FOMO in equity markets?
Concentration risk in (sustainable) investing

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Abstract

This paper revisits the financial consequences of imperfectly diversified portfolios – in light of the trend towards concentrated (sustainable) portfolios among some institutional investors. Based on a large global sample of stocks over 1985-2023, we find that – in contrast to common beliefs and prior studies – it takes considerably more than 30-40 stocks to fully diversify idiosyncratic risk. Our second key finding is that concentrated portfolios involve a hitherto unstudied risk: FOMO (Fear Of Missing Out) – just 2% of stocks account for all stock market wealth creation and smaller portfolios have a greater probability of missing out on these top-performing stocks. We find similar diversification and FOMO effects for portfolios constructed based on ESG screens, exclusion of sin industries, and portfolio weight optimization.

Keywords: concentrated portfolios, diversification, stock return skewness, ESG, FOMO

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1. Introduction

In the past few decades, institutional investors like pension funds and insurance companies have predominantly followed investment strategies that closely track broad market indices. The resulting equity portfolios generally contain 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 have 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 (that new regulations such as the European Union's Corporate Sustainability Due Diligence Directive should 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 involve 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. A often-cited empirical paper in the literature on diversification is Statman (1987), who concludes that it takes only 30-40 stocks fully diversify idiosyncratic risk. 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 on random draws out of 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 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 to assess the implications of recent findings by Bessembinder (2018) and Bessembinder, Chen, Choi, and Wei (2023) 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 is that portfolios containing fewer stocks have a greater probability of missing 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, it is possible that some of our findings are due to "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 start only in 2003 and are thus based on a relatively short sample period. Related, some investors argue that concentrated portfolios allow for better management of climate risks (and other ESG risks), which may only to a limited extent be observed 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.

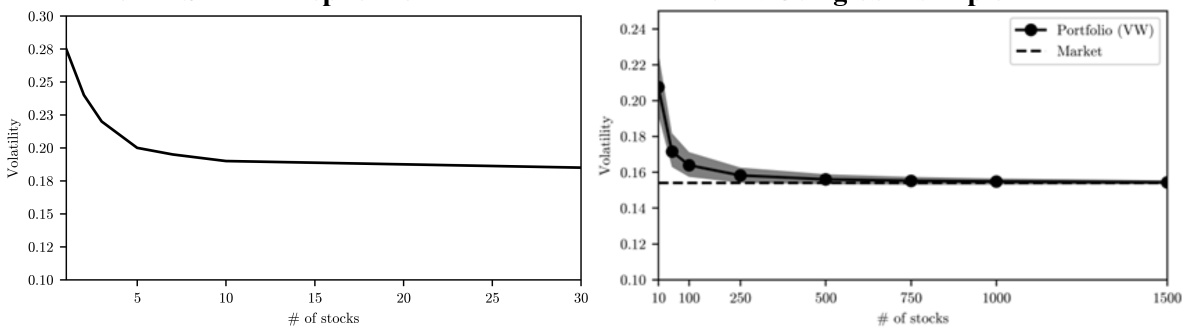
Before running our backtests, we examine some basic features of our global sample of stocks. The equity premium (return on a value-weighted index of all stocks in our sample in excess of the risk-free rate) over our almost 40-year sample period from 1985 to 2023 is 6.9% per annum, with an annual volatility 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) that 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 of Figure i below. 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.

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

Panel A (Panel A of Figure 1 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 2) 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**



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 $N = 10, \ldots, 1500$. 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, which we deem of specific interest in light of the findings of 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.[1] 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.

We demonstrate 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 below. 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. FOMO risk in global stock portfolios
This figure (Panel B of Figure 4 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).

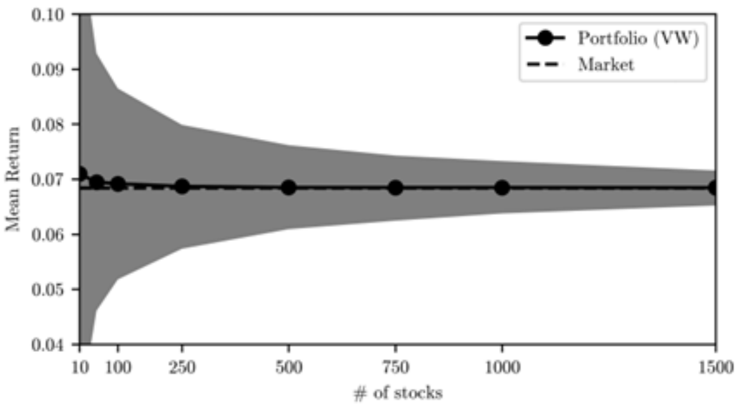


Figure ii shows that FOMO risk only decreases relatively slowly when *N* gets larger – notably slower than volatility in Panel B of Figure i. The spread in stock returns between the 2.5th and 97.5th percentile of the return distribution across draws in Figure ii equals almost 2% per annum for *N* = 500 and still around 1% for *N* = 1000. Even return differences of 1% per annum can amount to large wealth differences over long horizons; compounding a constant 7%

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

return over 30 years yields a final wealth of €7.6 for every €1 invested, while compounding a constant 6% return yields only €5.7 for every €1 invested (difference of one third).

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.

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 probability that concentrated portfolios miss out on the small fraction of top-performing stocks, potentially hurting their ex post financial performance (returns, Sharpe ratio) in a material way. 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; Koijen 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 had been possible 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 would have been possible (e.g., in light of mandates) and/or 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 use the largest 2,500 stocks based on their market capitalization each month instead. 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 had, exhibits very similar country and sector weights to the actual MSCI ACWI at this point in time.[2]

[2] See: https://www.msci.com/documents/10199/8d97d244-4685-4200-a24c-3e2942e3adeb.

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 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 annum over 1985-2023, with an annual volatility of 15.5%, a Sharpe ratio of 0.44, and a drawdown -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 further 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 10 years of our sample period (6.0% vs. 7.2%) – illustrating the potentially large influence of a small number of stocks. In contrast, 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 on their composite ESG rating across the five ESG ratings. We note that our ESG data are limited to 2003-2021.

Table 3 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 3 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, which is relevant since it suggests that the returns of portfolios 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, albeit with a weaker size effect (not surprisingly since it is well-known the size effect is driven by very small stocks not included in this sample) and a weaker profitability effect.

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 drawn stock 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 in part 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 to 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.[3]

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:

- *Factor 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).

[3] 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 90s.

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 a 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 much exceeds the number of factors F, as what used to be a problem of order $O(N^3)$ becomes $O(F^3)$, with $F << N$.

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-statistics[4], 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.[5]

[4] 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 we reduce the weights for high beta stocks for which we have less observations relative to similarly high beta stocks with more observations.

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

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.

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.[6] This study remains highly influential, as illustrated by the replication of its main result in the widely used *Investments* textbook by Bodie, Kane, and

[6] 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). 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.

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 1 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 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 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 1 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 2, we show similar graphs as in Figure 1 but then based on our own global sample of stocks over 1985-2023 (all stocks in Panel A and 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 2 relative to Figure 1 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 2 and Figure 1 is quite striking. Although the graphs in Figure 2 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 2. 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 horizonal 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 3 shows very similar graphs as in Figure 2 but then for drawdown (based on all stocks in Panel A and the MSCI ACWI sample in Panel B) as well as tracking error (all stocks in Panel C and MSCI ACWI in Panel D), again including 95% confidence bands in gray. For the drawdown, 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 2, 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 3. Second, the gray confidence bands around the mean portfolio drawdown are much wider than the confidence bands around the mean portfolio volatility in

[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 2) is considerably lower than in their NYSE sample (around 19%, see Panels A and C of Figure 1), highlighting the benefits of diversification across international stock markets – which may require more stocks.

Figure 2 (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 3 (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. 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. In the words of Bessembinder et al. (2023, p. 36), 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. These findings underscore that the ex post financial performance (return, Sharpe ratio) of concentrated portfolio may significantly depend on the degree to which they include the stocks that have shown the best performance over the period the portfolio was held, possibly giving rise to substantial FOMO effects.

We investigate and quantify this FOMO risk in Figure 4. 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).[9]

The salient finding in Panels A and B of Figure 4 is the large 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 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

[9] For small *N*, mean returns are slightly above market returns because of a size effect (see also Table 3). 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).

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 that she did not pick a much better performing portfolio of 100 stocks out of the bigger sample of all stocks.

Furthermore, even in Panel B of Figure 4 (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 more than 5% per annum. For $N = 500$, the spread in stock returns between the 2.5th and the 97.5th percentile 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 €7.6 for every €1 invested, while compounding a constant 6% return yields only €5.7 for every €1 invested – a difference of almost 200 percentage points.

When plotting Sharpe ratios in Panels C and D of Figure 4, 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 (97.5th) percentile of the distribution of Sharpe ratios across the 10,000 draws is around 0.40 (0.48) 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, to a considerable extent 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.

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 on "optimal" portfolios in particular.

In Figure 5, 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 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 5, we reproduce the Sharpe ratio graph of our baseline specification for the MSCI ACWI sample (taken from Panel D of Figure 4). 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 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, an economically substantial effect. Second, using minimum variance portfolio weights increases the speed of diversification to some degree. In contrast to Panel B, Panel C shows no discernable further diversification benefits beyond $N = 250$.[10]

The third notable difference between the graphs in Panels B and C of Figure 5 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 (97.5th) percentile of the distribution of Sharpe ratios across the 1,000 draws is around 0.46 (0.50) and thus indicates 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.

[10] 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 4 and footnote 4. Second, due to the smaller number of draws in Figure 5 (1,000 vs. 10,000 in Figure 4), the mean Sharpe ratio may be subject to slightly greater estimation uncertainty. In other words, Panel C-F of Figure 5 may somewhat overestimate the speed of diversification.

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 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 choosing 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 the 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 5 based on optimal portfolios. In Panel D, we not only let the weights but also the drawing probability be dependent on minimum variance optimization. The pattern 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 are dependent on tangency optimization. Remarkably, these graphs are very similar to those in, respectively, Panel C and Panel D. 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 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 4, we again reproduce the Sharpe ratio graph of our baseline specification for the MSCI ACWI sample (taken from Panel D of Figure 4). 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 5; 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 portfolios, 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. That said, 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 disregard 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 6 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 6 show, respectively, the portfolio volatility, return, and Sharpe ratio for the baseline backtest (equal drawing probability, value-weighted portfolios; reproduced from, respectively, Panel B of Figure 2 and Panels B and D of Figure 4). 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 portfolios. The results of Figure 6 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 7 shows the relation between portfolio performance (volatility, return, and Sharpe ratio) and the number of stocks *N* in the portfolio when portfolios are selected based on 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). Like in Figure 6, Panels A, C, and E (left column) of Figure 7 show, respectively, the portfolio volatility, return, and Sharpe ratio 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 questioning the finding that sin stocks tend to have greater returns (Blitz and Fabozzi, 2017). Third, the portfolio Sharpe (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 height of the confidence bands around the mean Sharpe ratio in Panel F is 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 studies (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 affect 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% 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 when 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 occurs (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 real-life investors have in doing so. Figure A2 in the Appendix shows the result. Like in Figures 6 and 7, Panels A, C, and E (left column) of Figure A2 show, respectively, the portfolio volatility, return, and Sharpe ratio 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, for the sake of our analysis it does not matter whether you 100% redraw portfolios each month or redraw only 20% of the portfolio 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: $w_{max} = \max\left(\frac{2.5}{N}, 0.025\right)$. In case the value-weight for a particular stock exceeds w_{max}, the weight is capped at w_{max} 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. Like 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 weights 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 3 and footnote 4). Imposing a maximum weight brings the value-weighted portfolios in our backtests closer to an equally-weighted portfolio, 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 drawn portfolio closer to 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 relatively low stock correlations across different industries. The results are in Figure A4. Like 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 from Panel B of Figure A4. This is expected, as the drawn portfolios now have a similar industry composition as the market and therefore do 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, and again the effect dissipates for portfolio sizes beyond 250, whilst 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 3 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 selecting only small stocks from 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.

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 – in contrast 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: 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 also potentially by lower returns. 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.

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 different portfolios that could have been 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, e.g., 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 predict the "next Magnificent 7." But we know from a large literature on active investing and market efficiency that this is very difficult.

We acknowledge that there may be non-pecuniary reasons for institutional investors to construct concentrated portfolios, such as ethical considerations and the objective of making 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 considering concentrated portfolios should take both dimensions of concentration risk (incomplete diversification and FOMO) seriously as inputs to their decision-making.

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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%**
Return	11,694,235	0.82%	17.55%	-7.08%	-0.37%	6.59%
Size	11,694,235	1,556	12,731	27	113	531
Beta	8,815,430	1.04	0.61	0.67	0.99	1.34
B/M	9,899,024	1.10	1.90	0.35	0.68	1.23
Profitability	8,827,103	0.28	0.34	0.10	0.21	0.38
Investment	9,751,190	0.35	4.62	-0.05	0.05	0.20
Momentum	10,730,106	0.14	0.80	-0.24	0.01	0.30
Quality	7,330,018	0.00	1.00	-0.86	0.00	0.87
Idio vol	8,786,308	2.78%	2.52%	1.35%	2.09%	3.34%
ESG FTSE	267,331	0.00	1.00	-0.78	-0.01	0.78
ESG ISS	349,339	0.00	1.00	-0.76	-0.22	0.62
ESG MSCI	835,315	0.00	1.00	-0.66	-0.03	0.65
ESG Refinitiv	797,362	0.00	1.00	-0.80	-0.08	0.75
ESG S&P	669,376	0.01	1.00	-0.72	-0.34	0.47
ESG	1,235,467	-0.05	0.81	-0.62	-0.11	0.45
Panel B: ACWI						
	obs.	**mean**	**std**	**25%**	**50%**	**75%**
Return	1,170,000	0.61%	10.76%	-4.95%	0.45%	5.94%
Size	1,170,000	12,584	38,485	2,042	5,037	11,021
Beta	1,009,356	1.02	0.48	0.72	0.99	1.26
B/M	1,055,721	0.56	0.54	0.25	0.45	0.74
Profitability	917,341	0.30	0.29	0.13	0.24	0.40
Investment	1,037,034	0.22	2.64	0.00	0.08	0.20
Momentum	1,119,732	0.21	0.58	-0.07	0.12	0.35
Quality	868,076	0.33	0.89	-0.36	0.42	1.10
Idio vol	1,047,673	1.58%	0.97%	0.96%	1.35%	1.92%
ESG FTSE	149,271	0.16	0.98	-0.58	0.20	0.92
ESG ISS	182,026	0.01	0.98	-0.74	-0.19	0.62
ESG MSCI	383,421	0.04	1.01	-0.64	0.01	0.71
ESG Refinitiv	374,699	0.14	1.02	-0.68	0.11	0.94
ESG S&P	363,912	0.10	1.03	-0.68	-0.25	0.75
ESG	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 considered universe (although two rows of the table report the equity premium based on an equally-weighted portfolio). *All stocks (1985-2023)* is the universe all stocks in our global sample over 1985-2023. *All stocks EW (1985-2023)* is the equally-weighted index based on the universe 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 (2014-2023)* 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 (2014-2023)* 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, Sharpe ratio, and drawdown corresponding to the 2.5% percentile of the return distribution.

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

Table 3. 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 from 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)
Beta	0.023	0.057	0.077		0.079
	(0.18)	(0.44)	(0.70)		(0.47)
ln(Size)	-0.101***	-0.085***	-0.137***		-0.117***
	(-3.34)	(-2.73)	(-5.45)		(-4.21)
B/M	0.328***	0.367***	0.392***		0.126
	(6.71)	(7.70)	(8.40)		(1.57)
Profitability		0.710***	0.346***		0.316*
		(6.10)	(2.78)		(1.70)
Investment		-0.265***	-0.312***		-0.074
		(-4.26)	(-5.12)		(-0.77)
Return t-1			-0.022***		-0.011*
			(-6.60)		(-1.89)
Momentum			0.743***		0.429
			(6.22)		(1.60)
Quality			0.242***		0.115**
			(9.50)		(2.29)
Idio vol			-12.364***		-10.363*
			(-4.32)		(-1.93)
ESG				-0.021	0.012
				(-0.56)	(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

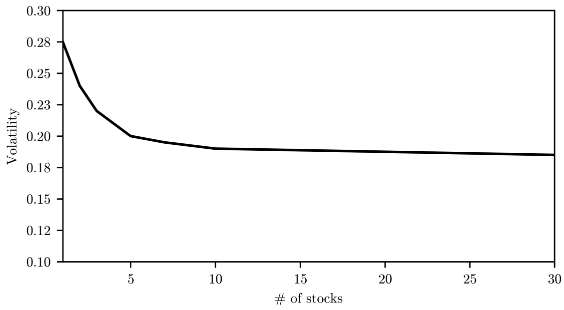
Table 3 – continued

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

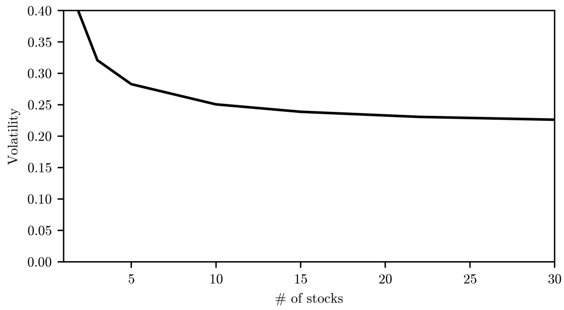
Figure 1: Replication of Statman's (1987) diversification result

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 the replication result when constructing value-weighted (VW) portfolios of *N* stocks in the BKM sample.

Panel A: BKM Statman replication



Panel B: Our Statman replication (EW)



Panel C: Our Statman replication (VW)

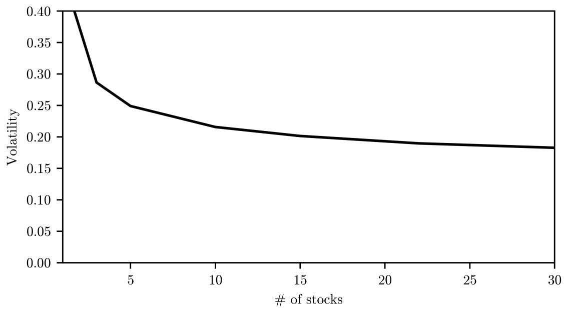
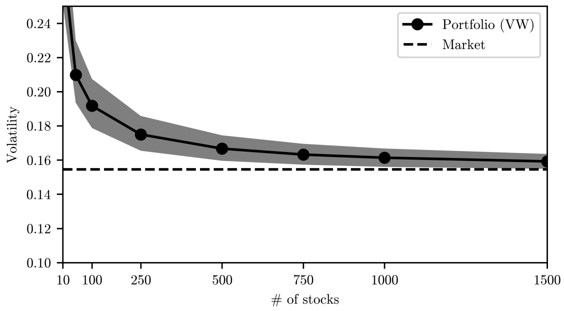


Figure 2: Portfolio volatility vs. number of stocks in our global sample

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.

Panel A: Volatility (all stocks)



Panel B: Volatility (ACWI)

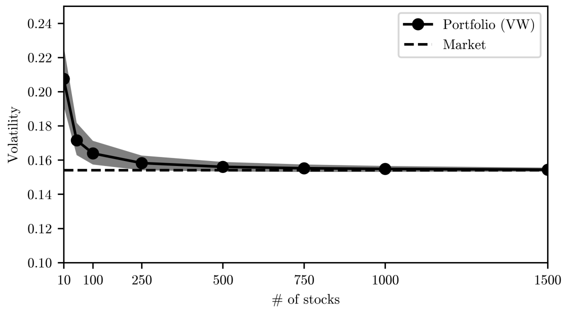
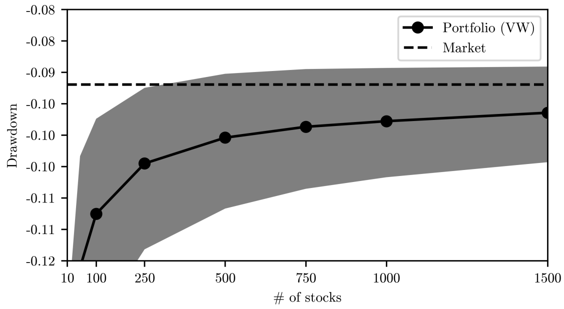


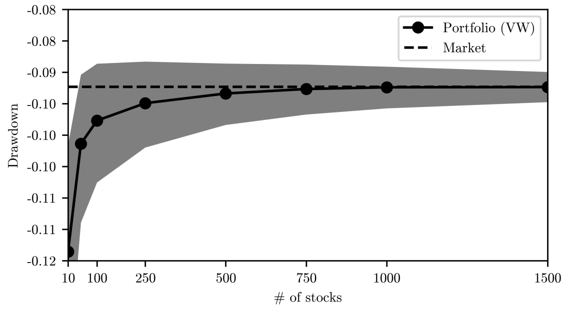
Figure 3: Portfolio drawdown and tracking error vs. number of stocks

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, respectively portfolio tracking error; 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 respective sample. We refer to Figure 2 and Section 2.3 for a more detailed description of the backtests and data.

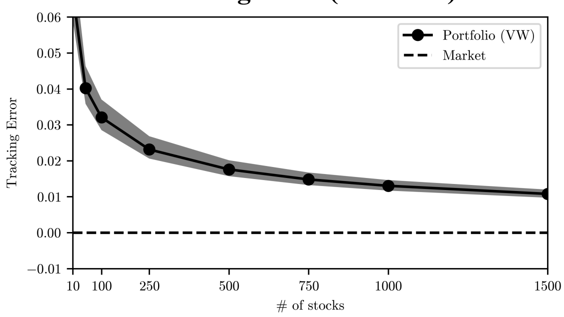
Panel A: Drawdown (all stocks)



Panel B: Drawdown (ACWI)



Panel C: Tracking error (all stocks)



Panel D: Tracking error (ACWI)

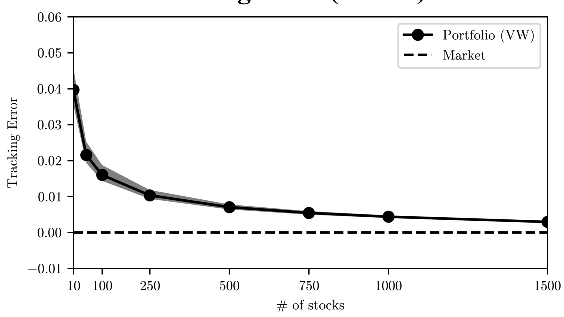
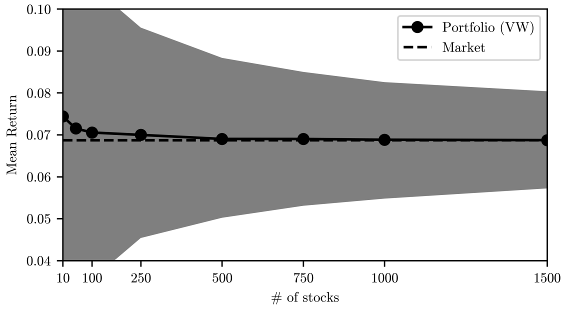


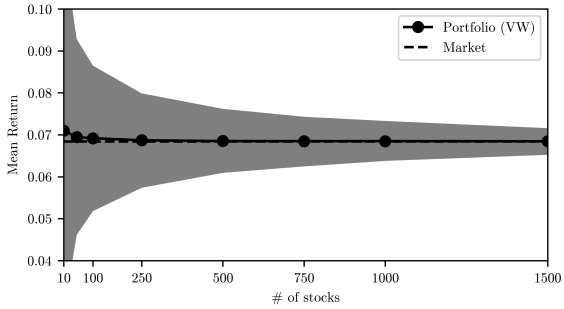
Figure 4: FOMO – Portfolio return and Sharpe ratio vs. number of stocks

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 and 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, respectively portfolio Sharpe ratio; 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 respective sample. We refer to Figure 2 and Section 2.3 for a more detailed description of the backtests and data.

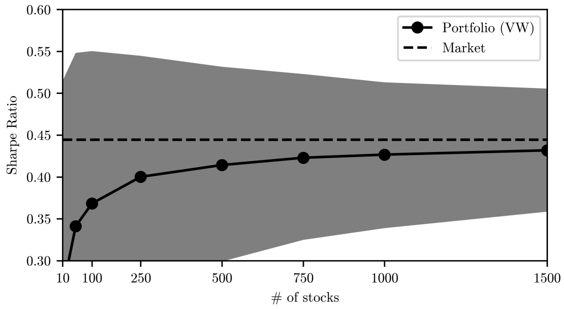
Panel A: Return (all stocks)



Panel B: Return (ACWI)



Panel C: Sharpe ratio (all stocks)



Panel D: Sharpe ratio (ACWI)

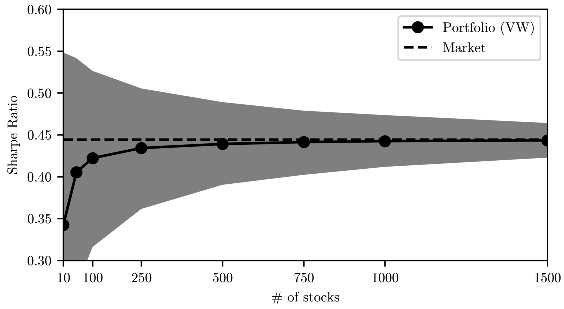


Figure 5: Optimal portfolios – Sharpe ratio vs. number of stocks

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 from Panel D of Figure 4). 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 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 respective sample. We refer to Figure 2 and Sections 2.3 and 2.4 for a more detailed description of the backtests and data.

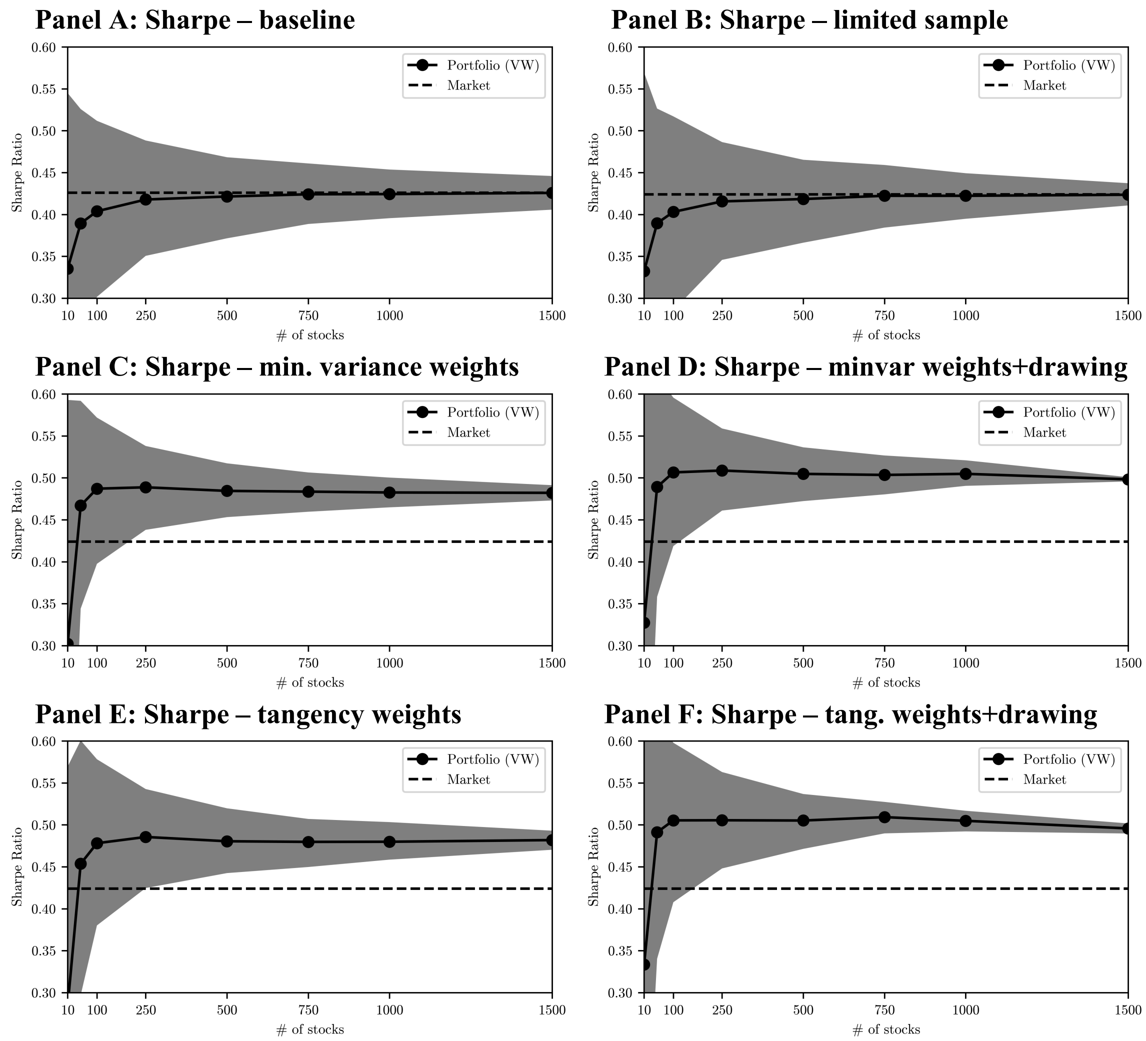
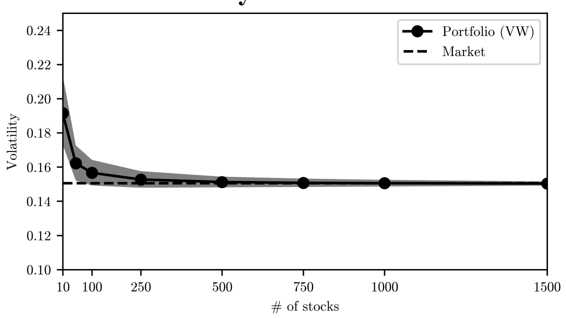


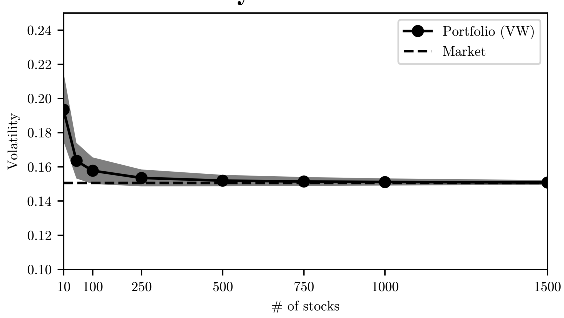
Figure 6: ESG portfolios – Volatility, return, and Sharpe ratio vs. number of stocks

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 dependent 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 for 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 2). 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 4). 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 4). 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, respectively, portfolio volatility, return, and Sharpe ratio; 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 respective sample. We refer to Figure 2 and Section 2.3 for a more detailed description of the backtests and data.

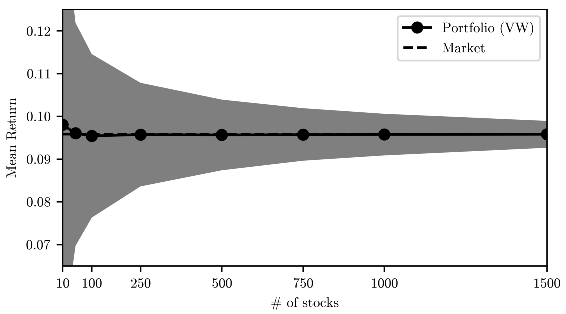
Panel A: Volatility – baseline



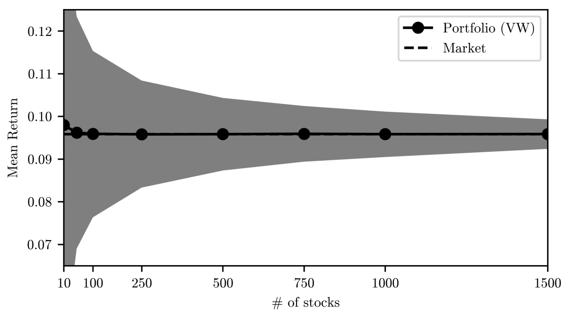
Panel B: Volatility – ESG-based



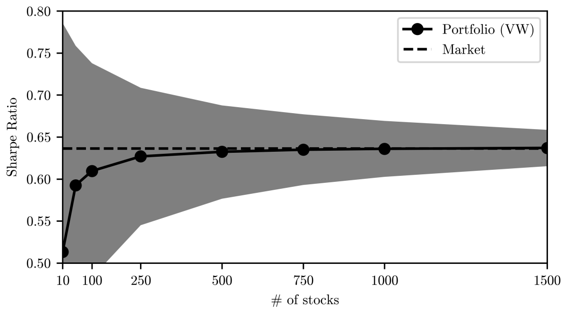
Panel C: Returns – baseline



Panel D: Returns – ESG-based



Panel E: Sharpe – baseline



Panel F: Sharpe – ESG-based

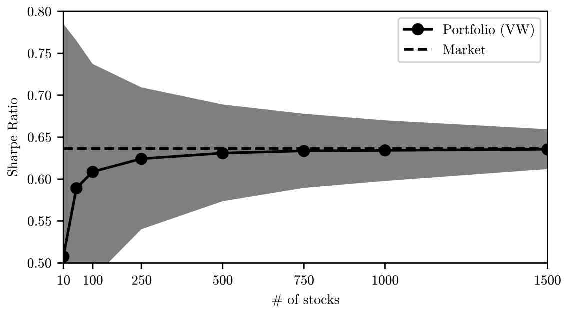
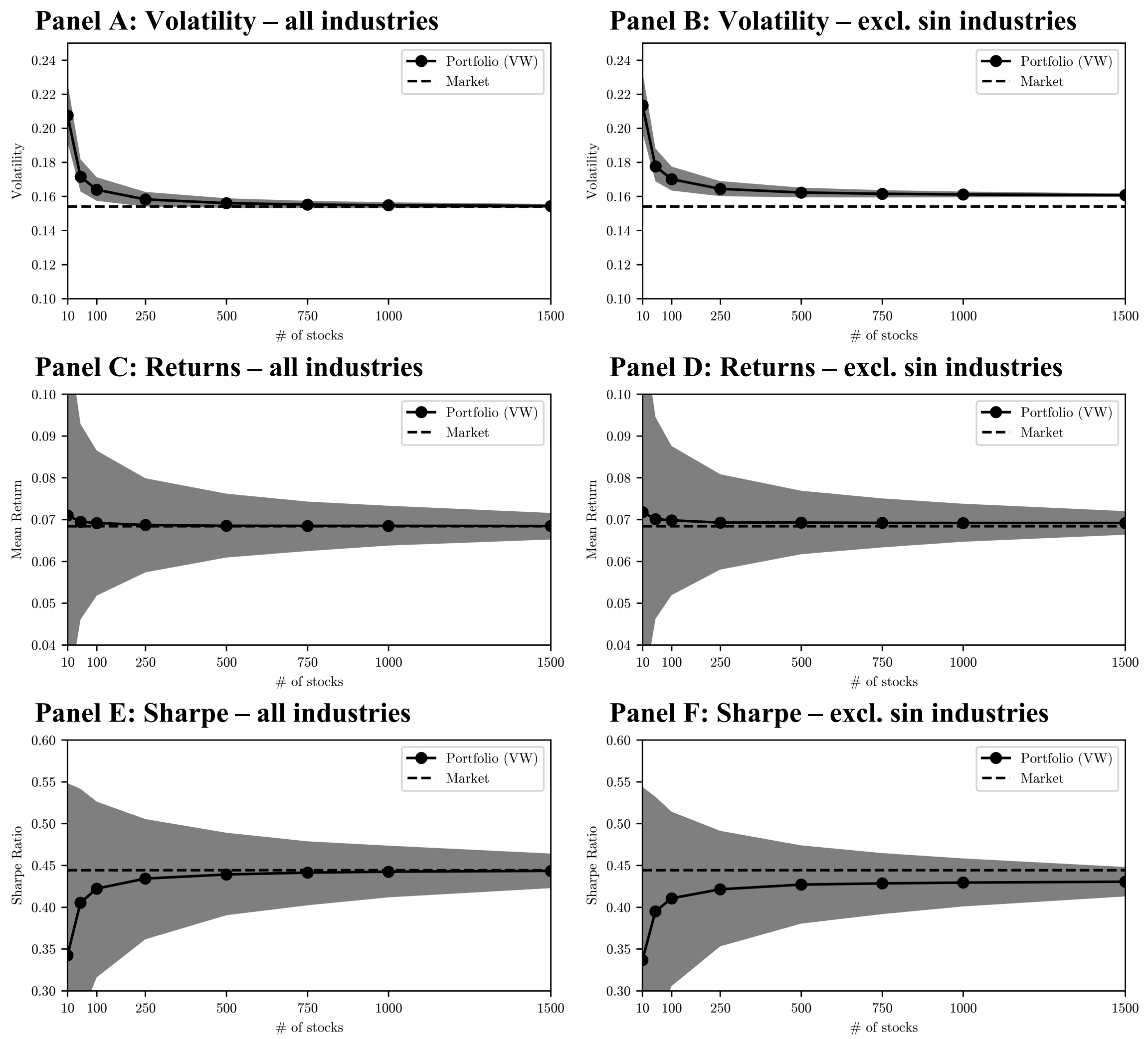


Figure 7: Sinless portfolios – Volatility, return, and Sharpe ratio vs. number of stocks

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 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 Kenneth French). Panel A shows the portfolio volatility for the baseline backtest (equal drawing probability, value-weighted portfolios; reproduced from Panel B of Figure 2) 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 4). 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 4). 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, respectively, portfolio volatility, return, and Sharpe ratio; 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 respective sample. We refer to Figure 2 and Section 2.3 for a more detailed description of the backtests and data.

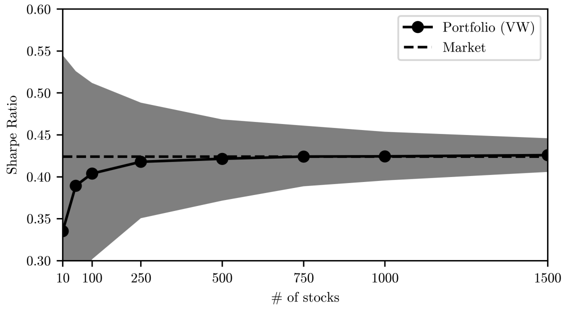


Appendix

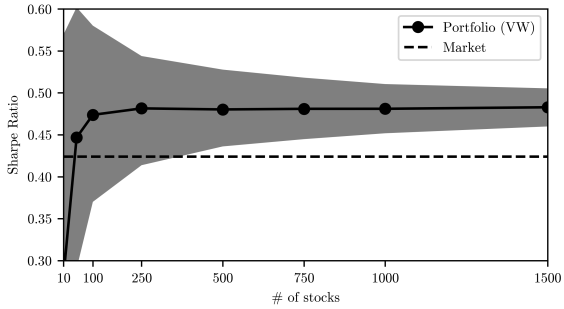
Figure A1: Additional optimal portfolios – Sharpe ratio vs. number of stocks

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 from Panel D of Figure 4). 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 respective sample. We refer to Figure 2 and Section 2.3 for a more detailed description of the backtests and data.

Panel A: Sharpe – value-weighted



Panel B: Sharpe – Black-Litterman



Panel C: Sharpe – mixed BL-tangency

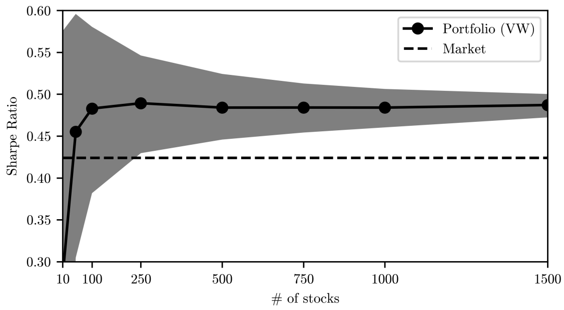
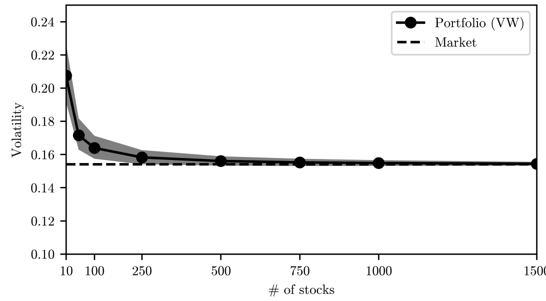


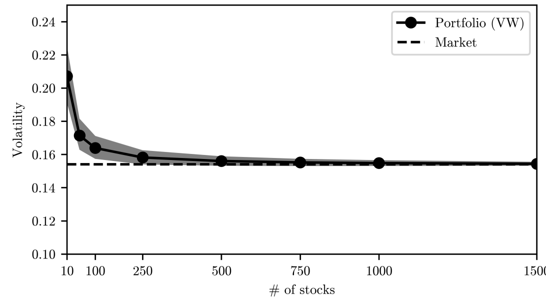
Figure A2: Monthly vs. annual portfolio rebalancing – Volatility, return, and Sharpe ratio vs. number of stocks

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 2). 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 4). 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 4). Panel F shows the portfolio Sharpe ratio for the backtest with 20% rebalancing each year. Black dots and lines show the means of, respectively, portfolio volatility, return, and Sharpe ratio; 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 respective sample. We refer to Figure 2 and Section 2.3 for a more detailed description of the backtests and data.

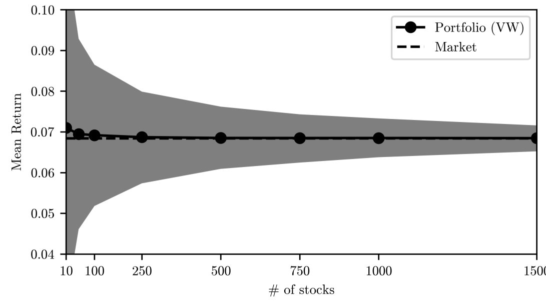
Panel A: Volatility – monthly rebalancing



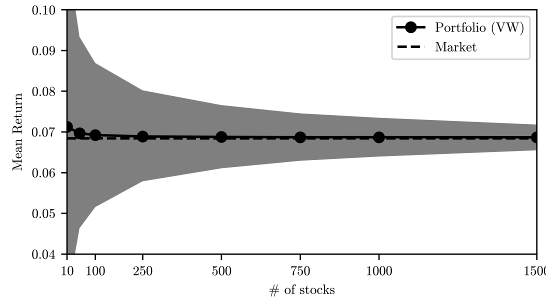
Panel B: Volatility – annual rebalancing



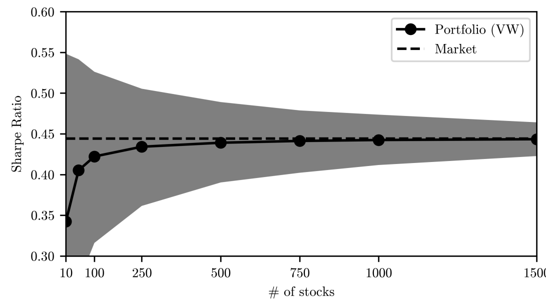
Panel C: Returns – monthly rebalancing



Panel D: Returns – annual rebalancing



Panel E: Sharpe – monthly rebalancing



Panel F: Sharpe – annual rebalancing

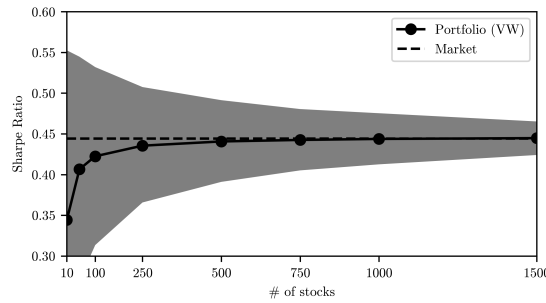


Figure A3: Maximum weight for individual stocks – Volatility, return, and Sharpe ratio vs. number of stocks

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 max 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 w_{max} 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 2). 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 4). 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 4). 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, respectively, portfolio volatility, return, and Sharpe ratio; 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 respective sample. We refer to Figure 2 and Section 2.3 for a more detailed description of the backtests and data.

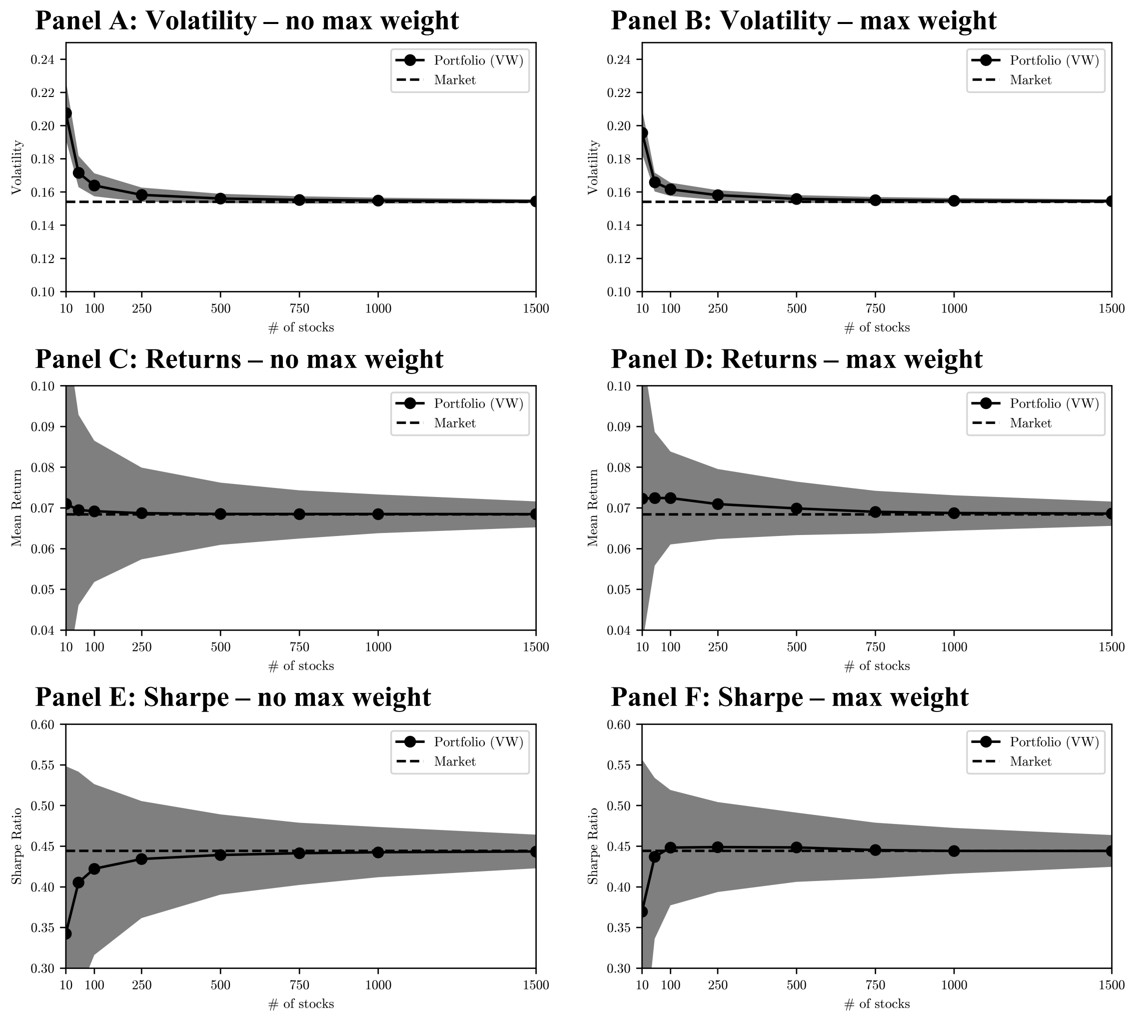
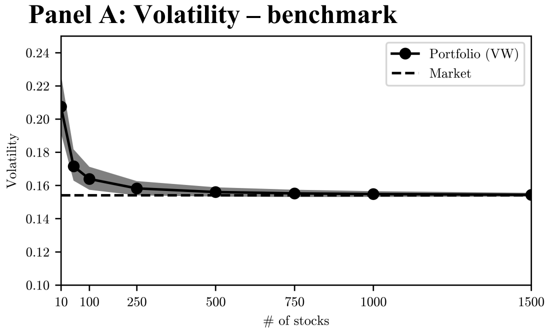


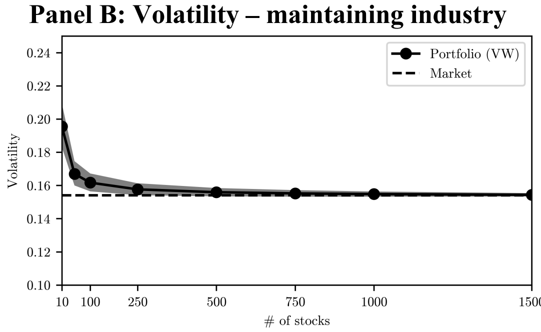
Figure A4: Maintaining industry composition – Volatility, return, and Sharpe ratio vs. number of stocks

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 I) and then we form an industry portfolio by value-weighting within 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 2). 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 4). 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 4). 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, respectively, portfolio volatility, return, and Sharpe ratio; 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 respective sample. We refer to Figure 2 and Sections 2.3 and 2.4 for a more detailed description of the backtests and data.

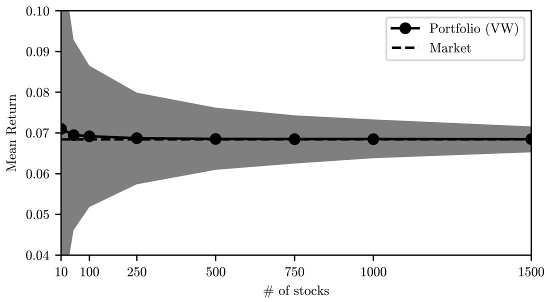
Panel A: Volatility – benchmark



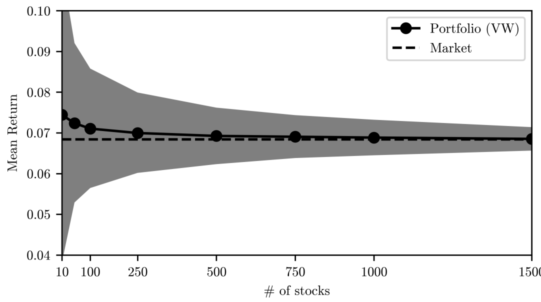
Panel B: Volatility – maintaining industry



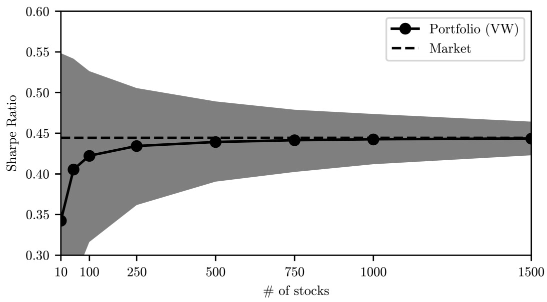
Panel C: Returns – benchmark



Panel D: Returns – maintaining industry



Panel E: Sharpe – benchmark



Panel F: Sharpe – maintaining industry