composition in concentrated portfolios decreases portfolio volatility for small N . That said, complete diversification still requires considerably more than 30-40 stocks.

It is even harder to alleviate FOMO risk in concentrated portfolios. Conceptually speaking, FOMO occurs in anticipation of regret (Lin et al., 2006; Bourgeois-Gironde, 2010; Goossens, 2022) experienced by investors when the ex post performance of the portfolio they have chosen falls short of the performance of other portfolios that they could have

considered as viable alternatives ex ante (for example, by excluding some of the stocks that turn out to be top performers ex post). Even though it may be possible to improve the decisions made in portfolio choice in an ex ante sense, there is always the possibility that (altogether) different portfolios do better ex post - resulting in FOMO. FOMO thus extends beyond simply selecting which stocks to include in the portfolio to, for example when deciding on their portfolio weights, the rebalancing frequency, and the trading strategy. The only true way to reduce FOMO risk would be to follow a portfolio choice strategy that diminishes the probability of missing out on the top performing stocks going forward and thus predicting the "next Magnificent 7." But we know from the large body of literature on active investing and market efficiency that this is very difficult.

We acknowledge that there may be relevant non-pecuniary considerations for institutional investors when constructing concentrated portfolios, such as ethical considerations and the objective of creating impact on firms through engagement. We also recognize several important limitations to our analysis (as outlined in the introduction) and that choosing the number of stocks may involve complex tradeoffs. But, in our view, our findings indicate that investors, when considering concentrated portfolios, should seriously take both dimensions of concentration risk - incomplete diversification and FOMO - as inputs to their decision-making.

References

- Alexeev, V. and Tapon, F., 2014. The number of stocks in your portfolio should be larger than you think: Diversification evidence from five developed markets. *Journal of Investment Strategies*, 4(1), 43-82.
- Alves, R., Krueger, P. and van Dijk, M., 2025. Drawing up the bill: Are ESG ratings related to stock returns around the world? *Journal of Corporate Finance*, 93, p.102768.
- Bender, J. and Sun, X., 2024. How many is too few? Revisiting the number of names in equity portfolios. *Journal of Portfolio Management*, 50(4), 7-21.
- Bessembinder, H., 2018. Do stocks outperform treasury bills? *Journal of Financial Economics*, 129(3), pp.440-457.
- Bessembinder, H., Chen, T.F., Choi, G. and Wei, K.J., 2023. Long-term shareholder returns: Evidence from 64,000 global stocks. *Financial Analysts Journal*, 79(3), pp.33-63.
- Black, F. and Litterman, R., 1992. Global portfolio optimization. *Financial Analysts Journal*, 48(5), pp.28-43.
- Blitz, D. and Fabozzi, F.J., 2017. Sin stocks revisited: Resolving the sin stock anomaly. *Journal of Portfolio Management*, 44(1), p.105.
- Blitz, D. and Swinkels, L., 2023. Does excluding sin stocks cost performance? *Journal of Sustainable Finance & Investment*, 13(4), 1693-1710.
- Brandt, M.W., Santa-Clara, P. and Valkanov, R., 2009. Parametric portfolio policies: Exploiting characteristics in the cross-section of equity returns. *Review of Financial Studies*, 22(9), 3411-3447.
- Bodie, Z., Kane, A. and Marcus, A.J., 2023, *Investments*, 13th international student edition. McGraw-Hill.
- Bourgeois-Gironde, S., 2010. Regret and the rationality of choices. *Phil. Trans. R. Soc. B*, 365, 249-257.
- Caldecott, B., Clark, A., Koskelo, K., Mulholland, E. and Hickey, C., 2021. Stranded assets: environmental drivers, societal challenges, and supervisory responses. *Annual Review of Environment and Resources*, 46(1), 417-447.
- Campbell, J.Y., 2006. Household finance. *Journal of Finance*, 61(4), 1553-1604.
- DeMiguel, V., Galluppi, L. and Uppal, R., 2009. Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies*, 22(5), pp.1915-1953.
- Dyakov, T., Jiang, H. and Verbeek, M., 2020. Trade less and exit overcrowded markets: Lessons from international mutual funds. *Review of Finance*, 24(3), pp.677-731.
- Emery, L.P. and Koëter, J., 2024. The size premium in a granular economy. Working paper.
- Evans, J.L. and Archer, S.H., 1968. Diversification and the reduction of dispersion: An empirical analysis. *Journal of Finance*, 23(5), 761-767.
- Fama, E.F. and French, K.R., 2017. International tests of a five-factor asset pricing model. *Journal of Financial Economics*, 123(3), pp.441-463.
- Goetzmann, W.N. and Kumar, A., 2008. Equity portfolio diversification. *Review of Finance*, 12(3), 433-463.
- Goossens, J., 2022. Regret and asset pricing. Netspar paper 2022-037.
- Hong, H. and Kacperczyk, M., 2009. The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, 93(1), pp.15-36.
- Hou, K. and van Dijk, M.A., 2019. Resurrecting the size effect: Firm size, profitability shocks, and expected stock returns. *Review of Financial Studies*, 32(7), 2850-2889.
- Investment & Pensions Europe, 2024, Dutch doctors fund switches to concentrated equity portfolio, December 6.
- Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. *Journal of Finance*, 45(3), 881-898.
- Jensen, T.I., Kelly, B. and Pedersen, L.H., 2023. Is there a replication crisis in finance? *Journal of Finance*, 78(5), pp.2465-2518.
- Jiang, H., Vayanos, D. and Zheng, L., 2025. Passive investing and the rise of mega-firms. Working paper.

- Koijen, R.S. and Yogo, M., 2019. A demand system approach to asset pricing. *Journal of Political Economy*, 127(4), 1475-1515.
- Lassance, N., Vanderveken, R. and Vrins, F.D., 2024. Optimal Portfolio Size under Parameter Uncertainty. Working paper.
- Lin, C.H., Huang, W.H. and Zeelenberg, M., 2006. Multiple reference points in investor regret. *Journal of Economic Psychology* 27, 781-792.
- Market Screener, 2025. Alecta broadens its 'hyper-concentrated' portfolio after the misses, according to CEO, May 3.
- Markowitz, H.M., 1952, Portfolio selection. *Journal of Finance*, 7 (1), pp.77-91.
- Menkveld, A.J., Dreber, A., Holzmeister, F., Huber, J., Johannesson, M., Kirchner, M., (...) and Khomyn, M.K. (2024). Non-standard errors. *Journal of Finance*, 79(3), 2339-2390.
- Schoenmaker, D. and Schramade, W., 2019. Investing for long-term value creation. *Journal of Sustainable Finance & Investment*, 9(4), pp.356-377.
- Soebhag, A., van Vliet, B. and Verwijmeren, P., 2024. Non-standard errors in asset pricing: Mind your sorts. *Journal of Empirical Finance*, 78, 101517.
- Solnik, B.H., 1974. Why not diversify internationally rather than domestically? *Financial Analysts Journal*, 30(4), 48-54.
- Statman, M., 1987. How many stocks make a diversified portfolio? *Journal of Financial and Quantitative Analysis*, 22(3), pp.353-363.
- Statman, M., 2002. How much diversification is enough? SSRN Working Paper 365241.
- van Dijk, M.A., 2011. Is size dead? A review of the size effect in equity returns. *Journal of Banking & Finance*, 35(12), 3263-3274.
- Zaimovic, A., Omanovic, A. and Arnaut-Berilo, A., 2021. How many stocks are sufficient for equity portfolio diversification? A review of the literature. *Journal of Risk and Financial Management*, 14(11), 1-30.

Appendix

Figure A1: Additional optimal portfolios – Sharpe ratio vs. number of stocks

This figure shows additional results for optimal portfolios: the relation between portfolio Sharpe ratio and the number of stocks N in the portfolio in our global sample, where the portfolios are “optimized” using modern portfolio theory in the sense of assigning optimal weights to the stocks in the portfolio and/or making the drawing probability of stocks into the portfolio dependent on optimal weights. Panel A shows the portfolio Sharpe ratio for the baseline backtest (equal drawing probability, value-weighted portfolios) for the MSCI ACWI sample (reproduced from Panel D of Figure 5). Panel B shows the portfolio Sharpe ratio with Black-Litterman portfolio weights. Panel C shows the portfolio Sharpe ratio with weights that are for 50% determined by Black-Litterman weights and for 50% by tangency weights. Black dots and lines show the means of the portfolio Sharpe ratio; the gray area indicates the 95% confidence band around the mean; and the dashed horizontal line shows the Sharpe ratio of the value-weighted market index based on the sample involved. We refer to Figure 3 and Section 2.3 for a more detailed description of the backtests and data.

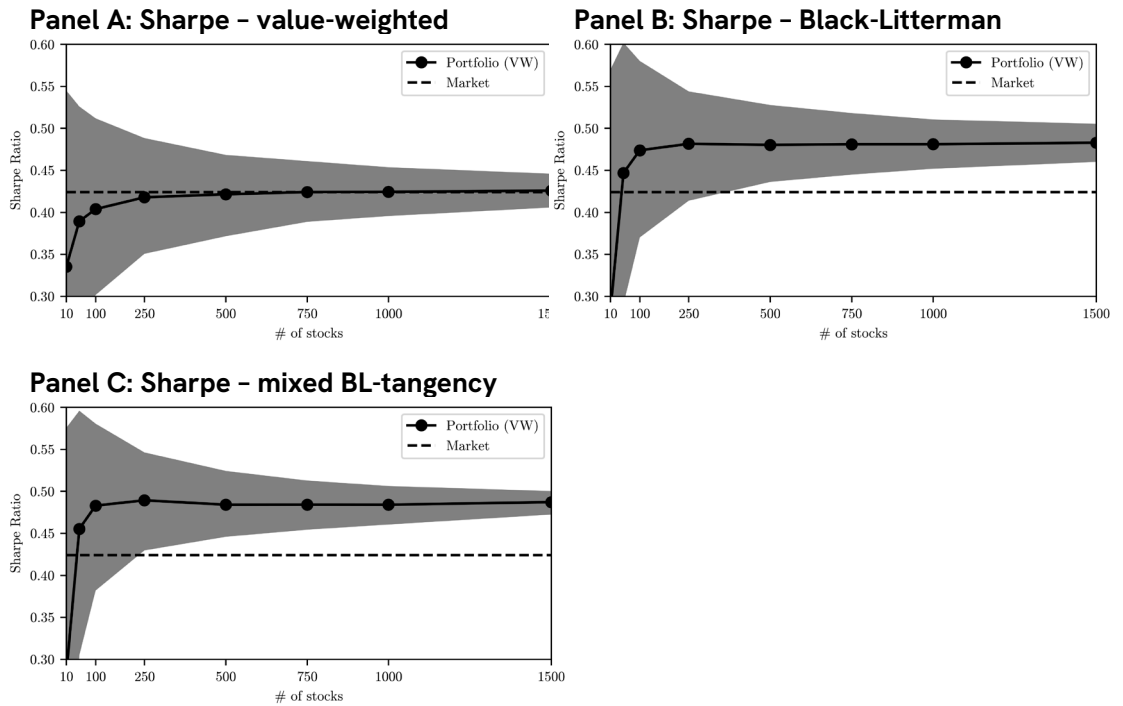
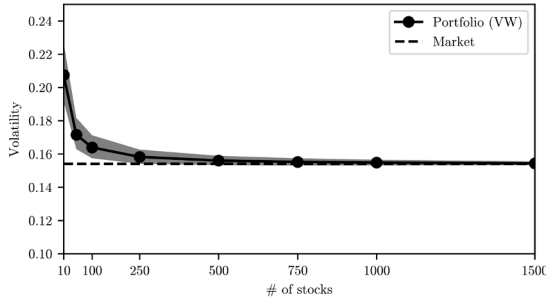


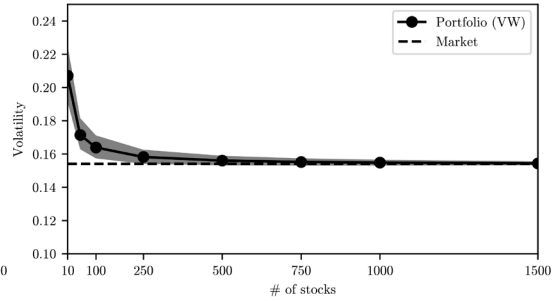
Figure A2: Monthly vs. annual portfolio rebalancing - Volatility, return, and Sharpe ratio vs. number of stocks

This figure shows the results of our backtests when 20% of a portfolio is randomly rebalanced each year, instead of our baseline backtests where 100% of a portfolio is rebalanced each month. The figure is based on the MSCI ACWI sample. Panel A shows the portfolio volatility for the baseline backtest (equal drawing probability, value-weighted portfolios, 100% rebalancing each month; reproduced from Panel B of Figure 3). Panel B shows the portfolio volatility for the backtest with 20% rebalancing each year. Panel C shows the portfolio return for the baseline backtest (reproduced from Panel B of Figure 5). Panel D shows the portfolio return for the backtest with 20% rebalancing each year. Panel E shows the portfolio Sharpe ratio for the baseline backtest (reproduced from Panel D of Figure 5). Panel F shows the portfolio Sharpe ratio for the backtest with 20% rebalancing each year. Black dots and lines show the means of portfolio volatility, return, and Sharpe ratio, respectively; the gray area indicates the 95% confidence band around the mean; and the dashed horizontal line shows the volatility, return, and Sharpe ratio of the value-weighted market index based on the sample involved. We refer to Figure 3 and Section 2.3 for a more detailed description of the backtests and data.

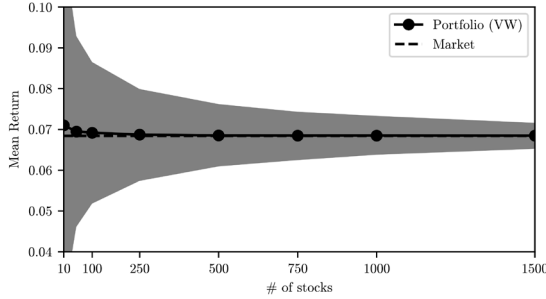
Panel A: Volatility - monthly rebalancing



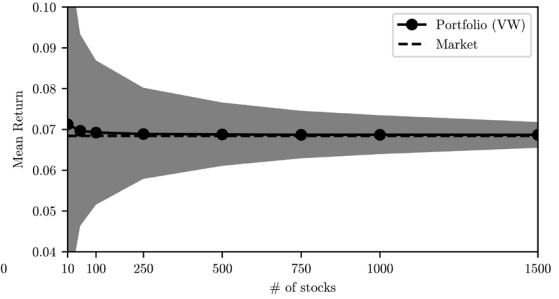
Panel B: Volatility - annual rebalancing



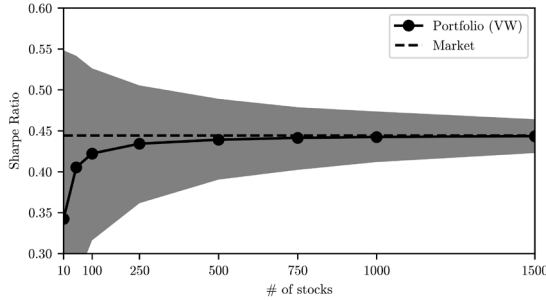
Panel C: Returns - monthly rebalancing



Panel D: Returns - annual rebalancing



Panel E: Sharpe - monthly rebalancing



Panel F: Sharpe - annual rebalancing

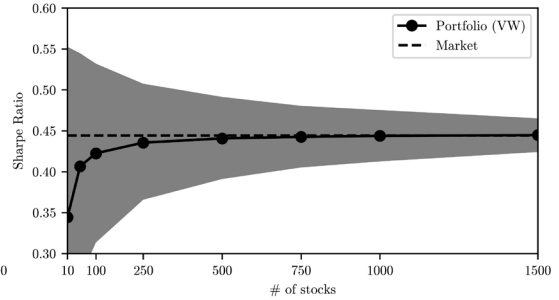
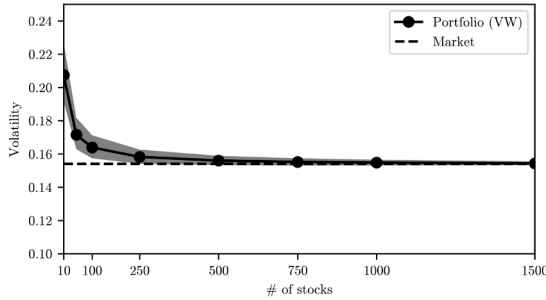


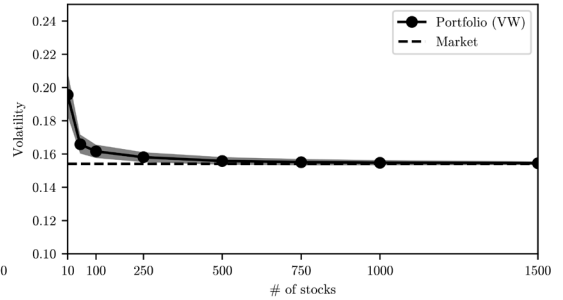
Figure A3: Maximum weight for individual stocks - Volatility, return, and Sharpe ratio vs. number of stocks

This figure shows the results of our backtests when we impose a maximum weight for individual stocks that depends on the number of stocks N in the portfolio. The maximum weight invested in a stock for a randomly drawn portfolio is defined as follows: $w_{max} = \max\left(\frac{2.5}{N}, 0.025\right)$. In case the value-weight for a particular stock exceeds w_{max} , the weight is capped at and the remainder is allocated in a value-weighted manner to the other stocks in the portfolio (this is continued until the constraint is met for all weights). The figure is based on the MSCI ACWI sample. Panel A shows the portfolio volatility for the baseline backtest (equal drawing probability, value-weighted portfolios, no maximum weight; reproduced from Panel B of Figure 3). Panel B shows the portfolio volatility for the backtest with a maximum weight for individual stocks within the portfolio. Panel C shows the portfolio return for the baseline backtest (reproduced from Panel B of Figure 5). Panel D shows the portfolio return for the backtest with a maximum weight for individual stocks. Panel E shows the portfolio Sharpe ratio for the baseline backtest (reproduced from Panel D of Figure 5). Panel F shows the portfolio Sharpe ratio for the backtest with a maximum weight for individual stocks. Black dots and lines show the means of portfolio volatility, return, and Sharpe ratio, respectively; the gray area indicates the 95% confidence band around the mean; and the dashed horizontal line shows the volatility, return, and Sharpe ratio of the value-weighted market index based on the sample involved. We refer to Figure 3 and Section 2.3 for a more detailed description of the backtests and data.

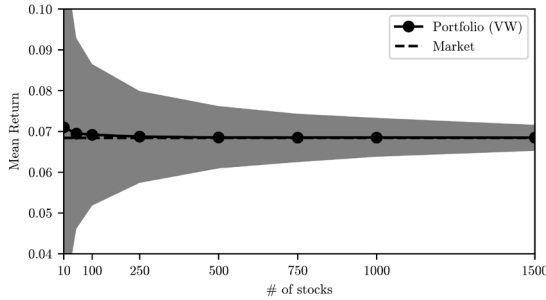
Panel A: Volatility - no max weight



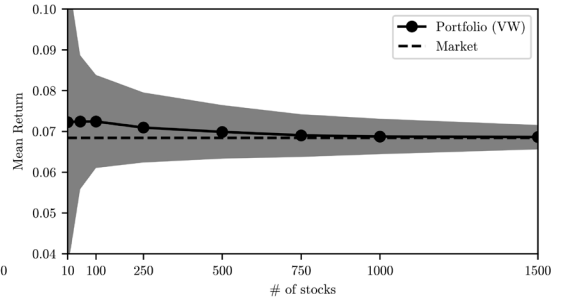
Panel B: Volatility - max weight



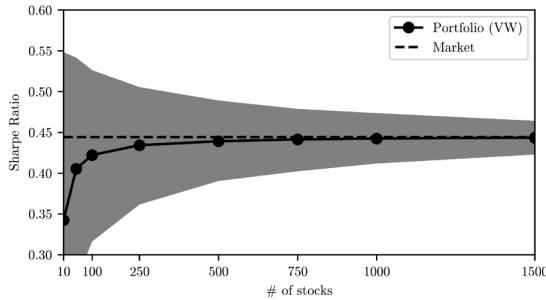
Panel C: Returns - no max weight



Panel D: Returns - max weight



Panel E: Sharpe - no max weight



Panel F: Sharpe - max weight

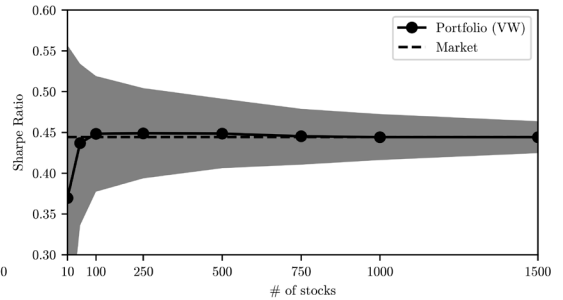
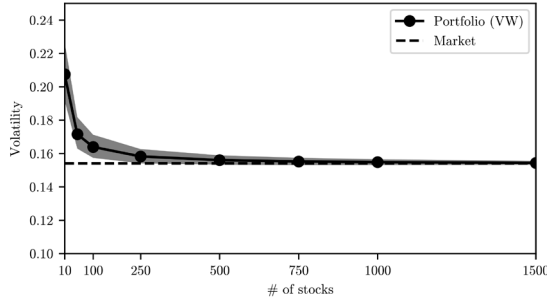


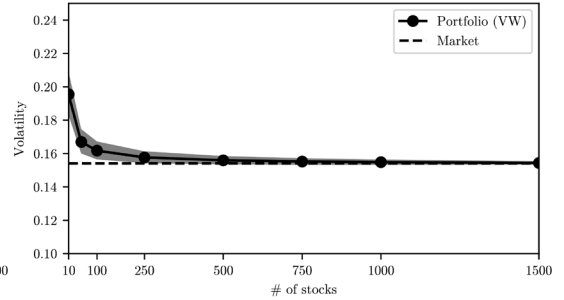
Figure A4: Maintaining industry composition – Volatility, return, and Sharpe ratio vs. number of stocks

This figure shows the results of our backtests when we maintain the industry composition of the MSCI ACWI index in the drawn portfolio. In order to maintain the industry composition (based on SIC Divisions) of the MSCI ACWI index, we select a number of stocks for each of the industries relative to the market weight of that industry (i.e. approximately $N \cdot w_i$, where w_i is the market weight of industry), and then we form an industry portfolio by value-weighting within each industry. To arrive at the return for the drawn portfolio, we value-weight the industry portfolios with the market weight of each industry. The figure is based on the MSCI ACWI sample. Panel A shows the portfolio volatility for the baseline backtest (equal drawing probability, value-weighted portfolios, no maximum weight; reproduced from Panel B of Figure 3). Panel B shows the portfolio volatility for the backtest with a maximum weight for individual stocks within the portfolio. Panel C shows the portfolio return for the baseline backtest (reproduced from Panel B of Figure 5). Panel D shows the portfolio return for the backtest with a maximum weight for individual stocks. Panel E shows the portfolio Sharpe ratio for the baseline backtest (reproduced from Panel D of Figure 5). Panel F shows the portfolio Sharpe ratio for the backtest with a maximum weight for individual stocks. Black dots and lines show the means of portfolio volatility, return, and Sharpe ratio, respectively; the gray area indicates the 95% confidence band around the mean; and the dashed horizontal line shows the volatility, return, and Sharpe ratio of the value-weighted market index based on the sample involved. We refer to Figure 3 and Sections 2.3 and 2.4 for a more detailed description of the backtests and data.

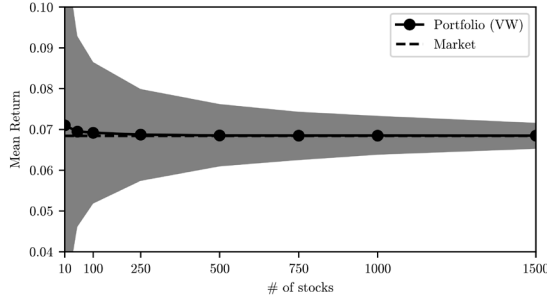
Panel A: Volatility – benchmark



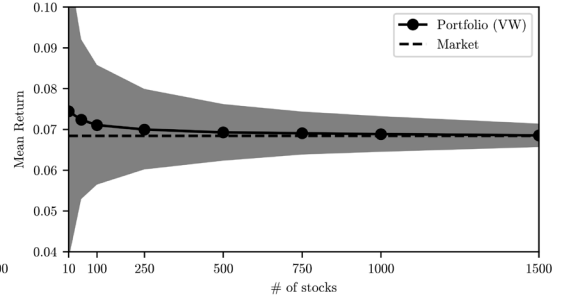
Panel B: Volatility – maintaining industry



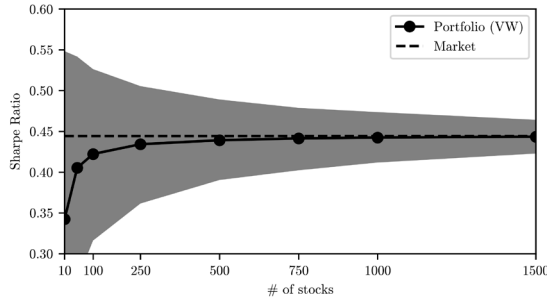
Panel C: Returns – benchmark



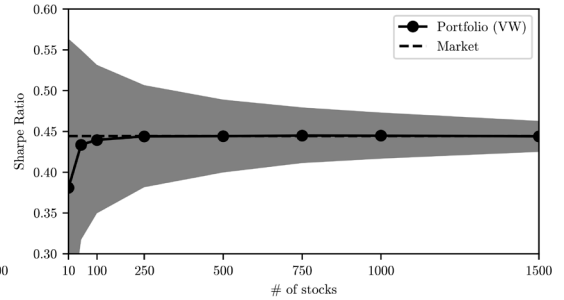
Panel D: Returns – maintaining industry



Panel E: Sharpe – benchmark



Panel F: Sharpe – maintaining industry





Network for Studies on
Pensions, Aging and Retirement

This is a publication of Netspar
Mei 2026

T +31 13 466 2109
E info@netspar.nl

[netspar.nl](https://www.netspar.nl)