SDF-Based Portfolio Choice

Jaffe Greenwald[*] | Richard Priestley[†] | Kevin Schneider[‡]
University of Cambridge | BI Norwegian Business School | University of Oxford

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Abstract

We document large gains in out-of-sample performance when investors incorporate asset pricing models into portfolio construction. Estimating expected returns as covariances with an SDF rather than as noisy sample means improves out-of-sample portfolio performance relative to equally weighted ($1/N$) and traditional mean-variance strategies. Sharpe ratios and alphas increase, while turnover and tail risk decrease. Even SDFs based solely on macroeconomic quantities improve portfolio performance, highlighting the role of business cycle information. Consistent with this mechanism, SDF-based portfolios outperform in booms and recessions and in recent samples. Overall, we provide empirical evidence that SDFs are practically useful to investors.

Keywords: Portfolio choice, stochastic discount factor, tail risk, macro-factors, out-of-sample performance.

JEL Classification: G11, G12, G17

[*]University of Cambridge, UK, e-mail: j.greenwald@jbs.cam.ac.uk
[†]Corresponding author, BI Norwegian Business School, Norway, e-mail: richard.priestley@bi.no
[‡]University of Oxford, UK, e-mail: kevin.schneider@eng.ox.ac.uk

1 Introduction

Portfolio choice is easy in theory, but hard in practice. Large standard errors of sample moment estimators lead to portfolios with unstable weights, excessive leverage, and meager out-of-sample performance (DeMiguel et al., 2009b). The expected return in particular remains difficult to estimate (Barroso and Saxena, 2022). In this paper, we offer a simple solution from asset pricing theory and estimate expected returns as the covariance of returns with a stochastic discount factor (SDF).

Asset pricing rests on the Euler equation $\mathbb{E}_t[M_{t+1}R_{t+1}] = 0 \Leftrightarrow \mathbb{E}_t[R_{t+1}] = -\frac{\mathbb{C}\text{ov}_t(M_{t+1},R_{t+1})}{\mathbb{E}_t[M_{t+1}]}$. Different from the sample mean, idiosyncratic return volatility uncorrelated with the SDF has little impact on this model-based estimator. Intuitively, noise in realized returns plaguing the sample mean estimator does not change the SDF-estimator if the noise is orthogonal to the SDF, freeing the SDF-based portfolios from much estimation noise. Formally, we exchange the large standard errors in sample means for the assumption that the SDF is properly chosen (specification error) and the smaller standard error of the covariance matrix. We find this exchange beneficial across a range of SDFs, suggesting that our model-based estimator is useful for investors by leveraging economic theory.

We construct SDF-based portfolios by structurally estimating a linear asset pricing model using the generalized method of moments (GMM). Candidate models include the CAPM, the Fama and French (1993, 2015, 2016) three- to six-factor models, and the Hou et al. (2015, 2021) q-factor models, among others. We then calculate the covariance between the estimated SDF and the test assets in our investable universe and form out-of-sample mean-variance optimal portfolios based on the SDF-based expected return estimates.

SDF-based portfolios earn higher risk-adjusted returns than both the equal-weighted ($1/N$) and sample-mean-based ($1/T$) benchmarks. In our full sample, the $1/N$ and $1/T$ earn an out-of-sample Sharpe ratio of 0.49 and 0.44 p.a., respectively. Our ten SDF-based earn between 0.58 (CAPM) and 1.51 (Hou et al., 2021). In the recent sample starting in 2000, when factor risk premiums have declined, the $1/N$ and $1/T$ Sharpe ratios fall to 0.49 and 0.22, respectively, yet the average SDF-based portfolio still earns 0.91. We reach the same conclusion with Fama-French (2016) six-factor alphas. Static exposures to risk factors cannot explain the dynamic trading in SDF-based portfolios. SDF-based portfolios are cheap to implement with low turnover due to stable weights.

The superior Sharpe ratios of SDF-based portfolios come with lower risk. Average annualized volatility falls from 18.9% for the $1/N$ portfolio and 20.8% for the $1/T$ portfolio to as low as 6.1% for the SDF-based portfolios. Tail risk also declines sharply. The monthly 95% Value-at-Risk (VaR) improves from –8.40% for the $1/T$ portfolio to –2.2% for the Fama and French (2016) six-factor SDF. The conditional VaR (expected shortfall) shows a similar pattern. Thus, the gains in Sharpe ratios come from better risk control, not from taking on more leverage or factor exposure.

SDF-based portfolios perform well because of the improved expected return estimator. To drill down on this mechanism, we estimate cross-sectional regressions of future realized returns on expected returns. We reject that the sample mean is an unbiased estimator in the cross-section, but fail to do so for many SDF-based estimators. Indeed, the SDF-based expected return better reflects risk-return dynamics that allow SDF-based portfolios to perform well along the business cycle during booms and recessions.

We also study SDFs constructed from macro-finance theories such as habit models, long-run risk models, and ICAPM. These SDFs reflect macroeconomic quantities such as consumption growth, industrial production, the term spread, and intermediary leverage. Many of these factors are not directly tradable but contain valuable business-cycle information. Constructing SDF-based portfolios based on these deep asset pricing theories yields out-of-sample Sharpe ratios of up to 0.72, which is 50% higher than the Sharpe ratio for the $1/N$ and $1/T$ benchmarks. The results hold in both the full and the recent samples, confirming that macroeconomic state variables remain powerful sources of risk information even when traditional factor risk premiums weaken.

We conduct extensive robustness checks. We correct our expected return estimator using Bayes-Stein shrinkage and using a non-negativity sign constraint. We implement conditional SDF by scaling factors by Cooper and Priestley's (2009) output gap. We consider longer holding periods of one year with portfolios reflecting stale information. To address trading costs, we remove costly-to-trade test assets like portfolios sorted on market size or price momentum and calculate the portfolio turnover. Across all these tests, SDF-based portfolios compare favorably to equally weighted $1/N$ and sample-moment $1/T$ optimized strategies.

Our paper contributes to three strands of research. First, it builds on the portfolio-choice literature that documents the poor out-of-sample performance of mean-variance optimization because expected returns are difficult to estimate (Merton, 1980; Britten-Jones, 1999; Jagannathan and Ma, 2003). DeMiguel et al. (2009b) show that simple equal weighting ($1/N$) often outperforms optimized portfolios based on estimated moments. Subsequent research proposes improvements through Bayesian methods, shrinkage, and high dimensionality (Black and Litterman, 1992; Kan and Zhou, 2007; DeMiguel et al., 2014; Ledoit and Wolf, 2017; Guidolin et al., 2018; Ao et al., 2019; Barroso and Saxena, 2022; Kan et al., 2024). Our paper contributes to this literature by replacing the noisy sample-mean estimator with SDF-based covariances, providing a more stable and economically grounded expected return estimator that improves the risk–return trade-off in mean–variance portfolio choice.

Second, we contribute to the debate on the practical usefulness of asset pricing models. Early Bayesian portfolio problems combine factor models with parameter uncertainty (MacKinlay and Pástor, 2000; Pástor, 2000; Pástor and Stambaugh, 2000). However, recent work questions whether asset pricing research helps investors predict returns in real time (Goyal et al., 2024; Chen et al., 2025). Our approach differs from these studies by using asset pricing models to directly estimate expected returns and incorporating these estimates directly into portfolio choice in a fully out-of-sample implementation, allowing portfolios to exploit the macroeconomic information and risk-return dynamics embedded in asset prices. In this sense, our evidence rehabilitates asset pricing theory as a valuable tool for portfolio construction rather than a purely academic exercise.

Finally, we add to the growing literature on declining factor risk premiums. McLean and Pontiff (2016) show that anomaly returns decline after publication, while Green et al. (2017) document that many anomalies attenuate or disappear in more recent samples. Fama and French (2021) similarly report that factor risk premiums have become smaller and more volatile in recent decades. We show that even in recent samples with weaker factor risk premiums, SDF-based portfolios continue to outperform traditional benchmarks. This persistence suggests that the information embedded in asset pricing models remains useful for portfolio choice even when individual factor risk premiums decline.

2 Methodology

In this section, we explain the implementation details of our portfolio formation. We discuss what data we use, how we construct portfolios, and what candidate SDFs we employ.

2.1 Portfolio Construction

We consider three approaches to portfolio choice: an equally-weighted $1/N$ strategy and mean-variance efficient strategies whose expected returns are estimated from the sample mean ($1/T$) or covariances with SDF.

2.1.1 $1/N$ Portfolio

The "$1/N$ strategy" equally invests in all available assets in our investable universe, forming a non-parametric benchmark that does not rely on any optimization. The weights are

$$w_{1/N} = \frac{1}{N}, \tag{1}$$

where N denotes the number of assets in the investable universe. Given a large investable universe, the $1/N$ strategy resembles an investment in the equally-weighted market portfolio. However, the $1/N$ strategy is not the optimal solution to any standard portfolio problem and ignores the distribution of the returns on the test assets entirely. The $1/N$ portfolio strategy is always fully invested and does not use leverage or short sales.

2.1.2 Mean-Variance Optimization

Mean-variance optimal strategies choose portfolio weights w to maximize the risk-adjusted return of an investor with risk aversion coefficient γ,

$$\max_{w} \quad w'\mu - \frac{\gamma}{2} w'\Sigma w. \tag{2}$$

The closed-form solution is the tangency portfolio given by

$$w^* = \frac{1}{\gamma}\Sigma^{-1}\mu. \tag{3}$$

We take concerns about excessively long and short positions seriously and follow DeMiguel et al. (2009a) and Bessembinder et al. (2025) by rescaling the portfolio weights vector so that the sum of the absolute weights is one, $\|w\|_1 = 1$, where $\|\cdot\|_p$ is the p-norm. Jagannathan and Ma (2003) confirm that constraining portfolio weights is about as effective as shrinkage methods in portfolio choice. Rescaling also removes the need to choose γ. The weights of the equally-weighted portfolio satisfy $\|w_{1/N}\|_1 = 1$ by construction. We show in the internet appendix that imposing $\|w\|_2 = 1$ yields similar results. However, because the sum of weights does not necessarily equals one, our portfolios need not be fully invested in risky assets at all times. When comparing the out-of-sample performance, we always scale portfolio returns to a common average return, which makes the portfolio risks comparable. We rebalance the portfolio every month.

2.1.3 $1/T$ Portfolio

To operationalize Equation (3), we need to estimate the expected return vector μ and the covariance matrix Σ. The standard procedure is to use the sample moments,

$$\hat{\mu}_T = \frac{1}{T}\sum_{t=1}^{T} R_t, \tag{4}$$

$$\hat{\Sigma}_T = \frac{1}{T-1}\sum_{t=1}^{T}(R_t - \bar{R})(R_t - \bar{R})'. \tag{5}$$

As (biased-corrected) GMM estimators, they are consistent. We label the portfolio whose weights are derived from the sample-moment expected-return estimator as "$1/T$ strategy." We follow DeMiguel et al. (2009b) and construct our $1/T$ strategy by estimating the mean vector, $\hat{\mu}$, and covariance matrix, $\hat{\Sigma}$, from monthly returns on our test assets using rolling windows over the last five years. According to Equation (3), the portfolio weights are

$$w_{1/T} = \hat{\Sigma}_T^{-1}\hat{\mu}_T. \tag{6}$$

However, repeated studies show that the expected return in particular is noisy to estimate (Merton, 1980; Britten-Jones, 1999; DeMiguel et al., 2009b; Levy and Roll, 2010). Jagannathan and Ma (2003) lament the poor out-of-sample performance, where the "*primary reason is that the sample mean is an imprecise estimator of the population mean.*"

2.1.4 SDF-Based Portfolios

The main contribution of our paper is to replace the statistical estimator with a model-based estimator informed by financial theory. The Euler equation underpinning the optimality of an investor's asset allocation implies that expected returns reflect covariance with the SDF,

$$\mathbb{E}_t[M_{t+1}R_{t+1}] = 0 \Leftrightarrow \mathbb{E}_t[R_{t+1}] = -\frac{\mathbb{C}\text{ov}_t(R_{t+1}, M_{t+1})}{\mathbb{E}_t[M_{t+1}]}. \tag{7}$$

We normalize the SDF such that $\mathbb{E}_t[M_{t+1}] = 1$. Normalizing the SDF has no impact on the portfolio weights which are rescaled to match the $\|w\|_1 = 1$ leverage constraint. We thus estimate expected returns as follows

$$\hat{\mu}_M = -\frac{1}{T-1}\sum_{t=1}^{T}(R_t - \bar{R})(M_t - 1). \tag{8}$$

As the Euler equation and stochastic discount factor model remain silent about the covariance matrix, we make no changes to Equation (5). We label portfolios whose weights are derived from the SDF-based expected return estimator by the name of the SDF. According to Equation (3), the portfolio weights are

$$w_{SDF} = \hat{\Sigma}_T^{-1}\hat{\mu}_M. \tag{9}$$

Intuitively, SDF-based portfolios offer more precise statistical inference because idiosyncratic noise in returns uncorrelated with the SDF has no impact on the expected return estimate. Additionally, estimating expected returns as covariance with the SDF anchors the expected return in a robust economic model, giving it a higher chance to perform well out of sample.

SDF-based portfolios offer an alternative intuition. Suppose we project the SDF onto the returns on all test assets in the investable universe by estimating the time series regression

$$m_t = \alpha - R_t w_{SDF} + \varepsilon_t, \tag{10}$$

where the SDF m is $T \times 1$, the excess returns R are $T \times N$, and the weights w_{SDF} are $N \times 1$. The fitted part of that regression identifies the "SDF-mimicking portfolio" (or "maximum correlation portfolio"). Denoting demeaning by a tilde, the optimal weights are

$$w_{SDF} = -(\tilde{R}'\tilde{R})^{-1}\tilde{R}'m \tag{11}$$

$$= \hat{\Sigma}_T^{-1}\hat{\mu}_M, \tag{12}$$

where $\hat{\Sigma}_T$ is the sample covariance matrix of the excess returns, and $\hat{\mu}_M = -\tilde{R}'m = -\mathbb{C}\text{ov}(R, m) = \mathbb{E}[R]$ is the expected excess return on the test assets. Because the SDF is countercyclical, we study the negative of the replication portfolio. Thus, investing in the mean-variance efficient SDF-mimicking portfolio is equivalent to applying standard mean-variance optimization but with expected returns estimated from the SDF ($\hat{\mu}_M$) instead of sample means ($\hat{\mu}_T$). Our findings harken back to Hansen and Richard (1987) who show that the SDF-replicating portfolio is a tangency portfolio which prices all assets.

2.2 Stochastic Discount Factors

There are many candidate SDFs proposed in the asset pricing literature. Linear factor models with tradable factors sorted on characteristics are empirically most successful in explaining the cross-section of average stock returns (Cochrane, 2005). Thus, we begin our analysis by focusing on these models. We later expand our methodology to study linear factor models comprised of macroeconomic state variables which are non-tradable.

To estimate a linear asset pricing model, we employ the generalized method of moments (GMM). To be specific, we assume $m_t = 1 - b'F_t$ where F captures a low number of factors and b captures the prices of risk. We normalize the SDF to have a unit mean because our structural estimation only uses excess returns and does not identify the risk-free rate. We identify b by estimating the Euler Equation for excess returns, $\mathbb{E}_t[m_{t+1}R_{t+1}] = 0$. We also implement conditional asset pricing models with scaled factors using an instrument z_t. The Euler equation then reads as $\mathbb{E}_t[(m_{t+1} \otimes z_t)R_{t+1}] = 0$. In each estimation, we first use the identity matrix as weighting matrix and then find the optimal weighting matrix in a second stage from the residuals of the first-stage estimation. We confirm that our main results are robust to implementing a first-stage GMM estimation in the Internet Appendix.

We deliberately do not use the factors themselves as test assets. First, it would not work with macroeconomic factors which are non-tradable. Second, GMM reduces to mean-variance optimization when we estimate a linear asset pricing model using a first-stage GMM with an identity matrix as weighting matrix and only use the factors themselves as test assets. To see this, recall from Cochrane (2005, Section 13.2) that the closed-form solution for the prices of factor risk are

$$\hat{b}_1 = (d'd)^{-1}d'\hat{\mu}_T, \tag{13}$$

where $\hat{\mu}_T$ is the sample mean of the excess returns of the test assets and d is the sample second-moment matrix between excess returns of the test assets and the demeaned factor returns, $d = \mathbb{E}[R\tilde{f}]$. If the test assets are the factors themselves, d is square matrix and we obtain $\hat{b}_1 = \hat{\Sigma}_T^{-1}\hat{\mu}_T$. To mimic the SDF $m_t = 1 - \hat{b}_1' F_t$, we have to trade the test assets (factors) according to $w = \hat{b}_1 = \hat{\Sigma}_T^{-1}\hat{\mu}_T$. Thus, using the factors themselves as test assets simply recovers the mean-variance portfolios from Equation (3). Thus, having test assets (investable universe) different from the underlying factors themselves is an important feature of our implementation to improve upon the $1/T$ strategy.

Our methodology of investing in SDF-mimicking portfolios can handle any SDF, be it linear or non-linear, tradable or non-tradable. We simply choose to focus on linear SDFs to keep results comparable across factor models. However, as an exemplary additional benchmark, we also implement the minimum-variance SDF from Hansen and Jagannathan (1991) given by

$$m_t = 1 - \bar{R}'\hat{\Sigma}_T^{-1}(R_t - \bar{R}). \tag{14}$$

Unlike the linear factor models, the minimum-variance SDF does not exist in a conditional sense based on some instrument.

When we implement the SDF estimations, we are careful to avoid any look-ahead bias. Thus, we estimate the SDFs with GMM in an expanding window. Given the estimated SDF, we then find the SDF-mimicking portfolio over that same window and invest in this portfolio over the next month. We then expand the estimation window and estimate the SDF from scratch alongside its replicating portfolio. This method ensures that all results are truly out-of-sample and free of any look-ahead bias. We require an initial period of twenty years to perform the structural estimation. Keeping the length of the estimation window fixed at twenty years and rolling it forward gives quantitatively similar results.

2.3 Data

We use standard data when implementing our portfolio strategies. The test assets comprising the investable universe include fifty decile portfolios univariately sorted on market size, the book-to-market ratio, operating profitability, asset growth, and price momentum. The data are available on Ken French's website. Our choice allows us to capture a wide range of the cross-sectional variation in average stock returns that is available to investors in real time.

We include ten different financial factor models such as the full range of the models by Fama and French (1993, 2015, 2016), including the CAPM and Carhart (1997) model, the q^4 and q^5 factor models based on neoclassical investment theories from Hou et al. (2015) and Hou et al. (2021) respectively. We also include a purely cross-sectional AQR factor model which combines a monthly updated value factor (Asness and Frazzini, 2013) with price momentum (Asness, 1994, 1997), betting against beta (Frazzini and Pedersen, 2014), and quality minus junk (Asness et al., 2019). We complement our list with the four-factor mispricing model from Stambaugh and Yuan (2017).[1] We obtain all factor time series from the original authors' websites. Most factor data start in July 1963. Given our initial estimation window of twenty years, our out-of-sample portfolio evaluation sample covers the period from July 1983 to June 2024.

We also include ten asset pricing models based on economic theory and macroeconomic data. For consistency, we again implement linear factor models whose mean is normalized to one. We start with Lucas' (1978) consumption-based CAPM, which is a single-factor model based on quarterly growth in real consumption per capita (adding expenditures on nondurable goods and services). Inspired by Chen et al. (1986), we combine the market factor with industrial production, the term spread, the credit spread, and inflation. We only use realized inflation and do not estimate expected and unexpected inflation to keep the analysis in-sample. We implement the Campbell and Cochrane (1999) external habit model as a two-factor model with consumption growth and surplus consumption (estimated from consumption growth according to the law of motion in Chen's (2017) general equilibrium model). Following Bretscher et al. (2023), we augment habit preferences with recursive preferences and add the market factor as a proxy for the return on wealth (Epstein and Zin, 1989, 1991). We follow Petkova's (2006) ICAPM and combine treasury bills, the dividend yield, the term premium, and the default spread into a four-factor asset pricing model. Combining market returns and negative market returns allows us to replicate the two-factor downside risk model from Ang et al. (2006). We use He et al.'s (2017) institutional leverage data alongside the market return to test an intermediary-based asset pricing model. We

[1]We tested further models such as the six-factor model from Barillas and Shanken (2018) and the three-factor model from Daniel et al. (2020) and found the results to be similar to the ten reported factor models.

follow Liu and Matthies (2022) and use their news index as a single-factor model capturing long run risks. We implement Chabi-Yo et al.'s (2025) ICAPM model as a three-factor model comprising the market factor and two tradable factors mimicking news to long-term expected returns and volatility. Following Gonçalves et al. (2025), we include geopolitical risk as changes in the level of geopolitical threats and add it as a second factor next to the market portfolio. The data are retrieved from Ken French's website, Amit Goyal's website, the original authors' websites, and FRED.

When estimating conditional asset pricing models, we scale factors by the output gap. Output gap is detrended monthly log industrial production and a procyclical return predictor, both in-sample and out-of-sample (Cooper and Priestley, 2009; Goyal et al., 2024). We estimate the output gap recursively over the same window used to estimate the SDF, carefully avoiding any look-ahead bias.

3 Risk-Adjusted Performance

In this section, we report our main results, including the out-of-sample Sharpe ratios and Fama and French (2016) six-factor model alphas for our benchmark strategies ($1/N$ and $1/T$) and our various SDFs. Almost all SDFs outperform $1/N$ and $1/T$ with economic and statistical significance on a risk-adjusted basis. SDF-based portfolios have stable weights with low turnover.

3.1 High Sharpe Ratios

We start with the annualized Sharpe ratios and FF6 alphas reported in Table 1. Panel A focuses on the full sample while Panel B focuses on the more recent sample starting in 2000. For each sample, we report the out-of-sample Sharpe ratios of excess returns, the intercepts from factor regressions, and the corresponding t-statistics.

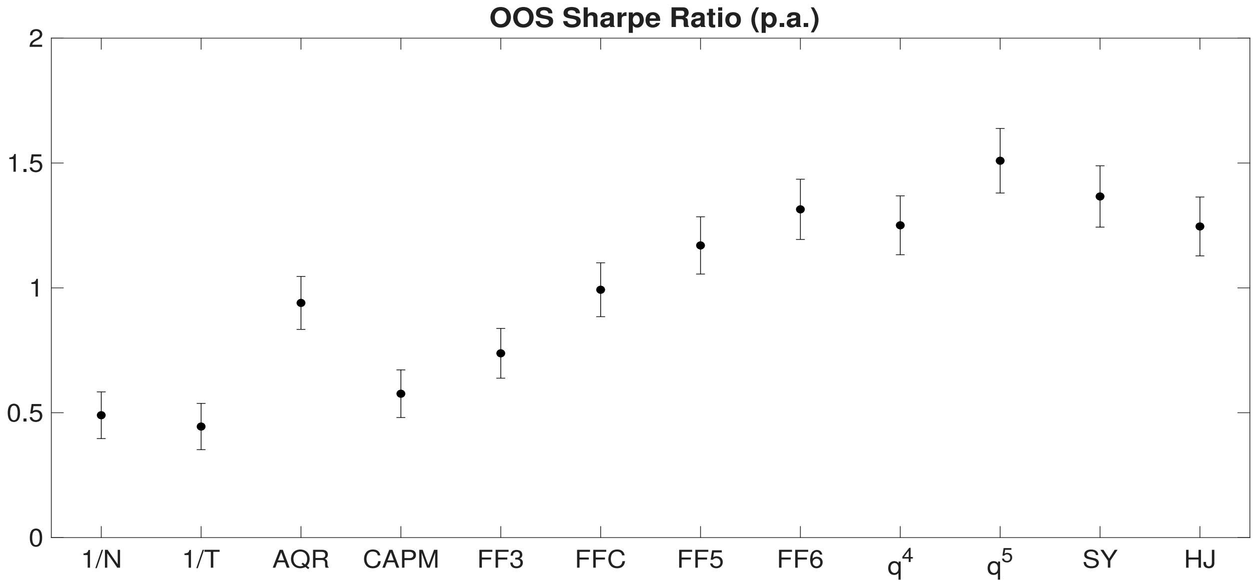


Figure 1: This figure plots the out-of-sample Sharpe ratio for an equally-weighted $1/N$ strategy, a sample-moment ($1/T$) based strategy, and ten strategies investing in an SDF-mimicking portfolio. Beyond models based on Fama and French (2016) and Hou et al. (2021), we consider an AQR factor that combines monthly-updated value, momentum, betting against beta, and quality minus junk. We also implement Stambaugh and Yuan's (2017) four-factor model and Hansen and Jagannathan's (1991) minimum-variance SDF. Error bars indicate 95% confidence intervals according to the standard errors from Jobson and Korkie (1981).

Table 1 about here.

Over the full sample, the $1/N$ strategy earns an out-of-sample Sharpe ratio of 0.49 p.a. which is higher than the 0.44 p.a. Sharpe ratio of investing in the sample-moment $1/T$ optimized portfolio using the sample mean. The poorer out-of-sample performance of the $1/T$ strategy replicates the findings of DeMiguel et al. (2009b). Each of our ten unconditional SDFs achieves a higher out-of-sample Sharpe ratio, with the CAPM earning the lowest (0.58) and the q^5 model earning the highest (1.51). While all our models are parsimonious, the models with more factors generally perform better. The purely cross-sectional AQR factor model, comprising HMLd, UMD, BAB, and QMJ, performs about as well as the Carhart (1997) four-factor model.

We visualize our benchmark results in Figure 1 by plotting the out-of-sample Sharpe ratio for classical portfolio strategies ($1/N$ and $1/T$) and for ten SDF-based portfolios. While $1/T$ performs worst, SDF-based portfolios can achieve annualized Sharpe ratios of up to 1.51 which is more than thrice that of $1/N$. As shown in Figure 1, as soon as SDFs become rich enough (say, have four factors or more), they outperform $1/N$ out-of-sample, suggesting that it is the common business cycle information encoded in the factor risk premiums that drives the pervasive outperformance.

SDF-based portfolios continue to outperform $1/N$ and $1/T$ even in the recent sample starting in 2000. Given that anomaly returns have declined in recent years (McLean and Pontiff, 2016), one might expect fewer alpha opportunities to be reflected in simple portfolio strategies. Our results show that the information in asset pricing models remains important and valuable to investors. For example, $1/N$ and $1/T$ strategies earn a Sharpe ratio of 0.49 p.a. and 0.22 p.a. in the recent sample, respectively. The average out-of-sample Sharpe ratio across the ten SDF-based portfolios is 0.91, with five SDFs yielding Sharpe ratios above one.

The annualized Sharpe ratio is proportional to the t-statistic testing whether the portfolios earn a statistically significant mean return ($t = \sqrt{T/12}SR$). Given our sample covers about 500 months (or 250 months in the recent sample), the common $t > 3$ rule translates into $SR > 3/\sqrt{500/12} = 0.46$ (or $SR > 3/\sqrt{250/12} = 0.66$ in the recent sample). Thus, Table 1 also confirms that all SDF-based portfolios earn a statistically significant average return (with the CAPM-SDF in the recent sample being the sole exception).

Finally, we illustrate the economic magnitudes of the Sharpe ratios in Figure 2. To make the differences in the Sharpe ratios more tangible, we scale the Sharpe ratios to the level of volatility from the market portfolio (about 17% p.a.). This scaling keeps the ordering of the factor models constant but translates Sharpe ratios into the implied average returns an investor would have earned if they chose to entertain the same amount of return volatility as the market portfolio. Panel A focuses on the full sample results while Panel B focuses on the recent sample starting in 2000. For example, the $1/N$ strategy would have earned an

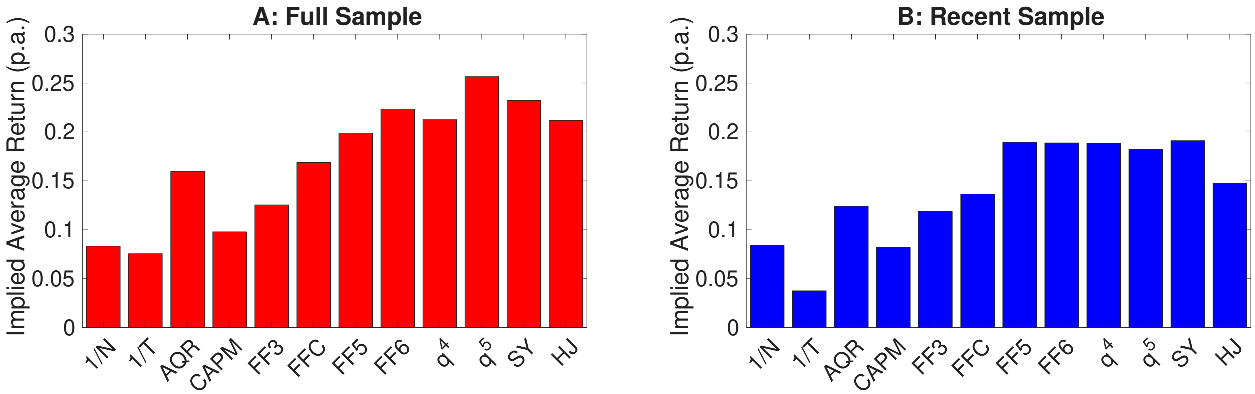


Figure 2: This figure plots the implied average return an investor could have earned by investing in the different portfolio strategies scaled to the volatility of the market portfolio (about 17% p.a.). Panel A plots the mean return for the full sample, while Panel B focuses on the recent sample beginning in 2000.

implied average excess return of 8.3% p.a. in the full sample while the $1/T$ strategy would only have reached 7.5%. The SDF-based portfolios would have achieved an average return ranging from 9.8% p.a. (CAPM) to 25.7% p.a. (q^5 model) in the full sample. In the recent sample, SDF-based portfolios would have doubled the average returns relative to the $1/N$ strategy. Overall, employing models for the stochastic discount factor enhances portfolio choice.

3.2 High Alphas

To capture risk-adjusted returns from a different angle, we next regress the out-of-sample excess returns of our various portfolio strategies on the Fama and French (2016) six factors and report the intercepts from these time series regressions in Columns (2) and (5) of Table 1. We account for the different leverage of our portfolio by scaling the alphas to ensure all strategies have the same exposure as $1/N$. Columns (3) and (6) report the corresponding t-statistic. Panel A focuses on the full sample, while Panel B focuses on the recent sample beginning in 2000.

Factor alphas are especially important to our analysis because our SDFs reflect factor-based asset pricing models. However, by recursively estimating the SDFs and tracking the out-of-sample performance of changing portfolio weights, we test if our SDF-based portfolios earn alpha from *dynamic* factor tilts that survive controlling for *static* style exposures.

The $1/N$ benchmark portfolio earns an annualized FF6 alpha of 2.08% (t-statistic: 3.27). The alpha emerges from factor interactions: Averaging many long-only characteristic-sorted portfolios creates exposure to factor interactions such as negatively correlated value, profitability, and momentum anomalies (Asness et al., 2013; Novy-Marx, 2013). The traditional $1/T$ portfolio earns a high albeit insignificant alpha of 6.00% (t-statistic: 1.77), pointing to the high volatility and unstable return dynamics induced by the estimation noise of the historical mean estimate (DeMiguel et al., 2009b).

Turning to the SDF-based portfolios, we find large and significant FF6 alphas. For example, estimating expected returns based on the Fama and French (2016) six-factor model generates a portfolio which earns a Fama-French (2016) six-factor alpha of 3.70% (t-statistic: 5.48). Conversely, the Hou et al. (2021) q^5 factor model even earns an alpha of 4.71 (t-statistic: 7.46). Risk-adjusted outperformance continues in the recent sample, in which all but the CAPM-SDF achieve significant alphas, with an average t-statistic of 3.10.

As a final note on portfolio performance, we report appraisal ratios and certainty-equivalent returns in Internet Appendix Table IA.1. The appraisal ratio divides the Fama and French (2016) six-factor alpha by the idiosyncratic volatility and compares the relative outperformance to the active risk of the portfolio. Overall, we draw similar conclusions to using Sharpe ratios and alphas. The SDF-based portfolios outperform $1/N$ and $1/T$ strategies, and they do so in both the full sample and the recent sample. We show robustness to using first-stage GMM estimations instead of our usual second-stage GMM estimations and imposing ℓ^2 leverage constraints instead of ℓ^1 leverage constraints in Internet Appendix Tables IA.2 and IA.3.

Overall, SDF-based portfolios earn high risk-adjusted returns and comfortably outperform the $1/N$ and $1/T$ benchmarks in terms of Sharpe ratios and Fama-French (2016) six-factor alphas. Even in the recent sample, when factor risk premiums are lower, the average SDF-based portfolio earns an out-of-sample Sharpe ratio of 0.91, while the $1/N$ benchmark earns only 0.49.

3.3 Low Trading Costs

Trading costs are a primary concern in portfolio allocations. We take this concern seriously and report portfolio turnover as well as the dispersion (standard deviation) and interquartile range of portfolio weights in Table 2. Following DeMiguel et al. (2009b), portfolio turnover is the sum of absolute changes in portfolio weights from one month to another and indicates the implementation cost of the different portfolio strategies. Given an out-of-sample window of T and an estimation window of M, the average turnover is

$$\text{Turnover} = \frac{1}{T-M} \sum_{t=1}^{T-M} \sum_{j=1}^{N} |w_{j,t+1} - w_{j,t^+}|, \tag{15}$$

where $w_{j,t}$ (w_{j,t^+}) is the weight in asset j at the beginning (end) of period t. Price movements during the holding period imply that w_{j,t^+} drifts away from $w_{j,t}$. Finally, the dispersion of portfolio weights informs us whether the portfolios suggest concentrated bets. Panel A covers the full sample whereas Panel B covers the more recent sample, starting in 2000.

Table 2 about here.

The $1/N$ strategy is cheap to implement with minimal turnover (as reported in DeMiguel et al., 2009b) and no dispersion in portfolio weights, suggesting maximal diversification. The turnover of the $1/T$ strategy is tenfold over the $1/N$ benchmark (again in close agreement with DeMiguel et al., 2009b) and shows widely dispersed portfolio weights. The SDF-based portfolios are characterized by low turnover, only slightly higher than the low-cost $1/N$ portfolio. However, the dispersion in weights in SDF-based portfolios is similar to that of the $1/T$ portfolio. Thus, the SDF-based portfolios do make active bets and deviate from a purely passive equal-weighting. However, the SDF-based allocations are stable over time, reflecting the lower estimation noise, which makes them cheap to trade. The results on turnover and weight dispersion are consistent across the full and recent sample, suggesting that the lower factor risk premiums in recent years did not cause SDF-based portfolios to become unstable and costlier to trade.

We explore the implementation of our SDF-based portfolios in more detail yet and report additional robustness tests in Internet Appendix Table IA.4. In this table, we report annualized out-of-sample Sharpe ratios for different sets of test assets. Specifically, we drop either the ten size-sorted portfolios (Columns (1) and (4)) or the ten momentum-sorted portfolios (Columns (2) and (5)) from the investable universe. The size and momentum factors are often difficult to trade because of high turnover and active bets on small stocks. Finally, Columns (3) and (6) use value-weighted portfolios as test assets. Each new version of the research design confirms our benchmark results of SDF-based portfolios outperforming $1/N$ and $1/T$ strategies. The factor models from Fama and French (2015, 2016) and Hou et al. (2015, 2021) perform consistently well and earn out-of-sample Sharpe ratios above one.

We visualize the full distribution of portfolio weights in Figure 3 to inspect for outliers that result from leverage or short sales. Each panel corresponds to a separate portfolio strategy (traditional $1/T$ or one of our ten SDF). In each case, we plot a histogram of the pooled weights for the full-sample results. The traditional $1/T$ strategy (Panel B) yields wildly dispersed portfolio weights with extreme tails, while the portfolio weights for the CAPM-based strategy (Panel A) are particularly concentrated near zero. The weights for all other SDFs behave broadly similarly to each other, center around zero, and do not show extreme tails indicating excess leverage or short selling.

Finally, we plot heatmaps of the average portfolios in the fifty test assets across time in Internet Appendix Figures IA.1 to IA.6. Bright gray indicates short positions whereas dark

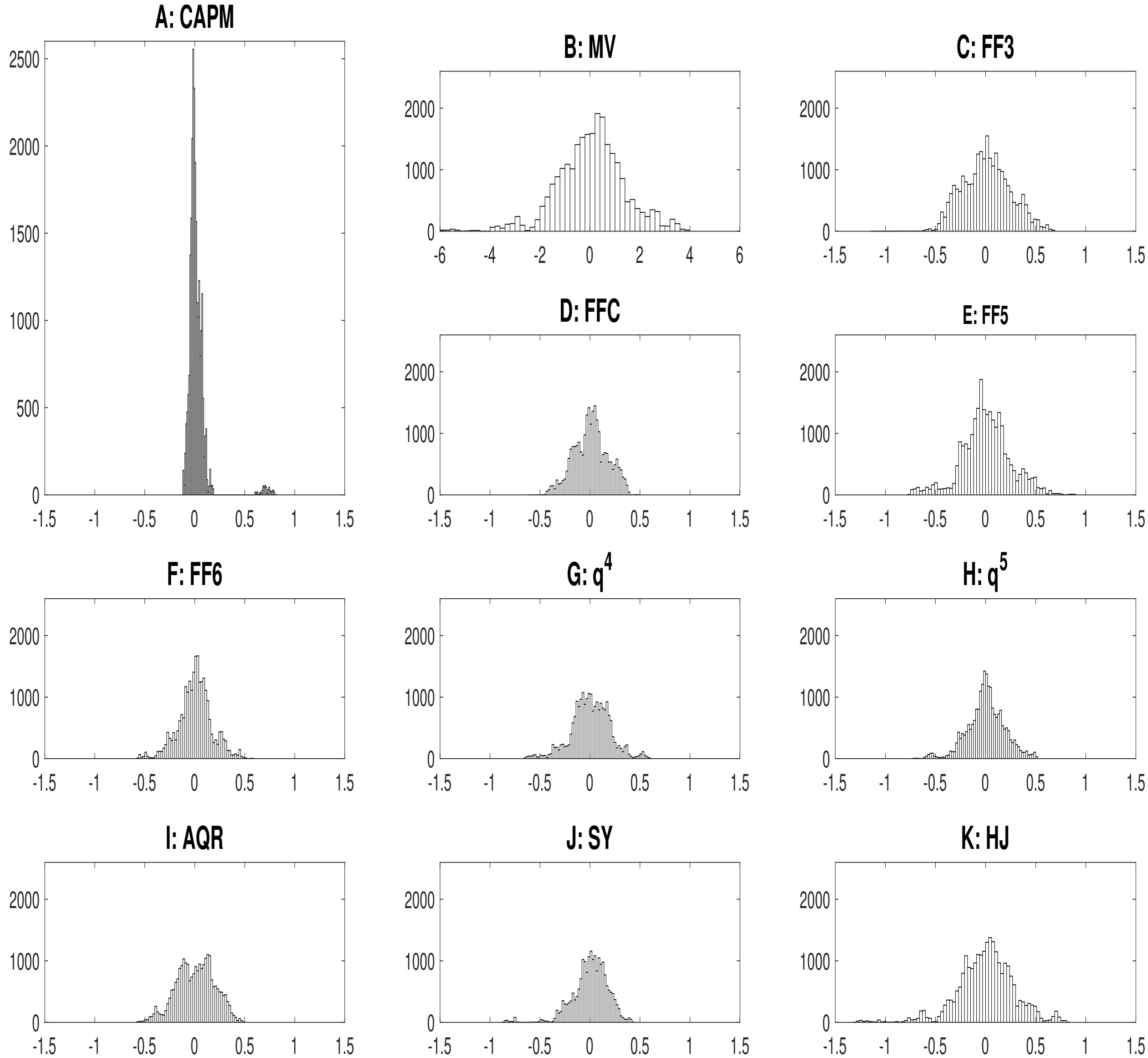


Figure 3: The figure visualizes histograms of the pooled portfolio weights employed for the $1/T$ and our ten SDF-based portfolio strategies. We consider the full sample, corresponding to Column (1) in Table 1. We scale portfolio weights to equalize average returns for comparability given the different levels of leverage.

gray positions indicate long positions. The figures demonstrate that the portfolio weights in the SDF-based portfolios are more stable over time and less susceptible to large short sales or excessive leveraged positions than the $1/T$ benchmark based on noisy sample means.

4 Mechanism

In this section, we drill down into the drivers of the outperformance of SDF-based portfolios. In particular, we document that incorporating SDFs into asset allocation decisions leads to more accurate expected return estimates, which translate into portfolios with less risk (especially tail risk). SDF-based portfolios also incorporate business cycle information from asset prices and insulate portfolios from exposure to the cycle of booms and recessions. Indeed, SDFs directly derived from macro-finance theories also outperform the $1/N$ benchmark portfolio. Taken together, the low tail risk and the grounding in economic theory make SDF-based portfolios an attractive investment proposition.

4.1 Improved Expected Return Estimator

Our SDF-based portfolios rely on the simple idea that the covariance with the SDF offers a better out-of-sample expected return estimator than the historical average (Welch and Goyal, 2008). We directly test this hypothesis with Fama and MacBeth (1973) cross-sectional regressions. Specifically, we regress one-month ahead realized excess portfolio returns on the ex-ante predicted portfolio excess returns, in the spirit of Lewellen (2015),

$$R_{i,t+1} = a_t + b_t \mathbb{E}_t[R_{i,t+1}] + \varepsilon_{i,t+1}. \tag{16}$$

We estimate the regression each month and report the average slope coefficient, the corresponding standard error, and the average R^2 in Table 3. An unbiased predictor would have an average slope coefficient of one.

<ins>TABLE 3 ABOUT HERE.</ins>

The historical mean estimator reported in Row 2 achieves an average slope of 0.35 (standard error: 0.15) which confirms that it is positively related to future realized returns but we can confidently reject the null hypothesis that the coefficient equals one. The SDF-based

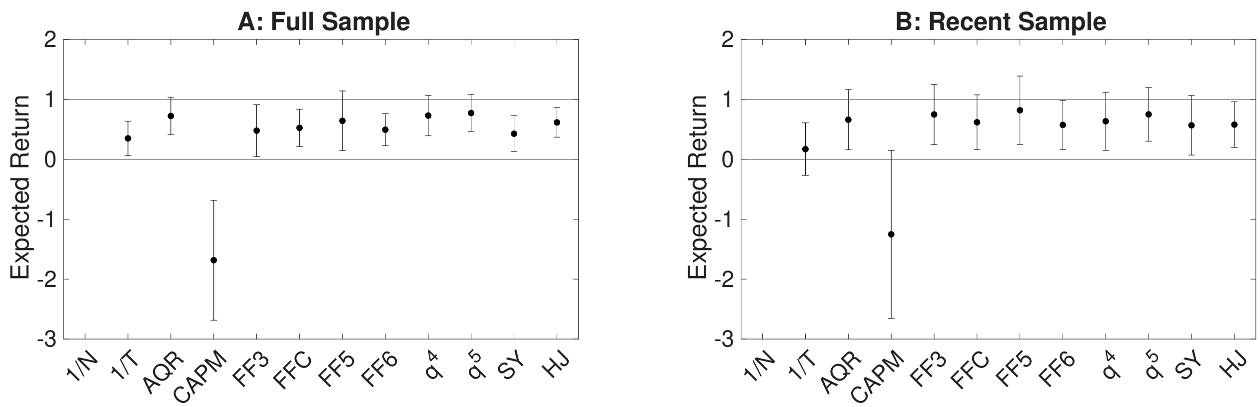


Figure 4: This figure plots the average slope coefficients along a 95% confidence interval from Fama-MacBeth (1973) regressions of future realized portfolio excess returns on predicted portfolio excess returns, as per Equation (16). Panel A plots the average slope coefficient for the full sample, while Panel B focuses on the recent sample beginning in 2000.

estimators which reflect the covariance of excess returns with the SDF achieve higher average slope coefficients. For example, the q^5 model achieves 0.77 (standard error: 0.16) which means we cannot reject that the coefficient is one. The SDFs based on Fama and French (2015) and Hou et al. (2015, 2021) all yield such a high average slope coefficient that we cannot reject their coefficients equal to one. The purely cross-sectional SDF based on AQR factors is another strong expected return estimator where we fail to reject the null hypothesis of unity. The only exception is the simple CAPM which proves to be a poor return predictor, in line with its generally poorer performance for out-of-sample Sharpe ratios and alphas and consistent with Fama and French (1997).

Turning to the recent sample starting in 2000, the slope coefficients are slightly larger, which explains why SDF-based portfolios have continued to outperform in recent years. Indeed, we fail to reject that the average slope is equal to one for seven out of ten SDFs (with another two being a close call). Our cross-sectional regressions achieve high R^2 values ranging between 0.10 and 0.22. The reason is that our cross-section comprises fifty well-diversified portfolios as test assets that have already removed a lot of idiosyncratic noise that usually plagues cross-sectional return predictability.

We visualize the regression fit in Figure 4. We plot the average slope coefficient from the Fama-MacBeth (1973) regressions in Equation (16) along a 95% confidence interval. The slope coefficient of the sample mean ($1/T$) differs statistically from one, suggesting it is a biased predictor in the cross-section of average returns. Many SDF-based expected return predictors, however, include one in their confidence interval, suggesting that we cannot reject the null hypothesis $H_0 : \bar{b} = 1$. The results in the recent sample starting in 2000 and depicted in Panel B are even stronger, with average slope coefficients closer to one.

Because Fama-MacBeth (1973) regressions are equivalent to portfolio sorts, our results suggest that one can construct a tradable factor strategy by longing test assets with a high expected return forecast and shorting those with a low expected return. Our SDF-based portfolios go one step further and additionally account for the covariance matrix and penalize risky allocations.

4.2 Insulation From Business Cycle Regimes

Successful asset pricing models reflect marginal utility, risk premiums, and systematic risk. Our GMM estimations ensure that even our reduced-form factor models capture the business cycle information in asset prices. To illustrate its use in portfolio choice, we next condition the performance of our portfolios on good and bad regimes identified by positive or negative growth in real GDP per capita and report the conditional Sharpe ratios in Columns (1), (2), (4), and (5) of Table 4. As always, Panel A focuses on the full sample and Panel B focuses on the recent sample starting in 2000.

Table 4 about here.

The $1/N$ benchmark portfolio earns an annualized Sharpe ratio of 0.74 in booms and –0.27 in recessions, making the strategy highly procyclical and dependent on the market regime (the unconditional Sharpe ratio is 0.49 per Table 1). Intuitively, as an average of many long-only strategies, the $1/N$ portfolio mimics the equity premium in its cyclicality. The

$1/T$ benchmark earns Sharpe ratios of 0.56 and –0.06 in booms and recessions, respectively, confirming its comovement with the business cycle. Our SDF-based portfolios largely have a different profile and perform well in both market regimes. The q^5 five-factor model, for example, earns a Sharpe ratio of 1.88 in booms and of 0.52 in recessions, ensuring it does not yield negative average returns during economic downturns. This regime independence insulates investors from macroeconomic shocks. Intuitively, our SDFs combine risk premiums of factors that perform well during different periods of the business cycle.[2] Our SDF-based portfolios use this information to provide stable portfolio dynamics that are regime-independent and offer positive risk-adjusted returns in booms and busts. The results remain consistent in the recent sample in which SDF-based portfolios again generally performed well during recessions. As usual, the CAPM remains an exception as it strongly relies on the equity premium as the sole driver of expected returns.

As a second measure for cyclicality, we turn to the market beta by regressing the out-of-sample portfolio returns in excess of the risk-free rate on the market factor. We report the slope coefficients in Columns (3) and (6) of Table 4. Unsurprisingly, the equally-weighted $1/N$ strategy has close to a unit beta, being an average of fifty long equity portfolios. Similarly, the CAPM-based portfolio that dynamically seeks to mimic the market factor has a beta close to one. The other SDF-based strategies that acknowledge that the market factor on its own is not the tangency portfolio have significantly lower market betas. Indeed, market betas range between –0.12 and 0.29 for the SDF-based strategies, indicating that the portfolios are largely market-neutral and do not simply earn their premiums by leveraging the equity premium.

[2] For example, Petkova and Zhang (2005) and Zhang (2005) show that the value premium is countercyclical, Novy-Marx (2013) and Kogan et al. (2023) show that the profitability premium is procyclical, and Asness et al. (2013) and Daniel and Moskowitz (2016) show that the momentum premium is procyclical.

4.3 Reduced Tail Risk

Incorporating SDF-implied expected return reduces portfolio risk dynamics. We report total risk measures like return volatility and tail risk measures like value-at-risk and expected shortfall (or conditional value-at-risk) in Table 5. Value-at-risk is the fifth percentile of the return distribution, whereas expected shortfall is the average return of returns below or equal to the fifth percentile. Tail risk is often a crucial dimension in risk management and is particularly important to large institutional managers who invest on behalf of pension funds, sovereign wealth funds, and endowments that cannot tolerate large declines in portfolio value. Indeed, next to costly turnover, high tail risk is a prime reason momentum trades are difficult in practice (Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016). We follow our usual table design by reporting results for the full sample in Panel A and for the recent sample starting in 2000 in Panel B of Table 5. To account for different amounts of leverage, we scale all portfolio returns to the same average return as the $1/N$ equally-weighted strategy.

TABLE 5 ABOUT HERE.

The volatility of the equally weighted strategy is around 19% per annum which is close to that of the aggregate stock market and only slightly higher in the recent sample. The traditional sample-moment strategy ($1/T$) delivers more volatile portfolio returns with an annualized standard deviation of 21% in the full sample and 45% in the recent sample. The high volatility of the $1/T$ portfolio explains the relatively poor Sharpe ratios reported in Table 1 and results from poorly estimated expected returns that create unstable portfolio allocations. Turning to the SDF-based portfolios, we find that all of them achieve a lower standard deviation than either the $1/N$ or $1/T$ strategy. The q^4 and q^5 factor models yield particularly stable portfolio returns with an annualized volatility of 7% and 6%, respectively. It is this low risk that drives the high Sharpe ratio of the SDF-based portfolios. The volatility dynamics are broadly similar in the full and recent samples.

Turning to left tail risk, the equally-weighted $1/N$ strategy has a VaR of –7.8%, suggesting that in five per cent of months, the realized monthly portfolio return will be equal to or below –7.8%. The $1/T$ strategy with a 95% VaR of –8.4% p.a. is exposed to greater tail risk. The VaR of the CAPM-based strategy is –7.7% and resembles that of the $1/N$ strategy. The other SDF-based strategies achieve significantly lower (i.e., less negative) values-at-risk. For example, basing portfolio choice on the six-factor model from Fama and French (2016) exposes investors to a low VaR of only –2.2%. Like other risk measures too, VaR is higher in the recent sample, reflecting the worsened risk-return trade-off with lower risk premiums and more volatile stock returns (Fama and French, 2021).

VaR may be a popular risk measure but it is not a coherent risk measure, for it does not satisfy the subadditivity property. Instead, the conditional value-at-risk (CVaR) or expected shortfall (ES) is a coherent risk measure and captures the average loss in the left tail of the return distribution if returns are below the VaR. Overall, CVaR paints a similar picture to VaR. The equally-weighted $1/N$ strategy serves as a benchmark whose performance is closely linked to that of the CAPM-based portfolio. The sample-moment $1/T$ strategy performs the worst among all portfolio strategies. SDF-based portfolios expose investors to CVaR that is almost up to one-third of that of the $1/N$ benchmark. For instance, the portfolio investing in the portfolio mimicking the q^5 model generates a monthly CVaR of –3.3%. Conditional values-at-risk are slightly higher in the recent sample starting in 2000 than in the full sample.

4.4 Pure Macro-Finance SDFs

Our main finding, that covariance with the SDF is a better return predictor than the sample mean, also applies to theoretical SDFs derived from macro-finance models. Reduced-form financial SDFs based on tradable factors incorporate price information more directly and better capture the risk-return dynamics of the investable universe (Cochrane, 2005). However, we also show that SDFs relying on macroeconomic data can also beat the $1/N$ benchmark. We continue to focus on linear factor models and consider macroeconomic factors available at both a monthly and quarterly frequency. For quarterly SDFs, we compound the returns on our test assets and work with these lower frequency returns. We report the Sharpe ratios, Fama-French (2016) six-factor alphas, and their t-statistics in Table 6.

TABLE 6 ABOUT HERE.

We begin analyzing macro SDFs in terms of their out-of-sample Sharpe ratios. As a reminder, the equally weighted $1/N$ strategy earns an annualized Sharpe ratio of 0.49 in the full sample and of 0.49 in the recent sample. The sample-mean based $1/T$ strategy achieves a lower Sharpe ratio of 0.44 and 0.22, respectively (see Table 1). All macro SDFs, bar the CCAPM, improve upon the traditional sample-moment $1/T$ strategy. The external habit models reach similar magnitudes to the $1/N$ benchmark and earn a significant six-factor alpha. The remaining macro SDFs outperform the $1/N$ strategy. Turning to the recent sample macro SDFs improves their outperformance to the $1/N$ portfolio, including external habit models. Generally, the dispersion in Sharpe ratios is small across macro-based SDFs, presumably because they reflect similar business cycle information. We stress that many macro models here are based on purely non-tradable state variables (such as consumption growth, dividend yields, intermediary leverage, or industrial production) and that tradable portfolios normally better price the cross-section (Cooper and Priestley, 2011; Giglio and Xiu, 2021). Beyond strict macro-financial theories, O'Doherty et al. (2025) show that many macroeconomic variables price the cross-section of average stock returns and are therefore likely candidates for predicting expected portfolio returns.

5 Robustness and Extensions

In this final section, we implement many robustness tests and extensions, ensuring that our main finding of SDF-implied expected returns enhancing portfolio performance remains true for various alterations of our research design. We show that SDF-implied expected returns enhance portfolio outcomes when we apply a Bayes-Stein shrinkage operator, Campbell and

Thompson (2008) sign restrictions, and implement conditional SDFs whose factors are scaled by Cooper and Priestley's (2009) output gap. We also show that reducing the rebalancing frequency to annual horizons and holding positions for a year continues to deliver superior out-of-sample Sharpe ratios. Finally, we investigate if assuming a factor structure in realized return that simplifies the covariance further helps with portfolio choice.

5.1 Bayes-Stein Shrinkage for Expected Return

In our first extension, we shrink the expected return predictor toward the average return of the minimum variance portfolio, following Jorion (1986) and DeMiguel et al. (2009b). To do so, and given our N assets and estimation window M, we set

$$\hat{\mu}_t^{\text{bs}} = (1 - \hat{\varphi}_t)\hat{\mu}_t + \hat{\varphi}_t \hat{\mu}_t^{\text{min}}, \tag{17}$$

$$\hat{\varphi}_t = \frac{N+2}{N + 2 + M(\hat{\mu}_t - \mu_t^{\text{min}})' \hat{\Sigma}_t^{-1} (\hat{\mu}_t - \hat{\mu}_t^{\text{min}})}, \tag{18}$$

where $0 < \hat{\varphi}_t < 1$, $\hat{\Sigma}_t = \frac{1}{M-N-2} \sum_{s=t-M+1}^{t} (R_s - \hat{\mu}_t)(R_s - \hat{\mu}_t)'$, and $\hat{\mu}_t^{\text{min}} = w_t^{\text{min}\prime} \hat{\mu}_t$. Otherwise, we keep our research design fixed and report the out-of-sample Sharpe ratio, Fama-French (2016) six-factor alpha, and its t-statistic for both the full sample (Panel A) and the recent sample (Panel B) in Table 7.

Table 7 about here.

Overall, our results improve slightly. For example, while Sharpe ratios only change by 0.01, the FF6 alpha of the CAPM-based portfolio rises from 0.69 (t-statistic: 1.50) without shrinkage to 2.18 (t-statistic: 2.77) with shrinkage. However, the overall gains are so marginal that there is little to be won by the extra computational complexity and model assumptions. Our findings align with those of DeMiguel et al. (2009b).

5.2 Sign Restrictions for Expected Return

We next turn to Campbell and Thompson (2008) who suggest that restricting model-implied expected returns to be non-negative improves out-of-sample predictability for the equity premium. We follow their approach and estimate expected portfolio returns by the maximum of zero and the covariance with the SDF. As usual, we then track out-of-sample portfolio returns and report Sharpe ratios, alphas, and their t-statistics in Table 8.

TABLE 8 ABOUT HERE.

Our results remain largely unchanged. For example, the portfolio basing its expected returns on the Fama and French (2016) six-factor model increases its Sharpe ratio from 1.31 to 1.37 over the full sample. The average magnitude of the t-statistics for the alphas increases slightly. Intuitively, our SDF-based estimator rarely predicts negative expected portfolio returns such that the sign restrictions add little value to our out-of-sample analysis.

5.3 Conditional SDFs

In our next extensions, we turn to SDFs with scaled factors to capture conditional risk-return dynamics. We scale the market factor by the recursively estimated output gap from monthly log industrial production, following Cooper and Priestley (2009). We also implemented a version scaling every factor by the output gap, but found little improvement. Intuitively, Cooper and Priestley (2009) argue that the output gap predicts market returns and scaling should therefore matter most for the equity premium. We report out-of-sample Sharpe ratios, Fama-French (2016) six-factor alphas, and their t-statistics in Table 9.

TABLE 9 ABOUT HERE.

The results suggest minor changes. For example, the Fama-French (2015) five-factor model achieves a Sharpe ratio of 1.17 and a six-factor alpha of 3.75% (t-statistic: 4.29) over the full sample in our benchmark results from Table 1. The scaled FF5 model generates an out-of-sample Sharpe ratio of 1.20 and an alpha of 4.54% (t-statistic: 5.10). However, there is no discernible pattern of which factor model improves and which ones do not benefit from the extra model complexity. Overall, performance is very similar in both the full sample and the recent sample to our benchmark results. Our findings align with Lewellen and Nagel (2006) and Gormsen and Jensen (2024), who find that conditional asset pricing models do not materially improve cross-sectional asset pricing.

5.4 One Year Holding Period

We next extend the holding period for portfolios in our out-of-sample evaluation and retain positions for one year. The original trading signal that generates the allocation is stale by then but our SDF-based portfolios continue to outperform the $1/N$ and $1/T$ benchmarks. We report Sharpe ratios, six-factor alphas, and corresponding t-statistics in Table 10. Panel A focuses on the full sample and Panel B on the recent sample starting in 2000.

TABLE 10 ABOUT HERE.

SDF-based portfolios perform well even if limited to stale information and slow rebalancing. The longer holding period implies that the $1/N$ portfolio earns a Sharpe ratio of 0.48 (almost unchanged) but no longer earns any statistically significant alpha in either the full or recent sample. SDF-based portfolios continue to hold up despite the delayed rebalancing. For example, the average Sharpe ratio across all ten SDFs still stands at 0.85 and 0.69 for the full and recent samples, respectively.

5.5 Factor Structure in Realized Returns

Our final extension turns the focus from the factor structure in the *expected* returns (as proposed by factor models for the SDF) to the more ambitious factor structure in *realized* returns, akin to a "multi-index model." We test if such a factor structure helps with portfolio choice by decomposing the covariance of returns into a factor covariance matrix and idiosyncratic volatilities,

$$\Sigma_R = \beta' \Sigma_F \beta + \text{diag}(\sigma_1, ..., \sigma_N). \tag{19}$$

This way, we only have to estimate $K \times N$ betas, $K \times K$ factor covariances, and N idiosyncratic volatilities instead of the full $N \times N$ return covariance matrix. As usual, we report out-of-sample risk-adjusted returns for the full and recent sample in Table 11.

Table 11 about here.

We do not find evidence that decomposing the covariance matrix into a systematic and idiosyncratic component improves out-of-sample portfolio performance. Sharpe ratios and alphas decline in both the full and recent samples. The pattern is consistent across all SDF-based portfolios as well as the sample-mean-based portfolio. Thus, either way of implementing it, there is little to be gained from this extra modeling assumption. The SDF framework, like macro-finance models, is tied to Euler equations and expected stock returns. Implications for the distribution of realized returns and factor structures in covariance matrices require additional assumptions for which we find no evidence in our portfolio evaluation. For example, industry exposures explain a lot of time series variation in realized returns (time series R^2) but explain little cross-sectional variability in expected returns (cross-sectional R^2).

6 Conclusion

Our central result is straightforward. Out-of-sample portfolio performance improves sharply when investors replace noisy sample estimates of expected returns with SDF-implied covariances. Across several factor models and different samples, SDF-based portfolios earn out-of-sample Sharpe ratios that are roughly twice those of equally weighted $1/N$ or sample-moment based $1/T$ benchmarks. These portfolios also exhibit lower volatility, tail risk, and turnover. SDF-based portfolios perform well along the business cycle in booms and recessions and reflect business cycle information from macro-financial theories. SDF-based portfolios continue to outperform even when factor risk premiums decline after 2000. Our findings suggest that SDFs are practically valuable for portfolio choice.

References

Ang, Andrew, Joseph Chen, and Yuhang Xing, 2006, Downside risk, *Review of Financial Studies* 19, 1191–1239.

Ao, Mengmeng, Li Yingying, and Xinghua Zheng, 2019, Approaching mean-variance efficiency for large portfolios, *Review of Financial Studies* 32, 2890–2919.

Asness, Clifford S., 1994, Variables that explain stock returns, *Ph.D. Dissertation, University of Chicago*.

Asness, Clifford S., 1997, The interaction of value and momentum strategies, *Financial Analysts Journal* 53, 29–36.

Asness, Clifford S. and Andrea Frazzini, 2013, The devil in HML's details, *Journal of Portfolio Management* 39, 49–68.

Asness, Clifford S., Andrea Frazzini, and Lasse H. Pedersen, 2019, Quality minus junk, *Review of Accounting Studies* 24, 34–112.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse H. Pedersen, 2013, Value and momentum everywhere, *Journal of Finance* 68, 929–985.

Barillas, Francisco and Jay Shanken, 2018, Comparing asset pricing models, *Journal of Finance* 73, 715–754.

Barroso, Pedro and Pedro Santa-Clara, 2015, Momentum has its moments, *Journal of Financial Economics* 116, 111–120.

Barroso, Pedro and Konark Saxena, 2022, Lest we forget: Learn from out-of-sample forecast errors when optimizing portfolios, *Review of Financial Studies* 35, 1222–1278.

Bessembinder, Hendrik, Aaron Burt, and Christopher M. Hrdlicka, 2025, More factors matter and factors matter more than you might think: The role of time variation in factor premia, *Working paper, SSRN: 3992041*.

Black, Fischer and Robert Litterman, 1992, Global portfolio optimization, *Financial Analysts Journal* 48, 28–43.

Bretscher, Lorenzo, Alex Hsu, and Andrea Tamoni, 2023, The real response to uncertainty shocks: The risk premium channel, *Management Science* 69, 119–140.

Britten-Jones, Mark, 1999, The sampling error in estimates of mean-variance efficient portfolio weights, *Journal of Finance* 54, 655–671.

Campbell, John Y. and John H. Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205–251.

Campbell, John Y. and Samuel B. Thompson, 2008, Predicting excess stock returns out of sample: Can anything beat the historical average?, *Review of Financial Studies* 21, 1509–1531.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chabi-Yo, Fousseni, Andrei S. Gonçalves, and Johnathan A. Loudis, 2025, An intertemporal risk factor model, *Management Science* 71, 6518–6544.

Chen, Andrew Y., Alejandro Lopez-Lira, and Tom Zimmermann, 2025, Does peer-reviewed research help predict stock returns?, *Working Paper, SSRN: 4308069*.

Chen, Huafeng J., 2017, Do cash flows of growth stocks really grow faster?, *Journal of Finance* 72, 2279–2330.

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross, 1986, Economic forces and the stock market, *Journal of Business* 59, 383–403.

Cochrane, John H., 2005, *Asset Pricing: Revised Edition*, Princeton University Press, Princeton, NJ.

Cooper, Ilan and Richard Priestley, 2009, Time-varying risk premiums and the output gap, *Review of Financial Studies* 22, 2801–2833.

Cooper, Ilan and Richard Priestley, 2011, Real investment and risk dynamics, *Journal of Financial Economics* 101, 182–205.

Daniel, Kent, David Hirshleifer, and Lin Sun, 2020, Short-and long-horizon behavioral factors, *Review of Financial Studies* 33, 1673–1736.

Daniel, Kent and Tobias J. Moskowitz, 2016, Momentum crashes, *Journal of Financial Economics* 122, 221–247.

DeMiguel, Victor, Lorenzo Garlappi, Francisco J. Nogales, and Raman Uppal, 2009a, A generalized approach to portfolio optimization: Improving performance by constraining portfolio norms, *Management Science* 55, 798–812.

DeMiguel, Victor, Lorenzo Garlappi, and Raman Uppal, 2009b, Optimal versus naive diversification: How inefficient is the $1/N$ portfolio strategy?, *Review of Financial Studies* 22, 1915–1953.

DeMiguel, Victor, Francisco J. Nogales, and Raman Uppal, 2014, Stock return serial dependence and out-of-sample portfolio performance, *Review of Financial Studies* 27, 1031–1073.

Epstein, Larry G. and Stanley E. Zin, 1989, Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework, *Econometrica* 57, 937–969.

Epstein, Larry G. and Stanley E. Zin, 1991, Substitution, risk aversion, and the temporal behavior of consumption and asset returns: An empirical analysis, *Journal of Political Economy* 99, 263–286.

Fama, Eugene F. and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F. and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.

Fama, Eugene F. and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F. and Kenneth R. French, 2016, Dissecting anomalies with a five-factor model, *Review of Financial Studies* 29, 69–103.

Fama, Eugene F. and Kenneth R. French, 2021, The value premium, *Review of Asset Pricing Studies* 11, 105–121.

Fama, Eugene F. and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Frazzini, Andrea and Lasse H. Pedersen, 2014, Betting against beta, *Journal of Financial Economics* 111, 1–25.

Giglio, Stefano and Dacheng Xiu, 2021, Asset pricing with omitted factors, *Journal of Political Economy* 129, 1947–1990.

Gonçalves, Andrei, Alessandro Melone, and Andrea Ricciardi, 2025, The pricing of geopolitical tensions over a century, *Working Paper*.

Gormsen, Niels J. and Christian S. Jensen, 2024, Conditional risk, *Journal of Financial Economics* 162, 103933.

Goyal, Amit, Ivo Welch, and Athanasse Zafirov, 2024, A comprehensive 2022 look at the empirical performance of equity premium prediction, *Review of Financial Studies* 37, 3490–3557.

Green, Jeremiah, John R.M. Hand, and X. Frank Zhang, 2017, The characteristics that provide independent information about average US monthly stock returns, *Review of Financial Studies* 30, 4389–4436.

Guidolin, Massimo, Erwin Hansen, and Martín Lozano-Banda, 2018, Portfolio performance of linear SDF models: An out-of-sample assessment, *Quantitative Finance* 18, 1425–1436.

Hansen, Lars P. and Ravi Jagannathan, 1991, Implications of security market data for models of dynamic economies, *Journal of Political Economy* 99, 225–262.

Hansen, Lars P. and Scott F. Richard, 1987, The role of conditioning information in deducing testable restrictions implied by dynamic asset pricing models, *Econometrica* 55, 587–613.

He, Zhiguo, Bryan Kelly, and Asaf Manela, 2017, Intermediary asset pricing: New evidence from many asset classes, *Journal of Financial Economics* 126, 1–35.

Hou, Kewei, Haitao Mo, Chen Xue, and Lu Zhang, 2021, An augmented q-factor model with expected growth, *Review of Finance* 25, 1–41.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28, 650–705.

Jagannathan, Ravi and Tongshu Ma, 2003, Risk reduction in large portfolios: Why imposing the wrong constraints helps, *Journal of Finance* 58, 1651–1683.

Jobson, J. Dave and Bob M. Korkie, 1981, Performance hypothesis testing with the Sharpe and Treynor measures, *Journal of Finance* 36, 889–908.

Jorion, Philippe, 1986, Bayes-Stein estimation for portfolio analysis, *Journal of Financial and Quantitative analysis* 21, 279–292.

Kan, Raymond, Xiaolu Wang, and Xinghua Zheng, 2024, In-sample and out-of-sample Sharpe ratios of multi-factor asset pricing models, *Journal of Financial Economics* 155, 103837.

Kan, Raymond and Guofu Zhou, 2007, Optimal portfolio choice with parameter uncertainty, *Journal of Financial and Quantitative Analysis* 42, 621–656.

Kogan, Leonid, Jun Li, and Harold H. Zhang, 2023, Operating hedge and gross profitability premium, *Journal of Finance* 78, 3387–3422.

Ledoit, Olivier and Michael Wolf, 2017, Nonlinear shrinkage of the covariance matrix for portfolio selection: Markowitz meets Goldilocks, *Review of Financial Studies* 30, 4349–4388.

Levy, Moshe and Richard Roll, 2010, The market portfolio may be mean/variance efficient after all, *Review of Financial Studies* 23, 2464–2491.

Lewellen, Jonathan, 2015, The cross-section of expected stock returns, *Critical Finance Review* 4, 1–44.

Lewellen, Jonathan and Stefan Nagel, 2006, The conditional CAPM does not explain asset-pricing anomalies, *Journal of Financial Economics* 82, 289–314.

Liu, Yukun and Ben Matthies, 2022, Long run risk: Is it there?, *Journal of Finance* 77, 1587–1633.

Lucas Jr., Robert E., 1978, Asset prices in an exchange economy, *Econometrica* 46, 1429–1445.

MacKinlay, Craig A. and L'uboš Pástor, 2000, Asset pricing models: Implications for expected returns and portfolio selection, *Review of Financial Studies* 13, 883–916.

McLean, R. David and Jeffrey Pontiff, 2016, Does academic research destroy stock return predictability?, *Journal of Finance* 71, 5–32.

Merton, Robert C., 1980, On estimating the expected return on the market: An exploratory investigation, *Journal of Financial Economics* 8, 323–361.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

O'Doherty, Michael S., Feifei Wang, and Sterling Yan, 2025, On the macroeconomic foundations of the anomaly zoo, *Working Paper, SSRN: 5395852*.

Pástor, Ľuboš, 2000, Portfolio selection and asset pricing models, *Journal of Finance* 55, 179–223.

Pástor, Ľuboš and Robert F. Stambaugh, 2000, Comparing asset pricing models: An investment perspective, *Journal of Financial Economics* 56, 335–381.

Petkova, Ralitsa, 2006, Do the Fama-French factors proxy for innovations in predictive variables?, *Journal of Finance* 61, 581–612.

Petkova, Ralitsa and Lu Zhang, 2005, Is value riskier than growth?, *Journal of Financial Economics* 78, 187–202.

Stambaugh, Robert F. and Yu Yuan, 2017, Mispricing factors, *Review of Financial Studies* 30, 1270–1315.

Welch, Ivo and Amit Goyal, 2008, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455–1508.

Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67–103.

Table 1: Out-of-Sample Portfolio Performance

This table reports out-of-sample Sharpe ratios and Fama-French (2016) six-factor alphas, along with corresponding t-statistics for dynamic portfolio strategies. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported in annualized units.

	A: Full Sample			B: Recent Sample		
	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	0.49	2.08	3.27	0.49	2.39	2.69
$1/T$	0.44	6.00	1.77	0.22	7.51	0.79
CAPM	0.58	0.69	1.50	0.48	1.12	1.28
FF3	0.74	3.34	3.29	0.70	3.55	2.57
FFC	0.99	2.97	4.02	0.80	3.66	3.19
FF5	1.17	3.75	4.29	1.11	3.95	3.48
FF6	1.31	3.70	5.48	1.11	3.89	3.98
q^4	1.25	3.91	5.57	1.11	3.57	3.87
q^5	1.51	4.71	7.46	1.07	3.58	3.44
AQR	0.94	3.54	3.58	0.73	4.01	2.34
SY	1.37	3.16	4.58	1.12	3.02	2.80
HJ	1.25	4.50	4.84	0.87	3.82	2.25

Table 2: Portfolio Trading Costs

This table reports the average monthly portfolio turnover (sum of absolute weight changes), the cross-sectional dispersion (standard deviation) of portfolio weights, and the average cross-sectional interquartile range of portfolio weights for dynamic portfolio strategies. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported as percentages.

	A: Full Sample			B: Recent Sample		
	Portfolio Turnover	Weight Dispersion	Weight Range	Portfolio Turnover	Weight Dispersion	Weight Range
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	4.27	0.00	0.00	4.66	0.00	0.00
$1/T$	39.05	2.59	3.25	40.83	2.58	3.24
CAPM	6.05	4.41	2.51	6.21	4.38	2.58
FF3	5.70	2.50	3.44	5.92	2.46	3.51
FFC	5.90	2.50	3.44	5.98	2.47	3.73
FF5	6.11	2.66	2.99	5.94	2.68	2.94
FF6	6.42	2.65	3.00	6.05	2.72	2.91
q^4	6.40	2.59	3.29	6.17	2.65	3.18
q^5	7.36	2.65	3.12	6.76	2.66	3.15
AQR	5.61	2.45	3.49	5.78	2.44	3.69
SY	6.11	2.65	3.10	6.21	2.82	2.74
HJ	6.18	2.67	3.20	6.53	2.61	3.18

Table 3: Cross-Sectional Regressions of Realized Returns on Predicted Returns

This table reports time-series average slope coefficient, its standard error, and the average cross-sectional R^2 from monthly Fama-MacBeth (1973) cross-sectional regressions of one-month-ahead realized excess returns on ex-ante predicted excess returns implied by alternative estimators for an investable universe of fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we estimate expected returns from the historical sample mean $(1/T)$ and based on the return covariance with ten SDF. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000.

	A: Full Sample			B: Recent Sample		
	Average $\mathbb{E}_t[R_{t+1}]$	Std Err $\mathbb{E}_t[R_{t+1}]$	Average R^2	Average $\mathbb{E}_t[R_{t+1}]$	Std Err $\mathbb{E}_t[R_{t+1}]$	Average R^2
	(1)	(2)	(3)	(4)	(5)	(6)
$1/T$	0.35	0.15	0.17	0.17	0.22	0.16
CAPM	−1.68	0.51	0.22	−1.25	0.72	0.22
FF3	0.48	0.22	0.16	0.75	0.26	0.13
FFC	0.52	0.16	0.13	0.62	0.23	0.13
FF5	0.64	0.25	0.15	0.82	0.29	0.12
FF6	0.49	0.14	0.13	0.57	0.21	0.14
q^4	0.73	0.17	0.17	0.64	0.25	0.21
q^5	0.77	0.16	0.12	0.75	0.23	0.14
AQR	0.72	0.16	0.13	0.66	0.26	0.15
SY	0.43	0.15	0.15	0.57	0.25	0.16
HJ	0.62	0.13	0.10	0.58	0.19	0.11

Table 4: Out-of-Sample Portfolio Performance along the Business Cycle

This table reports out-of-sample Sharpe ratios conditional on economic expansions and contractions defined by positive or negative growth in real GDP per capita and market betas for dynamic portfolio strategies. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported in annualized units.

	A: Full Sample			B: Recent Sample		
	Sharpe in Booms	Sharpe in Busts	Market Beta	Sharpe in Booms	Sharpe in Busts	Market Beta
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	0.74	−0.27	1.08	0.88	−0.32	1.15
$1/T$	0.56	−0.06	0.07	0.33	−0.17	0.06
CAPM	0.86	−0.42	1.01	0.94	−0.54	1.28
FF3	0.91	0.23	0.20	0.91	0.20	0.29
FFC	1.40	−0.07	0.14	1.30	−0.22	0.17
FF5	1.26	0.86	0.12	1.20	0.88	0.18
FF6	1.62	0.51	0.06	1.44	0.42	0.10
q^4	1.51	0.60	0.04	1.37	0.52	0.08
q^5	1.88	0.52	0.09	1.42	0.29	0.16
AQR	1.39	0.08	−0.08	1.19	0.04	−0.12
SY	1.85	0.38	0.02	1.66	0.31	0.02
HJ	1.65	0.27	0.02	1.26	0.08	0.05

Table 5: Out-of-Sample Portfolio Tail Risk

This table reports annualized standard deviation, monthly 95% value-at-risk (VaR), and 95% expected shortfall (conditional VaR) for dynamic portfolio strategies. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported as percentages.

	A: Full Sample			B: Recent Sample		
	Standard Deviation	Value-at-Risk	Expected Shortfall	Standard Deviation	Value-at-Risk	Expected Shortfall
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	18.88	−7.83	−12.16	20.38	−8.71	−12.42
$1/T$	20.81	−8.38	−13.62	45.38	−19.77	−31.68
CAPM	16.06	−7.72	−10.73	20.90	−10.27	−13.44
FF3	12.54	−5.13	−7.56	14.41	−6.00	−8.53
FFC	9.32	−3.27	−5.72	12.52	−4.86	−7.69
FF5	7.91	−2.71	−3.95	9.02	−2.99	−4.40
FF6	7.04	−2.22	−3.91	9.05	−2.91	−5.13
q^4	7.40	−2.18	−4.07	9.06	−2.70	−5.19
q^5	6.13	−2.01	−3.25	9.37	−3.19	−5.22
AQR	9.85	−3.34	−5.83	13.78	−4.20	−8.23
SY	6.77	−1.93	−3.81	8.94	−2.58	−5.33
HJ	7.43	−2.19	−3.98	11.58	−3.49	−6.43

Table 6: Out-of-Sample Portfolio Performance with SDFs from Macro-Finance

This table reports out-of-sample Sharpe ratios and Fama-French (2016) six-factor alphas, along with corresponding t-statistics for dynamic portfolio strategies. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CCAPM, external habit models (with and without Epstein-Zin preferences), downside risk, geopolitical risk, long-run risks, intermediary risk, ICAPM variants, and APT-style specifications. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported in annualized units.

	A: Full Sample			B: Recent Sample		
	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	0.49	2.08	3.27	0.49	2.39	2.69
$1/T$	0.44	6.00	1.77	0.22	7.51	0.79
CCAPM	0.01	−0.85	0.00	−0.08	3.80	−0.13
Ext Habit	0.46	8.94	2.31	0.55	10.00	2.33
Ext Habit + EZ	0.47	8.74	2.31	0.54	8.63	1.92
Downside Risk	0.51	−0.98	−0.37	0.44	−2.27	−0.70
Geopol Risk	0.59	3.15	1.46	0.60	3.42	1.41
Long Run Risk	0.59	0.34	0.11	0.77	3.14	0.99
Intermediary Risk	0.63	2.47	1.33	0.56	1.53	0.68
ICAPM	0.70	5.91	2.82	0.73	6.07	2.77
LT-ICAPM	0.72	3.13	1.52	0.54	1.54	0.47
CRR-APT	0.72	4.31	2.14	0.63	4.89	1.75

Table 7: Out-of-Sample Portfolio Performance with Bayes-Stein Shrinkage

This table reports out-of-sample Sharpe ratios and Fama-French (2016) six-factor alphas, along with corresponding t-statistics for dynamic portfolio strategies where expected return estimates are shrunk toward the minimum-variance portfolio following Bayes-Stein methodology. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported in annualized units.

	A: Full Sample			B: Recent Sample		
	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	0.49	2.08	3.27	0.49	2.39	2.69
$1/T$	0.44	5.97	1.77	0.22	7.48	0.79
CAPM	0.62	2.18	2.77	0.50	2.16	1.84
FF3	0.76	3.37	3.46	0.71	3.61	2.67
FFC	1.00	2.99	4.12	0.81	3.70	3.27
FF5	1.18	3.76	4.35	1.12	3.97	3.52
FF6	1.32	3.71	5.51	1.11	3.91	4.01
q^4	1.26	3.92	5.61	1.11	3.60	3.91
q^5	1.51	4.71	7.50	1.08	3.60	3.48
AQR	0.95	3.57	3.64	0.74	4.06	2.40
SY	1.37	3.17	4.61	1.13	3.06	2.84
HJ	1.25	4.50	4.85	0.87	3.83	2.27

Table 8: Out-of-Sample Portfolio Performance with Sign Restrictions

This table reports out-of-sample Sharpe ratios and Fama-French (2016) six-factor alphas, along with corresponding t-statistics for dynamic portfolio strategies where expected return estimates are restricted to be non-negative following Campbell and Thompson (2008). The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported in annualized units.

	A: Full Sample			B: Recent Sample		
	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	0.49	2.08	3.27	0.49	2.39	2.69
$1/T$	0.17	10.19	1.18	0.19	7.47	0.70
CAPM	0.58	0.69	1.50	0.48	1.12	1.28
FF3	0.73	4.07	2.95	0.65	4.04	1.89
FFC	1.09	3.64	5.16	0.93	4.57	4.26
FF5	1.18	3.78	4.33	1.11	3.95	3.48
FF6	1.37	3.93	5.95	1.16	4.20	4.46
q^4	1.16	4.96	5.03	1.01	4.59	3.25
q^5	1.49	4.68	7.24	1.07	3.54	3.39
AQR	1.22	7.06	6.38	1.07	8.04	4.48
SY	1.43	3.52	5.16	1.21	3.59	3.38
HJ	1.25	4.50	4.85	0.87	3.82	2.25

Table 9: Out-of-Sample Portfolio Performance with Conditional SDFs

This table reports out-of-sample Sharpe ratios and Fama-French (2016) six-factor alphas, along with corresponding t-statistics for dynamic portfolio strategies. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten conditional SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Linear factor models containing the market portfolio include an extra scaled market factor using Cooper and Priestley's (2009) output gap. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported in annualized units.

	A: Full Sample			B: Recent Sample		
	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	0.49	2.08	3.27	0.49	2.39	2.69
$1/T$	0.44	6.00	1.77	0.22	7.51	0.79
CAPM	0.46	−0.56	−0.22	0.37	−2.40	−0.59
FF3	0.44	2.19	1.01	0.56	2.64	1.20
FFC	0.89	3.20	3.58	0.75	4.37	3.34
FF5	1.20	4.54	5.10	1.14	4.74	3.94
FF6	1.36	4.07	6.09	1.14	4.37	4.41
q^4	1.46	5.33	7.74	1.23	5.14	5.01
q^5	1.55	5.11	8.13	1.12	4.60	4.38
AQR	0.94	3.54	3.58	0.73	4.01	2.34
SY	1.29	3.25	4.39	1.08	3.68	3.13
HJ	1.25	4.50	4.84	0.87	3.82	2.25

Table 10: Out-of-Sample Portfolio Performance with One-Year Holding Periods

This table reports out-of-sample Sharpe ratios and Fama-French (2016) six-factor alphas, along with corresponding t-statistics for dynamic portfolio strategies. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one year before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported in annualized units.

	A: Full Sample			B: Recent Sample		
	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	0.48	1.14	0.79	0.46	0.60	0.28
$1/T$	0.35	−7.31	−0.86	0.27	−11.96	−0.96
CAPM	0.58	−0.32	−0.38	0.43	0.15	0.10
FF3	0.56	2.71	0.89	0.56	−1.52	−0.40
FFC	0.65	0.54	0.18	0.47	−4.72	−1.00
FF5	0.95	7.72	3.78	0.93	8.16	3.75
FF6	1.06	5.74	3.35	0.86	5.39	2.32
q^4	1.05	4.01	2.42	0.88	2.97	1.46
q^5	1.02	3.19	1.64	0.71	0.75	0.25
AQR	0.66	0.59	0.22	0.47	−3.19	−0.81
SY	1.08	3.26	1.51	0.91	0.57	0.18
HJ	0.93	3.96	1.62	0.67	1.74	0.52

Table 11: Out-of-Sample Portfolio Performance with Factors in Covariance Matrix

This table reports out-of-sample Sharpe ratios and Fama-French (2016) six-factor alphas, along with corresponding t-statistics for dynamic portfolio strategies. We model the return covariance matrix using a factor structure with systematic and idiosyncratic components. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported in annualized units.

	A: Full Sample			B: Recent Sample		
	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	0.49	2.08	3.27	0.49	2.39	2.69
$1/T$	0.46	−0.28	−0.14	0.37	−0.55	−0.15
CAPM	0.53	1.47	3.16	0.51	1.94	2.67
FF3	0.58	2.05	3.56	0.58	1.94	2.83
FFC	0.59	2.37	4.62	0.58	2.42	3.64
FF5	0.57	2.21	4.07	0.58	2.32	3.46
FF6	0.60	2.75	4.69	0.59	2.42	3.77
q^4	0.61	2.41	3.37	0.62	2.10	3.05
q^5	0.61	3.02	5.36	0.57	2.45	3.61
AQR	0.44	5.00	1.71	0.31	13.74	2.14
SY	0.63	3.13	4.81	0.64	3.20	3.88
HJ	1.25	4.50	4.84	0.87	3.82	2.25

Internet Appendix:

SDF-Based Portfolio Choice

In this internet appendix, we provide additional tables and figures supplementing our main paper.

Table IA.1: Out-of-Sample Portfolio Performance with Alternative Performance Metrics

This table reports out-of-sample Appraisal ratios, certainty-equivalent returns, and idiosyncratic return volatilities for dynamic portfolio strategies. Appraisal ratio and idiosyncratic return volatility are from the Fama-French (2016) six-factor model. The certainty equivalent is the mean return minus half the return variance. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported in annualized units.

	A: Full Sample			B: Recent Sample		
	Appraisal Ratio	Certainty Equivalent	Idiosyncratic Volatility	Appraisal Ratio	Certainty Equivalent	Idiosyncratic Volatility
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	0.54	7.47	3.83	0.57	7.98	4.16
$1/T$	0.29	7.09	20.38	0.17	−0.24	44.60
CAPM	0.25	7.96	2.78	0.27	7.87	4.09
FF3	0.54	8.47	6.13	0.55	9.02	6.48
FFC	0.67	8.82	4.45	0.68	9.27	5.37
FF5	0.71	8.94	5.28	0.74	9.65	5.33
FF6	0.91	9.01	4.08	0.85	9.64	4.58
q^4	0.97	8.98	4.05	0.82	9.64	4.33
q^5	1.30	9.07	3.63	0.73	9.62	4.88
AQR	0.59	8.77	5.97	0.50	9.11	8.04
SY	0.85	9.02	3.74	0.72	9.65	4.19
HJ	0.80	8.98	5.61	0.48	9.38	7.96

Table IA.2: Out-of-Sample Portfolio Performance with First-Stage GMM Estimations

This table reports out-of-sample Sharpe ratios and Fama-French (2016) six-factor alphas, along with corresponding t-statistics for dynamic portfolio strategies. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using first-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported in annualized units.

	A: Full Sample			B: Recent Sample		
	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	0.49	2.08	3.27	0.49	2.39	2.69
$1/T$	0.44	6.00	1.77	0.22	7.51	0.79
CAPM	0.58	0.69	1.50	0.48	1.12	1.28
FF3	0.79	3.30	3.71	0.71	3.24	2.62
FFC	0.95	2.98	3.82	0.77	3.36	2.77
FF5	1.35	4.64	5.57	1.13	4.26	3.27
FF6	1.26	3.97	5.77	1.00	4.13	3.76
q^4	1.27	4.09	6.16	1.11	3.45	3.77
q^5	1.52	5.56	7.57	0.90	3.86	2.51
AQR	0.97	4.17	3.67	0.85	4.51	2.54
SY	1.39	3.15	4.79	1.15	2.88	2.75
HJ	1.25	4.50	4.84	0.87	3.82	2.25

Table IA.3: Out-of-Sample Portfolio Performance with ℓ^2 Leverage Constraints

This table reports out-of-sample Sharpe ratios and Fama-French (2016) six-factor alphas, along with corresponding t-statistics for dynamic portfolio strategies. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^2 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported in annualized units.

	A: Full Sample			B: Recent Sample		
	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)	Sharpe Ratio	FF6 Alpha	t(FF6 Alpha)
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	0.49	2.08	3.27	0.49	2.39	2.69
$1/T$	0.45	6.11	1.84	0.22	7.63	0.81
CAPM	0.56	0.67	1.39	0.45	1.09	1.16
FF3	0.74	3.33	3.30	0.71	3.61	2.64
FFC	1.00	2.98	4.05	0.81	3.69	3.26
FF5	1.19	3.82	4.44	1.11	3.95	3.48
FF6	1.34	3.83	5.77	1.11	3.90	3.99
q^4	1.25	3.96	5.69	1.10	3.52	3.80
q^5	1.51	4.71	7.50	1.07	3.57	3.44
AQR	0.94	3.54	3.58	0.73	4.01	2.33
SY	1.41	3.36	4.99	1.12	3.02	2.76
HJ	1.22	4.33	4.57	0.86	3.72	2.18

Table IA.4: Out-of-Sample Portfolio Performance with Alternative Test Assets

This table reports out-of-sample Sharpe ratios for dynamic portfolio strategies. The investable universe comprises fifty decile portfolios univariately sorted on market capitalization, book-to-market, operating profitability, asset growth, and momentum. However, we remove the size-sorted deciles for Columns (1) and (4), the momentum-sorted deciles for Columns (2) and (5), and replace all fifty test assets with their value-weighted counterparts in Columns (3) and (6). At the end of each month, we form (i) the naïve equal-weight benchmark ($1/N$), (ii) the mean-variance tangency portfolio ($1/T$) based on historical sample mean returns, and (iii) ten SDF-based portfolios based on SDF-implied expected returns. We hold the position for one month before rebalancing. Portfolio weights are subject to an ℓ^1 leverage constraint. Candidate SDFs are estimated from linear factor models using second-stage GMM and include CAPM, Carhart, Fama-French factor models (three- through six-factor variants), q-factor models (q^4 and q^5), an AQR-style four-factor model (updated value, momentum, betting-against-beta, quality-minus-junk), the Stambaugh-Yuan (2017, SY) four-factor mispricing model, and the Hansen-Jagannathan (1991, HJ) minimum-variance SDF. Panel A uses the full sample while Panel B focuses on the recent sample starting in 2000. All statistics are computed from monthly portfolio returns and reported in annualized units.

	A: Full Sample			B: Recent Sample		
	No Size	No Momentum	Value-Weights	No Size	No Momentum	Value-Weights
	(1)	(2)	(3)	(4)	(5)	(6)
$1/N$	0.48	0.50	0.54	0.48	0.51	0.47
$1/T$	0.87	1.02	0.36	0.46	0.55	0.50
CAPM	0.55	0.64	0.57	0.44	0.66	0.46
FF3	0.77	0.91	0.41	0.76	0.85	0.40
FFC	0.80	1.05	0.56	0.77	0.82	0.47
FF5	1.24	1.23	0.79	1.12	1.10	0.81
FF6	1.24	1.41	0.82	1.12	1.09	0.79
q^4	1.20	1.25	0.64	1.13	1.03	0.71
q^5	1.18	1.55	0.72	1.02	1.12	0.74
AQR	0.97	0.86	0.33	0.92	0.58	0.17
SY	1.31	1.55	0.90	1.22	1.21	0.83
HJ	1.24	1.25	0.79	1.02	0.87	0.67

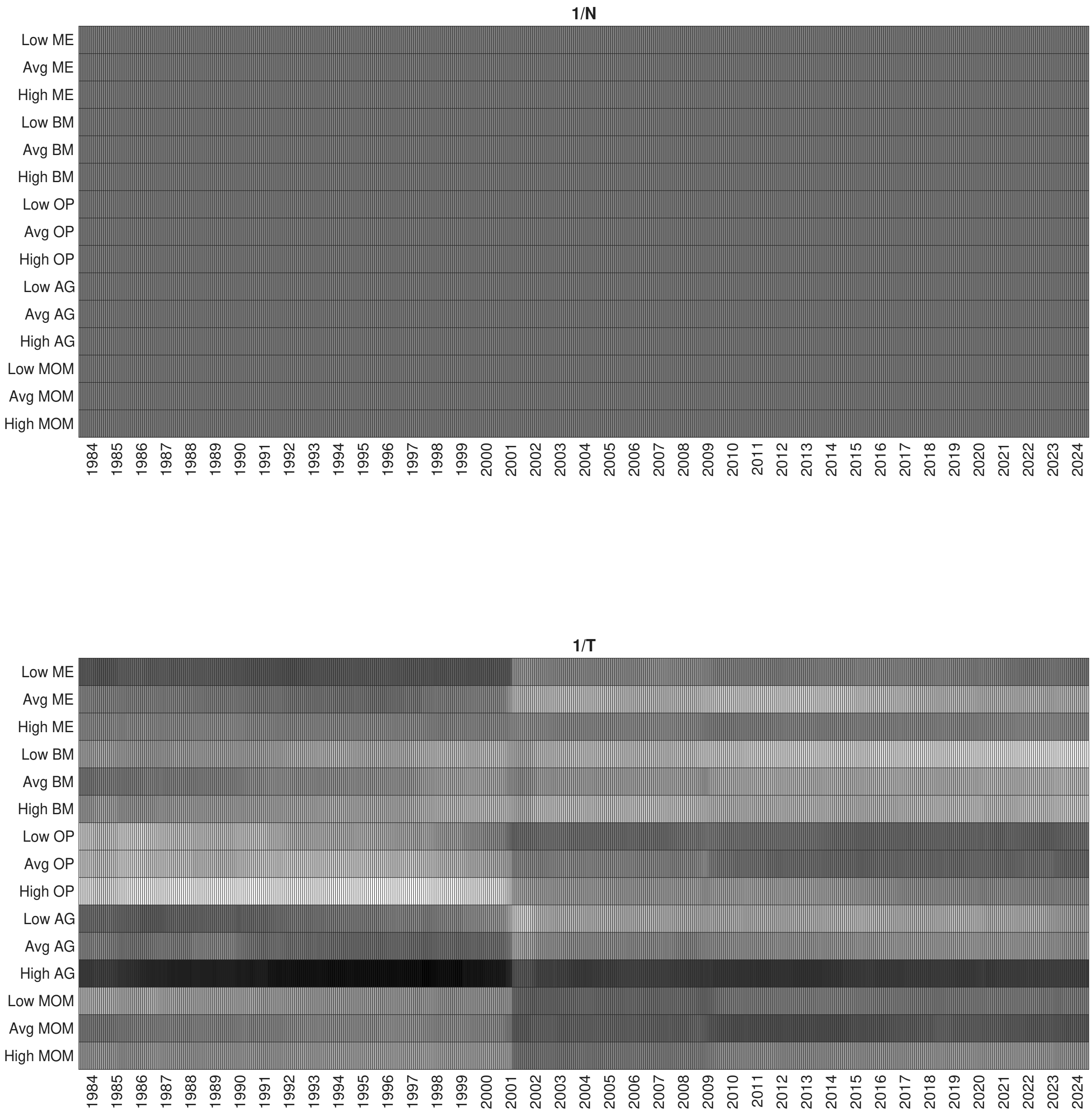


Figure IA.1: This figure plots a heatmap for the average portfolio weights in the fifty underlying test assets over time. We average the weights in the bottom three deciles ("low"), the middle four deciles ("avg"), and the top three deciles ("high"). Bright gray indicates short positions, dark gray indicates long positions. We show full sample results.

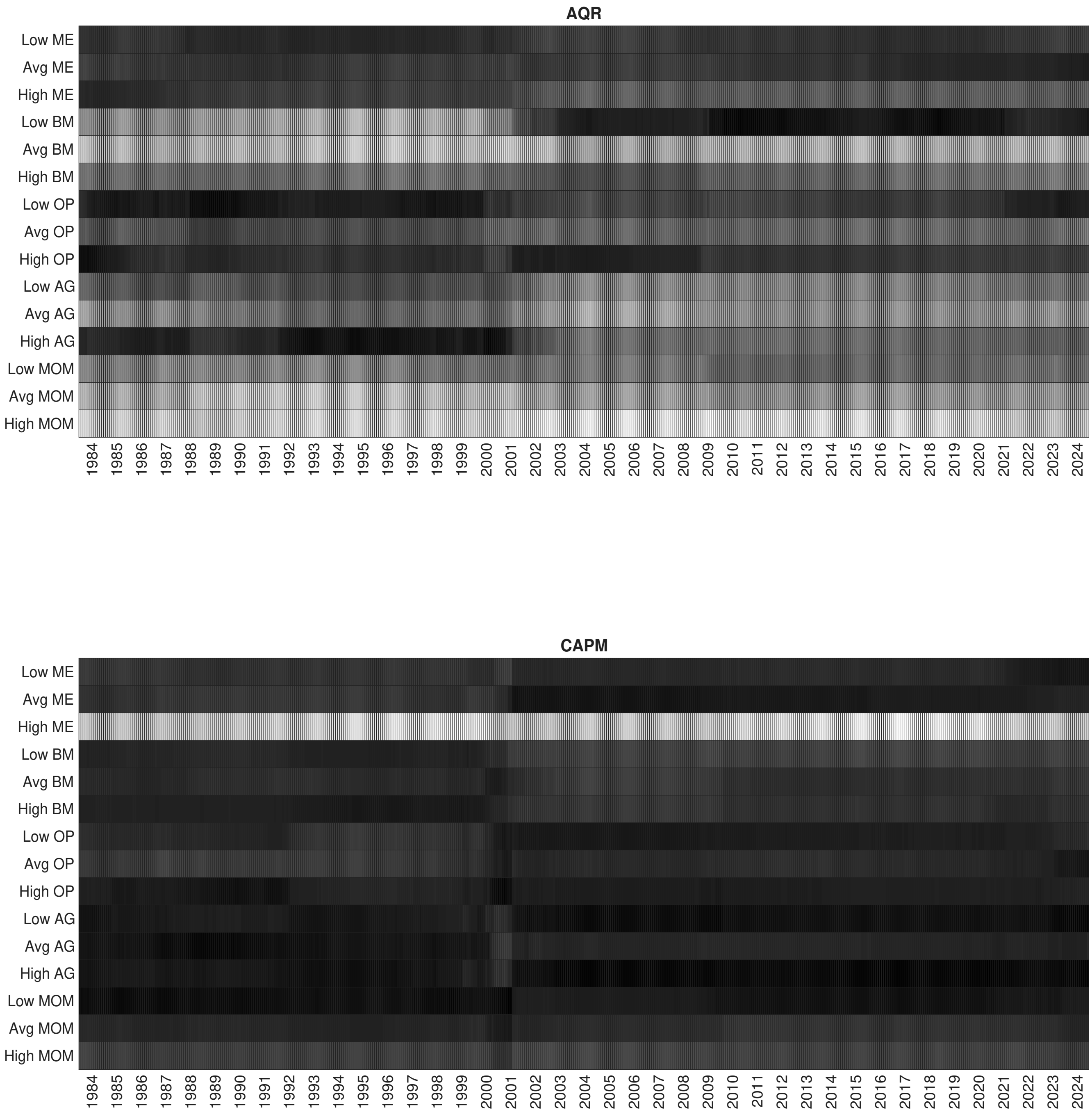
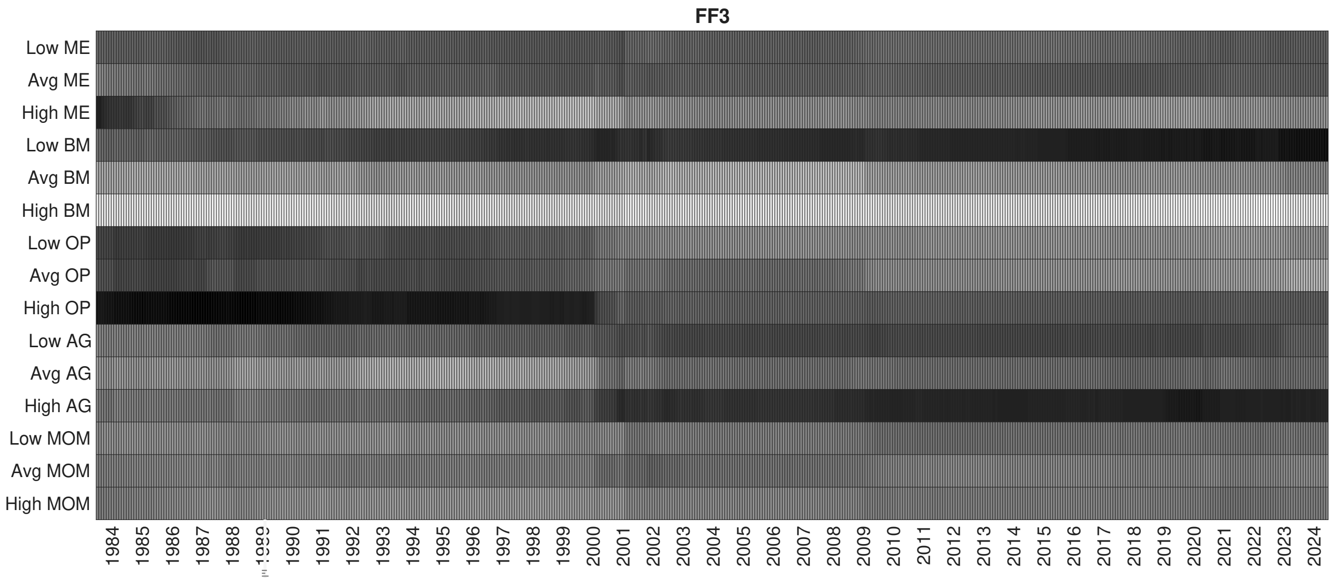


Figure IA.2: This figure plots a heatmap for the average portfolio weights in the fifty underlying test assets over time. We average the weights in the bottom three deciles ("low"), the middle four deciles ("avg"), and the top three deciles ("high"). Bright gray indicates short positions, dark gray indicates long positions. We show full sample results underlying Column (1) of Table 1.



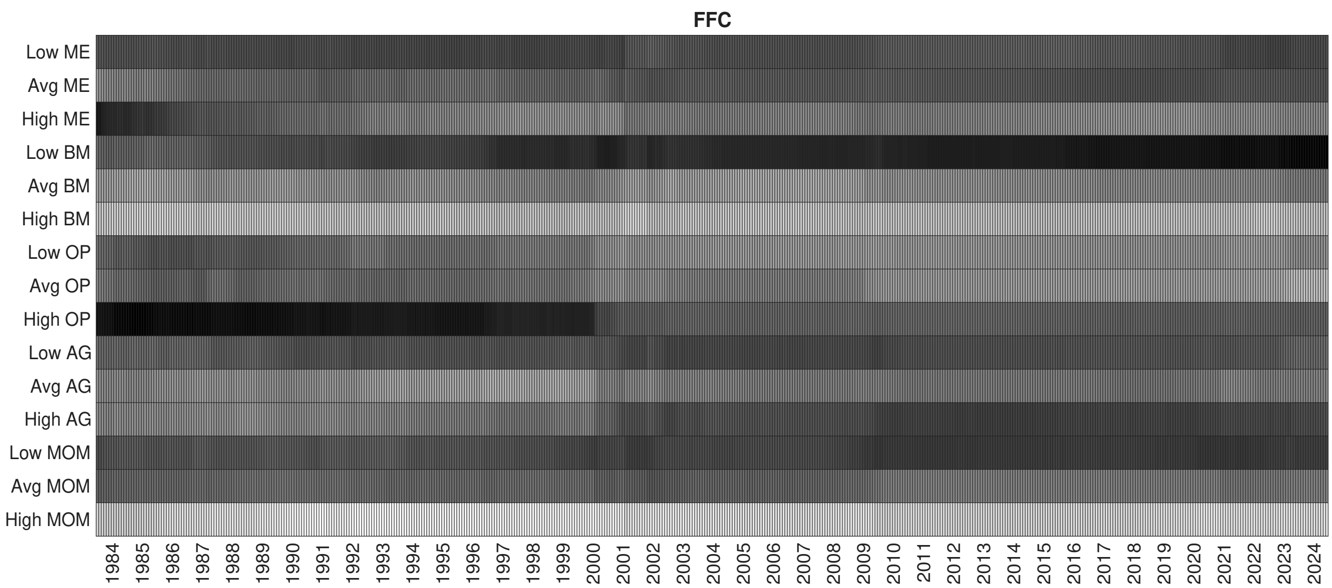


Figure IA.3: This figure plots a heatmap for the average portfolio weights in the fifty underlying test assets over time. We average the weights in the bottom three deciles ("low"), the middle four deciles ("avg"), and the top three deciles ("high"). Bright gray indicates short positions, dark gray indicates long positions. We show full sample results underlying Column (1) of Table 1.

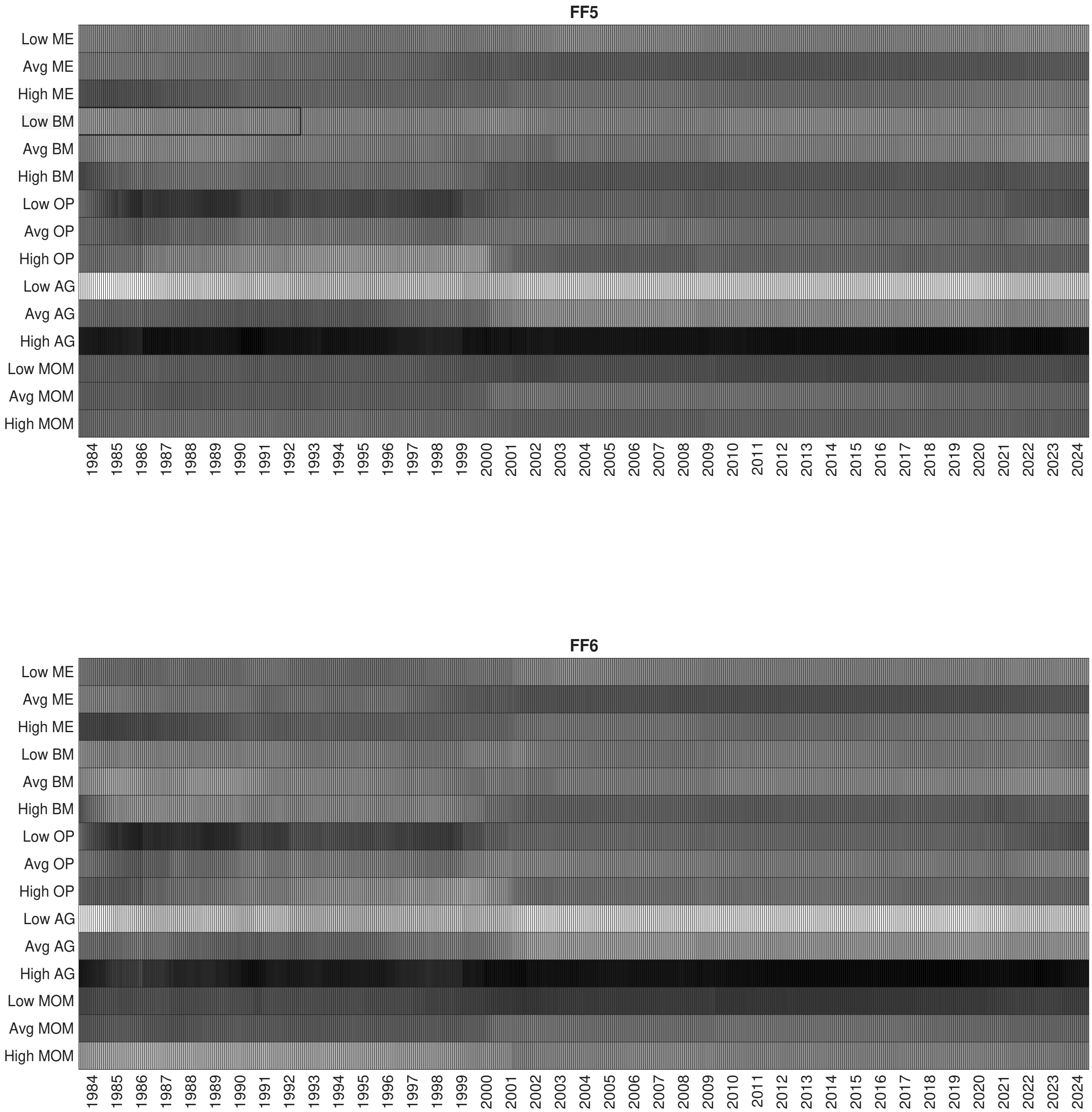
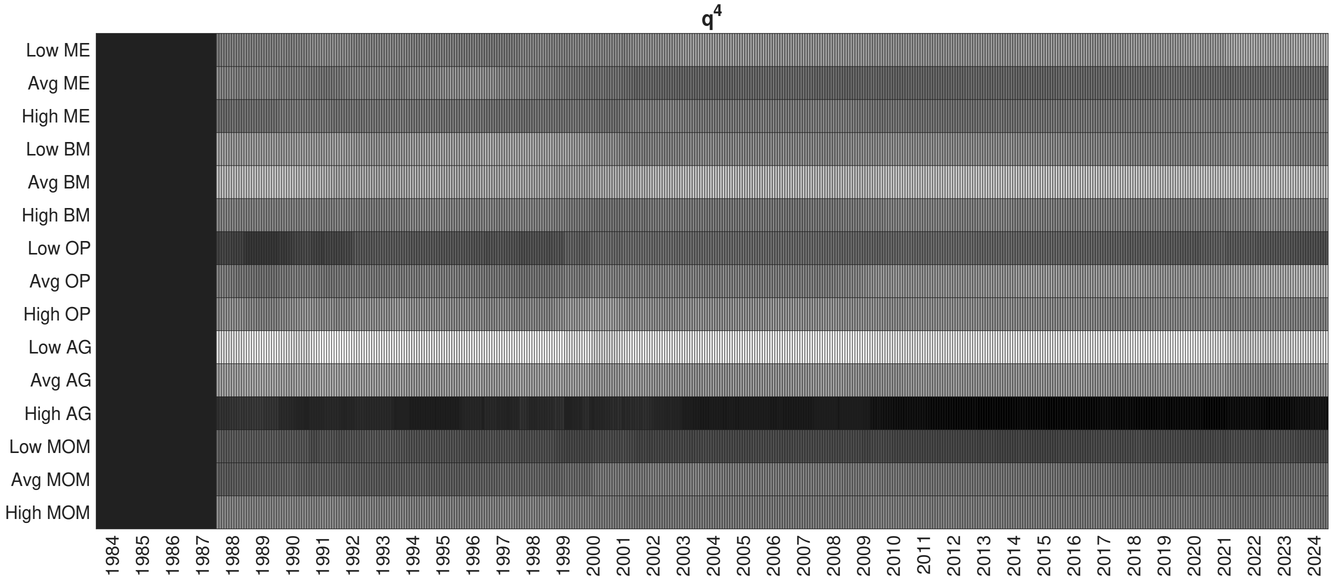


Figure IA.4: This figure plots a heatmap for the average portfolio weights in the fifty underlying test assets over time. We average the weights in the bottom three deciles ("low"), the middle four deciles ("avg"), and the top three deciles ("high"). Bright gray indicates short positions, dark gray indicates long positions. We show full sample results underlying Column (1) of Table 1.



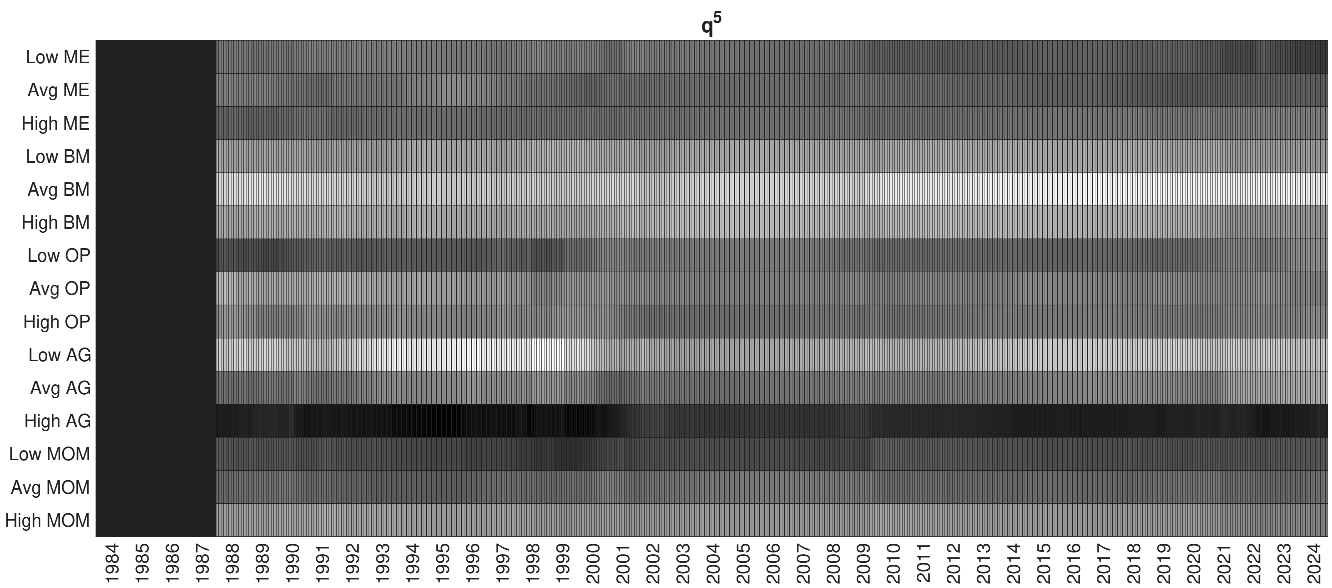


Figure IA.5: This figure plots a heatmap for the average portfolio weights in the fifty underlying test assets over time. We average the weights in the bottom three deciles (“low”), the middle four deciles (“avg”), and the top three deciles (”high”). Bright gray indicates short positions, dark gray indicates long positions. We show full sample result underlying Column (1) of Table 1. . Black boxes indicate the late start of the available sample for the underlying factor data.

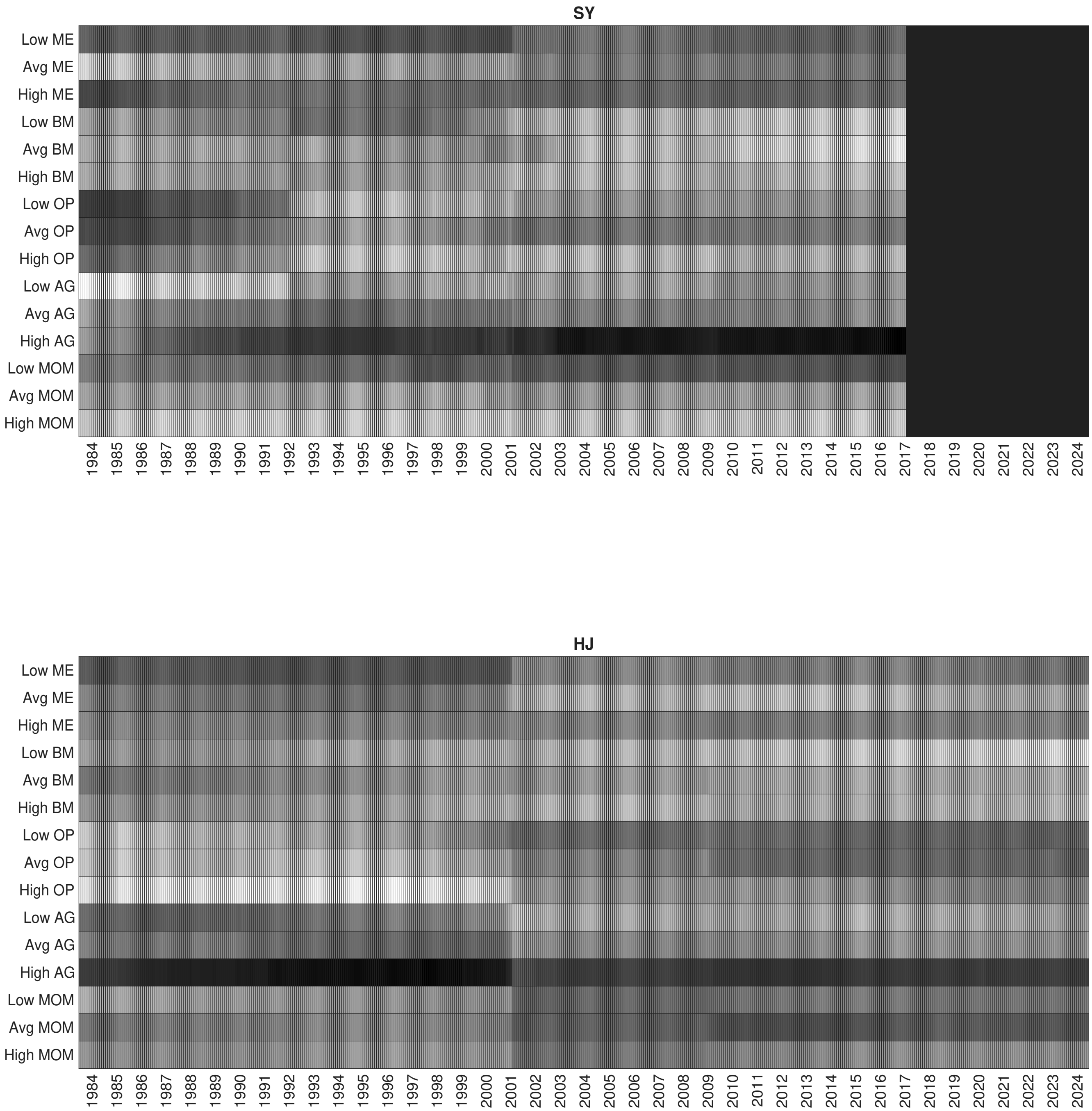


Figure IA.6: This figure plots a heatmap for the average portfolio weights in the fifty underlying test assets over time. We average the weights in the bottom three deciles ("low"), the middle four deciles ("avg"), and the top three deciles ("high"). Bright gray indicates short positions, dark gray indicates long positions. We show full sample results underlying Column (1) of Table 1. Black boxes indicate the early ending of the available sample for the underlying factor data.