Market Concentration, Capital Misallocation, and Asset Pricing

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Abstract

Superstar firms that dominate markets due to their large size and high markups can deter efficiency in capital allocation across firms. This paper empirically studies the asset pricing implications of superstars through the channel of capital misallocation, measured by cross-sectional dispersion in the marginal product of capital (MPK). I decompose this measure into three components: misallocation among superstars, misallocation among other firms, and misallocation between these two groups, referred to as "MPK spread". Shocks to the MPK spread are negatively priced in the cross-section of stock returns. Stocks negatively exposed to these shocks outperform stocks positively exposed to these shocks by 4.8% per year. In the long run, the MPK spread negatively predicts consumption growth, industrial production growth, employment growth, and stock market excess returns. In the short run, the MPK spread negatively predicts the innovation growth of non-superstar firms. Consistent with the ICAPM framework, capital misallocation between superstar and non-superstar firms is a key state variable and its shocks capture an important macroeconomic risk factor.

JEL classification: E22, G11, G12, G14.

Keywords: Superstars, capital misallocation, risk premium, cross-sectional asset pricing.

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1 Introduction

The decline in the number of US-listed firms (Doidge, Karolyi, and Stulz, 2017) as well as the rise of stock market concentration among a few mega-firms, so-called "superstars", lead to several macroeconomic consequences (Schlingemann and Stulz, 2022; Autor et al., 2020; Gutierrez and Philippon, 2019). Among the consequences, Bae, Bailey, and Kang (2021) show that rising stock market concentration leads to slower economic growth, by restricting the innovation of new and smaller firms. Capital misallocation, i.e. the degree to which capital is inefficiently distributed across firms, is one important deterrent of economic growth as it implies losses in total factor productivity (David, Hopenhayn, and Venkateswaran, 2016).

Do superstar firms affect asset pricing? This paper empirically studies this question through the channel of capital misallocation. An increase in capital misallocation represents negative news to investors whose marginal utility depends on future consumption growth, as a rise in capital misallocation determines economic growth through its impact on innovation (Dou, Ji, Tian, and Wang, 2023). My paper finds that shocks to a component of aggregate capital misallocation driven by superstar firms, defined by their size and market power, have several asset pricing consequences.

First, shocks to capital misallocation between superstars and non-superstars are a priced risk factor. Using Compustat quarterly data on US-listed firms, I decompose aggregate capital misallocation, measured by the cross-sectional dispersion in the marginal product of capital (MPK), into misallocation among superstars, among other firms, and between these two groups referred to as "MPK spread". In different cross-sections of stock returns, shocks to the MPK spread are negatively priced. In contrast, aggregate misallocation shocks, shocks to misallocation among superstars, and among other firms do not robustly yield significant prices of risk.

Second, stocks exposed to misallocation shocks between superstars and non-superstars carry a significant risk premium. Stocks with negative exposures to the shocks earn a higher expected return. These stocks appreciate when shocks to the MPK spread rise, making them risky. In contrast, stocks with positive exposures to the shocks earn a lower expected return. Their expected returns increase when shocks to the MPK spread rise, making them a hedge. The long-short portfolio sorted on individual stock exposure to shocks to the MPK spread, referred to as the MPK spread-mimicking portfolio, earns a significant expected return of 4.8% per year.

Third, a spanning test analysis shows that adding the MPK spread-mimicking portfolio improves the mean-variance efficiency of the aggregate misallocation shock-mimicking portfolio and misallocation shock-mimicking portfolio among superstars and non-superstar firms. When I formally form long-short portfolios based on stock exposure to each shock and perform spanning tests, only the MPK spread-mimicking portfolio prices the portfolio exposed to aggregate misallocation shocks. Whereas, the portfolio exposed to aggregate misallocation shocks, shocks to misallocation among superstars, and among other firms do not price the MPK spread-mimicking portfolio.

Fourth, capital misallocation between superstar and non-superstar firms is a key state variable as it has predictive power for future economic growth and investment opportunities. In the long term, the MPK spread negatively predicts consumption growth, industrial production growth, employment growth, and aggregate stock returns. In the short term, shocks to the MPK spread negatively predict aggregate innovation growth and especially innovation growth among non-superstars. In contrast, the aggregate capital misallocation, the misallocation among superstars and among non-superstars do not show predictive power and their shocks do not carry a significantly negative price of risk. Therefore, only the MPK spread is a candidate state variable.

Finally, shocks to capital misallocation as a risk factor are consistent with the Intertemporal CAPM (ICAPM) as they satisfy three restrictions proposed by Maio and Santa-Clara (2012). First, the MPK spread as a state variable negatively forecasts the aggregate stock returns. Second, shocks to the MPK spread as a factor earn a negative price of risk in the cross-sectional tests, consistent with the sign of forecast. Third, in the multi-factor model that includes market and shocks to the MPK spread, the market price of risk estimated from the cross-sectional tests is economically plausible as an estimate of the coefficient of relative risk aversion (RRA) of the representative investor.

These findings imply that a higher discrepancy in the mean productive use of capital between superstars and non-superstars discourages innovation in the economy, particularly among non-superstars. Thus, shocks to capital misallocation between superstars and non-superstars represent negative news to investors whose marginal utility depends on long-run risks. In the ICAPM framework, these shocks capture a macroeconomic asset pricing factor, highlighting superstars' role in shaping the risk premium associated with capital misallocation.

To identify superstar firms, I follow Autor et al. (2020) and Cheng, Vyas, Wittenberg-Moerman, and Zhao (2023) and select the top 5% firms in their industries based on market capitalization and market power. I estimate firm-level market power as markup from De Loecker, Eeckhout, and Unger (2020). I measure firm-level MPK as the log ratio of output-to-capital, implied from the standard Cobb-Douglas production function. I introduce shocks to capital misallocation as the annual changes in the cross-sectional dispersion of MPK to remove the seasonality in sales, measured for output. A time series of misallocation shocks shows that periods of high capital misallocation coincide with recessions, implying the countercyclical pattern of capital misallocation (David, Schmid, and Zeke, 2022; Dou, Ji, Tian, and Wang, 2023).

An innovation of this paper is decomposing capital misallocation into three components: misallocation among superstar firms, among other firms, and MPK spread, i.e. a component due to the difference in the mean MPK level between superstars and non-superstars. A time series of different moments of the MPK distribution shows that the MPK distribution is rightly skewed. Furthermore, superstar firms are on average above the 95th percentile of the MPK distribution.

To test the role of superstar firms, I examine the pricing of aggregate misallocation shocks and each component. The cross-sectional Fama-MacBeth regressions show that shocks to the MPK spread are significantly and negatively priced in the cross-section of 25 size×book-to-market, 10 momentum, 25 siz×investment, 25 size×operating profitability portfolios. This finding is robust to using Giglio and Xiu (2021)'s 202 portfolios. Whereas, the pricing of aggregate misallocation shocks, shocks to misallocation among superstars, and among non-superstars are not robust and consistent across different models and test portfolios. Hence, misallocation shocks between superstars and non-superstars mainly drive the negative price of risk of aggregate misallocation shocks.

Consistently, firms with higher book-to-market are more negatively exposed to shocks to the MPK spread. Parker and Julliard (2005) finds that expected excess return of value-minus-growth stocks predicts consumption growth, while higher capital misallocation predicts a lower consumption growth rate (David, Hopenhayn, and Venkateswaran, 2016). When examining factor loadings on the 25 size × book-to-market portfolios in the first stage of Fama-MacBeth regression, shocks to the MPK spread display a decreasing trend as portfolios are sorted from low to high book-to-market within each size quintile.

Next, I examine individual stocks' exposure to capital misallocation shocks and each component. For each stock, I regress the quarterly excess returns on each shock using a rolling window of 20 quarters. Then I sort stocks into quintiles based on their beta estimates each quarter. The value-weighted portfolios show that the average excess returns decrease as the stocks' exposure to shocks to the MPK spread increases. The long-short portfolio has an average annual excess return of -4.8%. The abnormal returns (alphas) of the long-short portfolio estimated from the CAPM, the Fama and French (1992, 1993)'s three-factor, and the Fama and French (2015)'s five-factor models are significantly negative. The post-formation portfolios also show a negative beta in the lowest quintile and a positive beta in the highest quintile. These findings are robust to an equally weighted portfolio.

Finally, I run the standard predictive regression of several macroeconomic variables on the lagged MPK spread. The MPK spread predicts a negative per capita real consumption growth (nondurables and services), industrial production growth, employment growth, and stock market returns in the next 4 to 12 quarters. The MPK spread also predicts negative aggregate innovation growth, especially innovation growth of non-superstar firms in the next 1 to 5 quarters. Thus, capital misallocation between superstars and non-superstars shows both pricing power in the cross-section and predictability power in the time series.

The main asset pricing results are robust to various specifications. Alternative definitions of superstars based on market capitalization show that the top 50 firms confirm the results in the main cross-sectional asset pricing tests and predictability. Besides, the results are robust to using a value-weighted measure for misallocation, separating misallocation by tangible and intangible capital, the pre-2000s and post-2000s subsamples, and using annual data.

The contribution of this paper is threefold. First, it links the macroeconomic consequences of superstars to asset pricing. Second, it proposes capital misallocation between superstars and non-superstars as a state variable and its shocks as a priced risk factor. Third, my findings highlight the role of superstars in shaping the price of risk associated with capital misallocation: superstar firms are a friction that prevents innovation in the economy particularly other firms, deterring efficiency in capital allocation, negatively affecting economic growth, consistent with Bae, Bailey, and Kang (2021) and Kung and Schmid (2015).

Related literature. The macroeconomic literature has documented several consequences for market concentration and the role of superstar firms. For example, Autor et al. (2020) argue that technological advances push sales toward the most successful firms in the service industry whose contribution to labor share is relatively low, leading to a decline in the share of aggregate labor. Gutierrez and Philippon (2020) also find that the contribution of superstars to aggregate labor productivity has decreased by 40% since the 2000s. Schlingemann and Stulz (2022) argue that the market capitalization of listed firms has become less informative about firms' contribution to aggregate output, due to the decline in the manufacturing industry oriented in tangible capital and the shift towards the service industry which favors intangible capital. Besides, Gutierrez and Philippon (2019) find that the contribution of superstar firms to aggregate productivity growth has decreased.

Capital misallocation is an important deterrent of total factor productivity (Eisfeldt and Rampini, 2006, 2008; Eisfeldt and Shi, 2018). Among the consequences, my paper focuses on how superstars raise capital misallocation. Bae, Bailey, and Kang (2021) show a concentrated stock market is less likely to allocate capital to firms that could use capital more efficiently. Therefore, market concentration predicts higher capital misallocation. On the other hand, a higher stock market concentration could affect future economic growth by restricting the financing and innovation activities of potentially new and smaller firms. Thus, rising stock market concentration predicts slower economic growth. Put differently, my paper finds that shocks to capital misallocation between superstars and non-superstars negatively predict innovation growth and economic growth. This finding is consistent with Kung and Schmid (2015) who show that innovation endogenously generates long-run fluctuation in economic growth.

Alternatively, Su (2022) shows that capital misallocation increases when the economy includes superstars. When firms face uncertainty in their product quality, superstars become riskier as they face more volatile fluctuations in their markups. My results are consistent with the fact that superstar firms have the largest degree of capital misallocation. When selecting superstars based on the firm-level markup, I find that these firms on average are above the 95th percentile of the MPK distribution[1].

Several papers have shown that markups are an important source of capital misallocation. Peters (2020) finds that as firms get older, they improve their productivity away from competitors, raising the markups that they can optimally change on their existing products. Capital misallocation rises as a result of a decline in creative destruction, i.e. the extent to which new firms replace older firms to maintain competition in the market. David and Venkateswaran (2019) estimate that markup heterogeneity explains a large share of 14% in the capital misallocation in the US. Consistently, I find that rising markup yields a higher MPK level for the superstars[2].

Yet, few papers have shown the consequences of superstars and market concentration on asset pricing. Cheng, Vyas, Wittenberg-Moerman, and Zhao (2023) show in product markets that firms with high exposure to superstars experience weaker financial performance and higher risk. Hou and Robinson (2006) shows on the industry level that firms in more concentrated industries earn lower expected returns[3]. My paper finds evidence for market-wide concentration

[1]Other papers also support the fact that the presence of superstars creates market inefficiency. For instance, Grullon, Larkin, and Michaely (2019) show firms in concentrated industries become more profitable by higher profit margins, rather than higher productivity. Thus, market concentration can yield profits to winners rather than enhancing the whole economy. Covarrubias, Gutierrez, and Philippon (2020) document a "bad concentration" in the market after the 2000s, since concentration increases the barrier to entry and reduces innovation.

[2]Baqaee and Farhi (2020) show that reallocation of market share toward high-markup firms improves the aggregate TFP growth in the U.S. The intuition is that firms with high markups were too small to begin with, so reallocation of labor and capital towards these firms improves TFP growth over time. My paper studies superstar firms that are very large in terms of size and markup each quarter and considers capital misallocation in a static production function.

[3]The risk-based explanations include: (1) A high barrier to entry insulates firms from un-diversifiable distress risk, so firms in concentrated industries with a high barrier to entry earn lower expected stock returns, and

and that stocks negatively (positively) exposed to misallocation shocks between superstars and non-superstars earn a higher (lower) expected return.

Besides, Neuhann and Sockin (2023) show that high market concentration made it difficult for large firms to share risk and efficiently reallocate capital via financial markets. Market concentration reduces market risk premium through two channels: (1) When investment misallocation is severe, then there is less total risky production in the economy, lowering the market risk premium, and (2) Market concentration distorts trading in financial markets, and if the distortions to state prices favor sellers, this inflates security prices.

Alternatively, Dou, Ji, Tian, and Wang (2023) show that shocks to aggregate misallocation carry a negative price of risk. As capital misallocation prevents optimal R&D and innovation, capital misallocation captures news about long-run economic growth. In their model, investors are willing to pay a sizeable premium to eliminate such long-run uncertainty about economic growth. The source of friction that drives misallocation is financial constraints, while my paper studies size and market power as the primary sources of friction.

Consistent with Dou, Ji, Tian, and Wang (2023), this paper examines the effect of capital misallocation on risk premia. Shocks to misallocation are a risk factor as capital misallocation influences the investors' stochastic discount factor (SDF) through its effect on consumption growth. Reversely, David, Schmid, and Zeke (2022) study the role of risks in generating misallocation and find that firms' exposure to systematic risk is an important source of misallocation. Misallocation increases in times when risk premia are high and thus is countercyclical. My paper confirms the cyclical patterns in the capital misallocation shocks.

The remaining organization of the paper is as follows. Section 2 discusses in detail the data construction. Section 3 shows the measure for aggregate misallocation shocks and derives a decomposition based on superstar vs non-superstar portfolios. Section 4 shows main cross-sectional asset pricing results. Section 5 examines the predictive power for future economic growth. Section 6 tests the restrictions for ICAPM. Finally, Section 7 discusses different tests for robustness, and Section 8 concludes.

2 Data construction

In this section, I discuss data and describe the method to identify superstar firms.

(2) Innovation is risky and this risk is priced, so firms in industries with more innovation earn higher expected returns. Firms in concentrated industries are less risky as they engage in less innovation. Thus, they require a lower expected return.

2.1 Sample

The sample contains CRSP common stocks (share codes 10 or 11) traded on NYSE, AMEX, or Nasdaq (exchange codes 1, 2, or 3). Following the standard literature, I exclude the financial sector (SIC 6,000 - 6,999), utilities (SIC 4,900 - 4,999), and public administration (SIC 9,000 - 9,999), since firms in these sectors have little capital. Then, I compute quarterly stock returns from the monthly stock file to merge with firm characteristics from Compustat Fundamentals Quarterly. I take stock returns as of the end of a quarter and accounting variables at the end of the previous quarter to ensure that accounting data are public on the trading date and that market participants have access to accounting variables. The results are also robust to without this timing convention.

I obtain firm market capitalization from Compustat (mkvaltq), which equals price times shares outstanding (prccq $\times$ cshoq) if the value is missing. The resulting market cap is closely identical to when I compute price times shares outstanding at quarter-end from CRSP. All nominal variables are adjusted for inflation using the GDP deflator (GDPDEF series from FRED at quarterly frequency). I also exclude micro-cap stocks whose prices are less than $1 and observations with negative values for sale (Compustat saleq) and physical capital (ppentq). The final sample contains 590,154 unique firm-quarter observations from 1975:Q2 to 2023:Q4, as capital is only available for most firms after 1974:Q4.

The variable for intangible capital (intanq) is often missing in Compustat. Therefore, I estimate intangible capital using the perpetual inventory method from Eisfeldt and Papanikolaou (2013) and Eisfeldt, Kim, and Papanikolaou (2020). Specifically,

$$INT_{it} = (1 - \delta)INT_{it-1} + SG\&A_{it}$$

where the initial value is $INT_{i0} = SG\&A_{i1}/(g + \delta), g = 0.1$, and $\delta = 0.2$. The estimation uses 100% SG&A (Compustat xsgaq). The Appendix reports the robust result when using 30% of (SG&A minus R&D) plus 100% of R&D as in Peters and Taylor (2017).

2.2 Identifying superstar firms

The literature often characterizes superstars as a top number of highly successful firms in the economy. For example, Bae, Bailey, and Kang (2021) select the largest 5 or 10 firms in each country based on their market cap at the end of each year. Schlingemann and Stulz (2022) select the top 1, 3, 5, or 10 firms in the whole economy or 3 in each of Fama-French's 48 industries based on their market cap each year. Although there is no unified definition, in this paper, I identify superstars based on Autor et al. (2020)'s discussion that superstars are firms *increasingly* *dominating* their industries, leading to rising product market concentration.

In each quarter, I select the top 5% firms in their SIC two-digit industries based on their market power. To proxy firms' market power, I estimate the firm-level markup ratio from De Loecker, Eeckhout, and Unger (2020), i.e. 0.85 times the ratio of sale to the cost of goods sold (0.85 × saleq/cogsq). De Loecker, Eeckhout, and Unger (2020) show that the output elasticity of variable input 0.85 is time-invariant and contributes little to the rise in markups, so I also fix this coefficient across all stocks. In some cases, the industries include less than 20 firms in a given quarter, so I follow Cheng, Vyas, Wittenberg-Moerman, and Zhao (2023) to assign the largest markup firm as the superstar in that industry.

As many papers identify mega-firms such as Apple and Amazon as superstars, I multiply this markup ratio by the firm-level market cap to take into account the size of firms (0.85 × saleq/cogsq × market cap)[4]. Finally, I also impose the condition that firms have to increase their markup shares within their industries compared to the previous 12 quarters (3 years) to follow that intuition from Autor et al. (2020) that superstars *increasingly dominate* the market[5].

2.3 Test portfolios

In the main analysis, the test portfolios for the Fama-MacBeth regressions include 25 size × book-to-market, 10 momentum, 25 size and investment, 25 size and operating profitability sorted portfolios. In the robustness section, I use the 202 portfolios used in Giglio and Xiu (2021): 25 size × book-to-market, 17 Fama-French industry, 25 operating profitability and investment, 23 size and residual variance, 25 size and net issuance, 25 size and accruals, 25 size and momentum, and 25 size and beta. I retrieve all factor data at a quarterly frequency and annual frequency for a robust check from Kenneth French's data library[6].

2.4 Macroeconomic variables

In addition, I construct several macroeconomic variables. The per capita real consumption is the total real consumption of nondurable goods and services, divided by the total population, obtained from the US Bureau of Economic Analysis (BEA). The industrial production index measures the real output of all relevant establishments in the US, retrieved from the Federal Reserve Bank of St. Louis (FRED). The monthly aggregate US unemployment rate is from the

[4] Cheng, Vyas, Wittenberg-Moerman, and Zhao (2023) multiply the market ratio by the sales. Robust results show that my main findings are robust to the choice of either sales or market cap to identify superstars.

[5] Figure A1 shows the rise in market concentration among superstar firms and the rise of aggregate capital misallocation.

[6] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Bureau of Labor Statistics (BLS), compounded to quarterly frequency.

Besides, following Bae, Bailey, and Kang (2021), I construct the aggregate innovation proxy as a natural logarithm of one plus the number of patents divided by the population. The aggregate number of patents are from the All Technology (Utility Patents) Reports from the US Patent and Trademark Office (USPTO)[7]. Similarly, I compute the innovation proxy in each portfolio as the natural logarithm of one plus the total number of patents divided by the total market capitalization in each portfolio. I use firm-level patent data from Kogan, Papanikolaou, Seru, and Stoffman (2017).

3 Measuring and decomposing capital misallocation

In this section, I discuss the empirical measure for capital misallocation. Furthermore, I decompose the aggregate capital misallocation into three components: misallocation among superstar firms, misallocation among other firms, and misallocation between superstars and other firms.

3.1 Measuring capital misallocation

The empirical measure for capital misallocation is based on a standard Cobb-Douglas production function for each firm,

$$Y_{it} = A_{it} K_{it}^{\alpha_1} L_{it}^{\alpha_2}.$$

A firm's marginal product of capital (MPK) is given by

$$\frac{\partial Y_{it}}{\partial K_{it}} = \alpha_1 A_{it} K_{it}^{\alpha_1 - 1} L_{it}^{\alpha_2} = \alpha_1 \frac{Y_{it}}{K_{it}}$$

Up to a constant, the log MPK is the difference between log output and log capital

$$mpk_{it} = \log(\alpha_1) + \log(Y_{it}) - \log(K_{it}) \approx y_{it} - k_{it}$$

Capital misallocation is defined as the firm-level log MPK dispersion. Following David, Schmid, and Zeke (2022) and David, Hopenhayn, and Venkateswaran (2016), I compute the misallocation as the cross-sectional variance across all firm MPKs within each quarter t as

$$\sigma^2_{mpk,t} = \frac{1}{N-1} \sum_{i=1}^{N} (mpk_{it} - \mu_{mpk,t})^2.$$

where $\sigma^2_{mpk,t}$ and $\mu_{mpk,t} = \frac{1}{N} \sum_{i=1}^{N} mpk_{it}$ denote the variance and the mean MPK of the economy.

The intuition of the capital misallocation is as follows. To minimize the total factor productivity (TFP) loss, the economy needs to allocate capital efficiently. The TFP loss is at the

[7] https://www.uspto.gov/web/offices/ac/ido/oeip/taf/h_at.htm

minimum if firm-level MPKs equalize, i.e. $\sigma^2_{mpk,t} = 0$, the allocation that maximizes the static production of all firms in the economy. If MPK varies substantially across firms, it implies that the economy forgoes the opportunity to increase the aggregate output by reallocating capital from low MPK to high MPK firms. A lower MPK among firms in the cross-section implies misallocated capital that high MPK firms could have more efficiently utilized.

Based on the production function, I compute the firm-level MPK as the log ratio of output to lagged capital. I use sales as output and net property, plant, and equipment (ppentq) as physical capital plus intangible capital estimated from Eisfeldt and Papanikolaou (2013). The misallocation shocks capture the recessions better when we take the lagged capital. I exclude firm-quarter observations with a ratio of intangible to tangible capital exceeding 10, because unlikely it is more than 10 times the mean ratio as discussed in David, Schmid, and Zeke (2022). Besides, I winsorize the log MPK at 1% and 99% in each quarter to avoid outliers.

Finally, capital misallocation, i.e. MPK dispersion, is the cross-sectional variance of firm-level MPK in each quarter. Furthermore, I propose shocks to capital misallocation as the log changes of capital misallocation with respect to the 4-quarter lag. I take annual log changes to remove seasonal fluctuations of sales that influence the measure

$$\Delta\sigma^2_{mpk,t} = \sigma^2_{mpk,t} - \sigma^2_{mpk,t-4}.$$

[Figure 1 about here.]

Figure 1 shows the MPK distribution over time. Panel A shows that the MPK distribution is right-skewed and the distribution becomes more heavily tailed over time. Panel B plots the percentiles of the MPK distribution in each quarter. Superstars are firms in the further right tail of MPK distribution, so the skewness of MPK distribution captures MPK of superstars. Positive changes in the skewness of MPK indicate increases in MPK of superstars relative to other firms, which raises the MPK spread.

3.2 Decomposing capital misallocation

To examine which component of misallocation is important for asset pricing and which subset of firms drives the misallocation, I decompose the capital misallocation into contributions by each subset of firms. In each quarter t, capital misallocation is given by the dispersion in firm-level (log) MPKs in the economy

$$\sigma^2_{mpk,t} = \frac{1}{N-1}\sum_{i=1}^{N}(mpk_{it} - \mu_{mpk,t})^2$$

where $\sigma^2_{mpk,t}$ and $\mu_{mpk,t} = \frac{1}{N}\sum_{i=1}^{N} mpk_{it}$ denote the variance and the mean MPK of the whole sample. Dropping the time subscript for convenience and expanding the variance yield

$$\begin{aligned}
\sigma^2_{mpk} &= \frac{1}{N-1}\sum_{i=1}^{N}(mpk_i - \mu_{mpk})^2 \\
&= \frac{1}{N-1}\sum_{i=1}^{N}(mpk_i^2 - 2mpk_i\mu_{mpk} + \mu^2_{mpk}) \\
&= \frac{1}{N-1}\sum_{i=1}^{N} mpk_i^2 - 2\frac{1}{N-1}\mu_{mpk}\sum_{i=1}^{N} mpk_i + \frac{1}{N-1}\sum_{i=1}^{N}\mu^2_{mpk} \\
&= \frac{1}{N-1}\sum_{i=1}^{N} mpk_i^2 - 2\frac{N}{N-1}\mu^2_{mpk} + \frac{N}{N-1}\mu^2_{mpk}
\end{aligned}$$

Hence,

$$\sigma^2_{mpk} + \frac{N}{N-1}\mu^2_{mpk} = \frac{1}{N-1}\sum_{i=1}^{N} mpk_i^2 \tag{1}$$

$$\iff (N-1)\sigma^2_{mpk} + N\mu^2_{mpk} = \sum_{i=1}^{N} mpk_i^2 \tag{2}$$

Assume that firms are sorted into K portfolios, in which we allow for different numbers of stocks in each portfolio and denote it as N_k, where $\sum_{k=1}^{K} N_k = N_1 + N_2 + \cdots + N_K = N$. We can derive Equation (2) analogously for each portfolio with the corresponding variance $\sigma^2_{mpk,k}$ and mean $\mu_{mpk,k}$. Furthermore, we can decompose the right-hand side of Equation (1) into

$$\begin{aligned}
\sigma^2_{mpk} + \frac{N}{N-1}\mu^2_{mpk} &= \frac{1}{N-1}\left[\sum_{i=1}^{N_1} mpk_i^2 + \sum_{i=1}^{N_2} mpk_i^2 + \ldots + \sum_{i=1}^{N_K} mpk_i^2\right] \\
&= \frac{1}{N-1}\left[\sum_{k=1}^{K}(N_k-1)\sigma^2_{mpk,k} + \sum_{k=1}^{K} N_k\mu^2_{mpk,k}\right] \\
\iff \sigma^2_{mpk} &= \frac{1}{N-1}\sum_{k=1}^{K}(N_k-1)\sigma^2_{mpk,k} + \frac{1}{N-1}\left[\sum_{k=1}^{K} N_k\mu^2_{mpk,k} - N\mu^2_{mpk}\right]
\end{aligned}$$

Since the total sample mean equals the weighted average of the subsample means, weighted by the number of observations,

$$\begin{aligned}
\mu_{mpk} &= \frac{N_1\mu_{mpk,1} + N_2\mu_{mpk,2} + \ldots + N_K\mu_{mpk,K}}{N_1 + N_2 + \ldots + N_k} \\
&= \frac{1}{N}\sum_{k=1}^{K} N_k\mu_{mpk,k} \\
\Rightarrow N\mu^2_{mpk} &= \frac{1}{N}\left(\sum_{k=1}^{K} N_k\mu_{mpk,k}\right)^2
\end{aligned}$$

Hence,

$$\begin{aligned}
\sigma^2_{mpk} &= \frac{1}{N-1}\sum_{k=1}^{K}(N_k-1)\sigma^2_{mpk,k} + \frac{1}{N-1}\left[\sum_{k=1}^{K} N_k\mu^2_{mpk,k} - \frac{1}{N}\left(\sum_{k=1}^{K} N_k\mu_{mpk,k}\right)^2\right] \\
&= \frac{1}{N-1}\sum_{k=1}^{K}(N_k-1)\sigma^2_{mpk,k} + \frac{N}{N-1}\left[\underbrace{\frac{1}{N}\sum_{k=1}^{K} N_k\mu^2_{mpk,k}}_{\mathbb{E}(\mu^2_{mpk,k})} - \underbrace{\left(\frac{1}{N}\sum_{k=1}^{K} N_k\mu_{mpk,k}\right)^2}_{\mathbb{E}(\mu_{mpk,k})^2}\right]
\end{aligned}$$

Recognizing that the second and the third terms capture the second and the (squared) first moment or the expected value of the subsample mean MPKs, we can further rewrite the aggregate misallocation as

$$\sigma^2_{mpk} = \underbrace{\sum_{k=1}^{K}\frac{N_k-1}{N-1}\sigma^2_{mpk,k}}_{\text{Within-group misallocation}} + \underbrace{\frac{N}{N-1}\mathrm{Var}(\mu_{mpk,k})}_{\text{Between-group misallocation}} \tag{3}$$

where $\mathrm{Var}(\mu_{mpk})$ denotes the variance of the portfolio mean MPKs. Thus, we can decompose the aggregate capital misallocation into the portfolio-specific misallocation, i.e., the misallocation among the firms in each portfolio and the dispersion in the *mean* MPKs across portfolios.

To separate superstars, I sort the sample into two portfolios each quarter: the superstar portfolio which includes superstar firms ($k = *$), and the non-superstar portfolio which includes the remaining firms ($k = 0$). The second term of Equation (3) simplifies to the case when $K = 2$. Specifically,

$$\begin{aligned}
\mathrm{Var}(\mu_{mpk,k}) &= \frac{1}{N}\sum_{k=1}^{2} N_k\mu^2_{mpk,k} - \left(\frac{1}{N}\sum_{k=1}^{2} N_k\mu_{mpk,k}\right)^2 \\
&= \frac{N_0}{N}\mu^2_{mpk,0} + \frac{N_*}{N}\mu^2_{mpk,*} - \frac{N_0^2}{N^2}\mu^2_{mpk,0} - \frac{N_*^2}{N^2}\mu^2_{mpk,*} - 2\frac{N_0N_*}{N^2}\mu_{mpk,0}\mu_{mpk,*} \\
&= \frac{N_0(N-N_0)}{N^2}\mu^2_{mpk,0} + \frac{N_*(N-N_*)}{N^2}\mu^2_{mpk,*} - 2\frac{N_0N_*}{N^2}\mu_{mpk,0}\mu_{mpk,*} \\
&= \frac{N_0N_*}{N^2}(\mu^2_{mpk,0} + \mu^2_{mpk,*} - 2\mu_{mpk,0}\mu_{mpk,*}) \\
&= \frac{N_0N_*}{N^2}(\mu_{mpk,0} - \mu_{mpk,*})^2
\end{aligned}$$

Hence, we can rewrite Equation (3) in this case as

$$\sigma^2_{mpk} = \underbrace{\frac{N_0-1}{N-1}\sigma^2_{mpk,0}}_{\text{Misallocation among non-superstars}} + \underbrace{\frac{N_*-1}{N-1}\sigma^2_{mpk,*}}_{\text{Misallocation among superstars}} + \underbrace{\frac{N_0N_*}{N(N-1)}(\mu_{mpk,0} - \mu_{mpk,*})^2}_{\text{MPK spread}} \tag{4}$$

Hence, I decompose the capital misallocation into three components: the misallocation among superstars, the misallocation among non-superstars, and the misallocation due to the (squared) difference in the *mean* MPK between the two portfolios, referred to as "MPK spread". Finally, we can decompose the misallocation shocks into

$$\begin{aligned}
\Delta\sigma^2_{mpk,t} &= \sigma^2_{mpk,t} - \sigma^2_{mpk,t-4} \\
&= \underbrace{\Delta \frac{N_{0t}-1}{N_t-1}\sigma^2_{mpk,0t}}_{\text{Misallocation shocks to non-superstars}} + \underbrace{\Delta \frac{N_{*t}-1}{N_t-1}\sigma^2_{mpk,*t}}_{\text{Misallocation shocks to superstars}} \\
&\quad + \underbrace{\Delta \frac{N_{0t}N_{*t}}{N_t(N_t-1)}(\mu_{mpk,0t} - \mu_{mpk,*t})^2}_{\text{Shocks to the MPK spread}}.
\end{aligned}$$

[Figure 2 about here.]

Figure 2 plots the time series of the misallocation shocks. Periods of high misallocation shocks coincide with the NBER recessions. This pattern implies the countercyclicality of capital misallocation: MPK dispersion rises during economic downturns (David, Schmid, and Zeke, 2022). Shocks to the MPK spread, i.e. the misallocation between superstars and non-superstars display the clearest cyclical patterns.

In an efficient market, capital flows towards its most productive uses, i.e. firms with the highest MPK would attract more investment. Intuitively, when superstar firms dominate this capital inflow, it may not always be due to their superior productivity or innovation. If these firms' higher MPKs result from market distortions, such as barriers to entry for competitors, then the higher MPK reflects an inefficiency rather than a pure productivity advantage. This misallocation can lead to slower economic growth by preventing capital from reaching potentially innovative but smaller competitors.

4 Asset pricing results

In this section, I show the cross-sectional asset pricing results of shocks to capital misallocation and its components. I first run the Fama-MacBeth regressions and then form the factor-mimicking portfolios sorted on individual stock exposure to the shocks.

4.1 Cross-sectional analysis

In this section, I examine whether the aggregate misallocation shocks and each component are priced in the cross-section of expected stock returns. Following the standard Fama-MacBeth two-stage procedure, for each test portfolio i, I first estimate the factor loadings (β_{ik}) using time-series regressions of portfolio excess returns on the risk factor(s)

$$R^e_{it} = \alpha_i + \sum_k \beta_{ik} f_{kt} + u_{it},$$

where k is the number of risk factors. Second, for each time t, I estimate the price of risk for each factor ($\lambda_{k,t}$) using cross-sectional regressions

$$R^e_{it} = \lambda_{0,t} + \sum_k \lambda_{kt} \hat{\beta}_{ik} + \varepsilon_{i,t}.$$

The risk premium for each factor k is then the time-series average of the price of risk $\lambda_k = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_{kt}$. As a convenience to compare the magnitudes of the asset pricing results, I standardize the misallocation shocks and each component. Table 1 reports results for the second-stage regressions. Panel A shows that results in the cross-section of 25 size × book-to-market and 10 momentum portfolios, the CAPM cannot explain the difference in average returns across portfolios since the price of risk is statistically insignificant in Model (1). The adjusted R-squared is close to zero. In contrast, when Model (2) includes the market factor and aggregate capital misallocation shocks, the aggregate misallocation shocks have a negative price of risk, although not significant.

[Table 1 about here.]

When the model includes shocks to each component as a separate factor, Model (5), (8), and (9) show that shocks to the MPK spread carry a negative price of risk. The price of risk is significantly priced at the 5% level across all models. Adding this factor to the CAPM increases the cross-section R-squared by 65%. In contrast, adding other shocks does not improve the fit any further. The findings are consistent in Panel B when the models include the Fama and French (1992, 1993) three factors and momentum factor and the cross-section includes 25 size × investment and 25 size × operating profitability portfolios. While the significance of the price of risk of other decomposed shocks is not robust to different t-ratios, the significance of the price of risk of shocks to the MPK spread remains consistent.

Intuitively, a positive shock to the MPK spread raises the difference in the mean MPK between superstars and non-superstars. Superstars on average have higher MPK, while other firms on average have lower MPK, leading to an increase in the MPK dispersion. The economy as a result operates as a higher capital misallocation. Thus, an increase in capital misallocation represents negative news for investors whose marginal utility depends on future consumption growth. If the rise in the MPK spread lowers economic growth, shocks to the MPK spread carry a negative price of risk. While other components do not yield significant results, these results imply that the price of risk of aggregate capital misallocation is mainly driven by the difference in the MPK level of superstars compared with other firms in the economy.

[Figure 3 about here.]

Figure 3 plots the realized versus predicted returns from the cross-section of 25 size $\times$ book-to-market and 10 momentum portfolios. Panel E shows that adding shocks to the MPK spread to the CAPM reduces the pricing error (RMSE) to 1.59. Panel F reports the same pricing error when the model includes other shocks. These results confirm an important role of superstars in asset pricing: The negative price of risk of capital misallocation shocks terms from the difference in the MPK level between the superstars and non-superstars.

The value premium, i.e. firms with high book-to-market have on average higher expected returns, is well documented in the literature. Parker and Julliard (2005) discuss that value stocks have high average returns because they pay off poorly before and early in recessions, captured by ultimate consumption risk. Thus, the expected excess return of value-minus-growth stocks predicts consumption growth. Since higher capital misallocation also predicts a lower consumption growth rate (Dou, Ji, Tian, and Wang, 2023; David, Hopenhayn, and Venkateswaran, 2016), firms' book-to-market and exposure to misallocation shocks must align in the sign direction.

Based on these mechanisms, I examine the factor loadings in the 25 portfolios formed on size $\times$ book-to-market ratio. I test separately the exposures to the aggregate misallocation shocks and shocks to each component, controlling for the market risk. If the negative price of risk lines up with the portfolios, mechanically firms with higher book-to-market ratios are more negatively exposed to shocks to the MPK spread. In other words, value stocks should have lower betas for shocks to the MPK spread than growth stocks.

[Table 2 about here.]

Table 2 reports the first-stage betas across the portfolios. In Panel A, the decreasing trend in the beta of the aggregate misallocation shocks, when portfolios are sorted from low to high book-to-market, reflects the mechanics for the negative price of risk. However, no betas are insignificant. In Panel B, the misallocation shocks in the non-superstar portfolio show no significant betas. Thus, these two factors are seemingly spurious factors. In Panel C, the misallocation shocks in the superstar portfolio, most betas are negative and large but weakly significant. Only shocks to the MPK spread shown in Panel D display a clear decreasing trend across the book-to-market portfolios within each size. Most betas (24/25) are significant, consistent with the hypothesis that value stocks load more negative exposure to the shocks than growth stocks.

4.2 Individual stock exposure analysis

Next, I create portfolios sorted on individual stock exposure to capital misallocation shocks and each component. To estimate the firm-level exposure, for each stock, I regress the quarterly excess returns either on misallocation shocks or on the decomposed misallocation shocks by a rolling window of 20 quarters (with a minimum of 12 quarters available).

$$R^e_{it} = \alpha_i + \beta_{it}\Delta z_t + \varepsilon_{it}, \quad t = t - 20 \rightarrow t. \quad z \in \{\sigma^2_{mpk}, \sigma^2_{mpk,0}, \sigma^2_{mpk,*}, \mathrm{Var}(\mu_{mpk,k})\}$$

The stock's exposure to the misallocation shocks equals the misallocation-beta estimated from these regressions. Each quarter, I sort stocks into quintiles based on their misallocation-beta, lagging by one quarter. I hold and rebalance the portfolio every quarter.

[Table 3 about here.]

Table 3 reports the average (expected) returns and the abnormal returns (alpha) when stocks are sorted into portfolios based on the exposure to the MPK spread. Portfolio returns are value-weighted by market cap. Across the portfolios, the average excess returns decrease as the exposure to shocks to the MPK spread rises from Quintile 1 (11.6%) to Quintile 5 (6.8%). Importantly, stocks in Quintile 1 have a negative exposure to exposure to shocks to the MPK spread. The expected return reduces when misallocation increases, i.e. a positive shock to misallocation, making these stocks risky. Hence, they carry higher risk premia. Whereas, stocks in Quintile 5 have a low expected return. These stocks have a positive exposure to shocks to the MPK spread. That is, their expected returns increase when misallocation rises, making them a hedge. Thus, these stocks carry lower risk premia. The long-short portfolio (Q5–Q1) has an average excess return of -4.8% per year with a t-statistic of -2.64, consistent with the negative price of risk of shocks to the MPK spread.

The long-short portfolio has a negative and significant abnormal return (alpha) in all asset pricing models - the CAPM, Fama and French (1992, 1993) three-factor, and the Fama and French (2015) five-factor models. Interestingly, the market beta is insignificant in the long-short portfolios across all models. The Appendix shows the same set of results for the exposure to the aggregate misallocation shocks and shocks to the misallocation within each portfolio. Yet, the results are insignificant. These results strengthen the mechanism for the negative price of risk of the shocks to the MPK spread.

Table A4 reports the results using the equally weighted returns. The average returns in each portfolio become higher but the long-short returns remain negative at −3.2% per year and significant at the 5% level. Across the CAPM, Fama and French (1992, 1993) three-factor, and the Fama and French (2015) five-factor models, the alphas are significantly negative so the standard asset pricing models cannot explain the abnormal returns to the exposure to shocks to the MPK spread.

Table A5 reports the value-weighted average characteristic of the stocks in each quintile portfolio. The results show that, on average, stocks negatively exposed to shocks to the MPK spread (Quintile 1) tend to be smaller (low market cap), lower market power (markup), value firma, young (lower duration), but more innovative than stocks positively exposes to shocks (Quintile 5). Thus, non-superstar firms tend to be negatively exposed to shocks to the MPK spread. Whereas, superstar firms tend to be positively exposed to theses shocks. Consistently, non-superstar firms tend to be risky, and superstar firms tend to provide a hedge during economic downturns against shocks to the MPK spread.

[Table 4 about here.]

After sorting stocks into the portfolios, we can examine in the post-formation period whether the beta of each portfolio lines up. Table 4 reports the coefficients from regressing value-weighted/equally weighted returns of each portfolio on the shocks to MPK spread and the market factor. The post-formation portfolios show a negative beta in the lowest quintile and a positive beta in the highest quintile. Furthermore, the intercept is insignificant, implying that no returns remain unexplained in the portfolio. Thus, the exposure to MPK spread of the long-short portfolio returns is consistent.

4.3 Spanning test analysis

Next, I study the diversification benefits of each portfolio. This section tests whether the portfolio exposed to shocks to the MPK spread adds to the mean-variance efficiency of other portfolios, and vice versa. I regress the returns of the test assets on the market and the returns of the benchmark assets. If the test assets exactly price the benchmark assets, then the intercept alphas should equal zero. This is known as the Jensen measure. Under the null hypothesis, the benchmark assets span the test assets. If the Jensen measure is significantly different from zero, then adding the test assets to the benchmark improves the mean-variance efficiency.

[Table 5 about here.]

Table 5 shows the results. In Panel A, the benchmark assets are the returns to the long-short portfolio exposed to the aggregate misallocation shocks. The Jensen measure is significantly different from zero for the portfolio exposed to shocks to the MPK spread as the test asset. Therefore, adding the portfolio exposed to shocks to the MPK spread to the portfolio exposed to the aggregate misallocation shocks improves the mean-variance efficiency.

Panel B shows the same set of results except that the benchmark assets are the returns to the long-short portfolio exposed to shocks to the MPK spread. The portfolio exposed to shocks to the MPK spread prices all benchmark portfolios. Hence, Adding the portfolio exposed to shocks to the MPK spread improves the mean-variance efficiency of the portfolio exposed to the total misallocation shocks and other portfolios.

5 Predicting future economic growth

A candidate for ICAPM state variables must forecast the investment opportunities. In this section, I examine the predictability of the MPK spread for future economic growth. Particularly, I use the non-standardized variables to avoid forward-looking bias and run the standard predictive regressions.

Panel A of Table 6 reports the results of the following predictive regression:

$$\Delta CG_{t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k}$$

where $CG_{t:t+k}$ is the per capita real consumption growth (nondurable and services) in k quarters. In each quarter, real consumption per capita is the total real consumption of nondurable goods and services, divided by the total population. The predictive variables z_t are the aggregate misallocation, misallocation among non-superstars, misallocation among superstars, and the MPK spread. The columns show results for $k = 1, 4, 8$ and 12 quarters. I calculate standard errors based on Hodrick (1992) and based on Newey and West (1987) with $k - 1$ lags.

[Table 6 about here.]

From 1 to 8 quarters ahead, the MPK spread negatively predicts changes in per capita real consumption growth. The coefficient is significant at 1% level, with an adjusted R-squared of more than 6% across the quarters. The magnitude of the forecast is also larger at a longer horizon. The aggregate misallocation, misallocation among non-superstars, and misallocation among superstars on the other hand are statistically and economically insignificant.

Panel B of Table 6 reports the results of the following predictive regression:

$$\Delta IP_{t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k}$$

where $IP_{t:t+k}$ is the industrial production growth in k quarters. From 8 to 12 quarters forward, the MPK spread also predicts negative changes in industrial production growth. Other variables in contrast yield no significant predictive results.

Panel C of Table 6 reports the results of the following predictive regression:

$$\Delta E_{t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k}$$

where $E_{t:t+k}$ is the log employment growth in k quarters. The MPK spread on the other hand predicts higher changes in employment growth. Other variables in contrast yield no significant predictive results.

Consistently, shocks to the MPK spread also robustly predict negative economic growth. Table 11 reports the same set of regressions when aggregate capital misallocation shocks and shocks to the MPK spread act as predictors. Shocks to the MPK spread negatively predict consumption growth, industrial growth, and employment growth. Although the aggregate capital misallocation shocks have some predictive power in some models, the positive sign is counter-intuitive since higher misallocation as in the literature predicts lower economic growth and hence consumption growth (David, Hopenhayn, and Venkateswaran, 2016).

Finally, I test the mechanism that the MPK spread dampens innovation activity in the short run. I test the predictability of the MPK spread for innovation growth using the following predictive regression:

$$\Delta I_{t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k}$$

where $I_{t:t+k}$ is the innovation growth in k quarters.

[Table 7 about here.]

Table 7 reports the results for $k = 1, 2, 3, 4, 5$ and 6 quarters. I construct the innovation proxy I_t as the natural logarithm of one plus the total number of patent applications divided by the total firm market cap on the aggregate level, within superstars, and within non-superstars portfolios. Panel A shows that the MPK spread predicts negative changes in innovation growth. Both statistical significance and economic significance are large comparing to the aggregate capital misallocation.

Panel B uses changes in innovation growth among non-superstars as the dependent variable. In all quarters, the MPK spread significantly predicts negative changes in innovation growth among non-superstars. Both economic significance and statistical significance increase with the horizon from 1 to 5 quarters. Whereas, the coefficients for aggregate misallocation across all quarters are not significant.

Yet, when Panel C uses changes in innovation growth among superstars as the dependent variable, no coefficients are statistically and economically significant. These results imply a higher discrepancy in the mean productive use of capital between superstars and non-superstars discourages innovation activity in the economy, especially among non-superstars, leading to lower economic growth in the long run. This implication is consistent with Bae, Bailey, and Kang (2021) who also find that higher stock market concentration is associated with lower innovation activity. It is also consistent with Kung and Schmid (2015) who show that innovation endogenously generates long-run fluctuation in economic growth. In contrast, the aggregate capital misallocation, the misallocation among superstars and among non-superstars do not show predictive power and their shocks do no carry a significantly negative price of risk. Therefore, only the MPK spread is a good candidate state variable.

6 Consistency with the ICAPM

In this section, I examine whether shocks to capital misallocation between superstar and non-superstar firms as a risk factor satisfy the restrictions under the ICAPM framework. Maio and Santa-Clara (2012) proposes three restrictions associated with the ICAPM. The first restriction concerns the forecasting power of state variables for investment opportunities. Specifically, the state variables must forecast the first moment (expected returns) or second moment (market volatility) of aggregate stock returns.

Subsequently, I examine whether aggregate capital misallocation or its component predicts future stock market excess returns. Table 8 reports the results of the following predictive regression:

$$R^e_{mkt,t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k} \tag{5}$$

where $R^e_{mkt,t:t+k} = R^e_{mkt,t+1} + \cdots + R^e_{mkt,t+k}$ is continuously compounded market excess return, using the CRSP value-weighted returns in excess of the US one-month Treasury Bills rate, from the end of quarter t to the end of quarter $t+k$.

I construct out-of-sample predictability following Campbell and Thompson (2008). I estimate the Equation (5) using all available returns up to quarter t with a minimum of 80 quarters. Then I use the estimates $\hat{\alpha}_t$ and $\hat{\beta}_t$, using data from the start of the sample period to quarter t, to forecast the k-quarter excess return from quarter t to $t+k$:

$$\hat{R}^e_{mkt,t:t+k} = \hat{\alpha}_t + \hat{\beta}_t z_t,$$

The out-of-sample R-squared for the predictive regressions uses the historical average excess market return as a benchmark as follows:

$$R^2_{OOS} = 1 - \frac{\sum_{t=80}^{T-k}(R_{mkt,t:t+k} - \hat{R}_{mkt,t:t+k})^2}{\sum_{t=80}^{T-k}(R_{mkt,t:t+k} - k\bar{R}_{mkt,1:t})^2},$$

where $\bar{R}_{mkt,1:t}$ is the average excess market return up to quarter t, and T represents the length of the return series. The summation covers all quarters starting in quarter 241. The out-of-sample R-squared can be negative if the predictive variable has poor out-of-sample predictability.

[Table 8 about here.]

As a result, the MPK spread negatively predicts the future stock market returns in all quarters. The coefficient is significant at the 5% level for 1 quarter and 1% level for 4 quarters ahead. The in-sample R-squared is approximately 1.8% for 1 and 4 quarters and 2.8% for 8 quarters. The out-of-sample R-squared is positive and is approximately 0.2% and 0.5%. Thus, the MPK spread satisfies the first restriction for the ICAPM although the goodness of fit is relatively low.

The second restriction concerns the relationship between the predictive power of the state variable and the risk premium of the risk factor. Specifically, if a state variable forecasts positive (negative) expected returns, then the innovation or changes in the state variable as a risk factor should earn a positive (negative) price of risk. Previous findings show that the MPK spread negatively predicts investment opportunities and shocks to the MPK spread are negatively priced in the cross-sectional tests. Thus, these findings satisfy the second restriction for the ICAPM.

Intuitively, an asset negatively exposed to innovations in a state variable also negatively covaries with future expected returns. Such an asset provides a hedge against reinvestment risk, as it delivers higher returns when aggregate returns are expected to be lower. Because it offers protection during economic downturns, a risk-averse investor would be willing to hold this asset even if it offers a lower expected return. Therefore, a negative covariance with the innovation of the state variable results in a negative price of risk for the factor, implying that investors accept lower returns for the benefit of hedging against future economic downturns.

The third restriction requires that the estimated market price of risk, which reflects the risk-aversion coefficient of the representative investor, must be economically plausible. The ICAPM in unconditional form with a hedging risk factor and the market has the form

$$\mathbb{E}(R^e_{i,t+1}) = \gamma_m \ \mathrm{Cov}(R^e_{i,t+1}, MKT_{t+1}) + \gamma_z \ \mathrm{Cov}(R^e_{i,t+1}, \Delta z_{t+1})$$

Intuitively, for an asset that does not provide a hedge against changes in current aggregate wealth, as it pays in good times (periods with high returns on wealth), a risk-averse investor would be willing to hold such an asset only if it offers a premium over the risk-free rate. Following Maio and Santa-Clara (2012), I estimate the price of risk of each factor γ using the GMM system with $N+2$ moment conditions:

$$g_T(\mathbf{b}) \equiv \frac{1}{T}\sum_{t=0}^{T-1}\begin{pmatrix} R^e_{i,t+1} - \gamma_m R^e_{i,t+1}(MKT_{t+1} - \mu_m) \\ -\gamma_z R^e_{i,t+1}(\Delta z_{t+1} - \mu_z) \\ MKT_{t+1} - \mu_m \\ \Delta z_{t+1} - \mu_z \end{pmatrix} = 0, \quad i = 1, \ldots, N. \tag{6}$$

The first factor in this model is the market with unconditional mean μ_m. The second factor is the shocks to the state variable z, where $z \in \{\sigma^2_{mpk}, \sigma^2_{mpk,0}, \sigma^2_{mpk,*}, \mathrm{Var}(\mu_{mpk,k})\}$. To test the goodness of fit, I construct the mean absolute pricing error (MAE)

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |\hat{\alpha}_i|,$$

where $\hat{\alpha}_i$, $i = 1, \ldots, N$ represents the pricing errors associated with the N test assets. The second measure is the cross-sectional OLS R-squared:

$$R^2_{\mathrm{OLS}} = 1 - \frac{\mathrm{Var}_N(\hat{\alpha}_i)}{\mathrm{Var}_N(\bar{R}_i)},$$

where $\bar{R}_i = \frac{1}{T}\sum_{t=0}^{T-1} R^e_{i,t+1}$ is the average excess return for asset i. R^2_{OLS} measures the fraction of the cross-sectional variance in average excess returns explained by the model.

[Table 9 about here.]

Table 9 reports the estimation of the first-stage GMM using equally weighted errors, using the same test portfolio as in Maio and Santa-Clara (2012). In particular, the coefficient of relative risk aversion (RRA) should fall within a reasonable range, typically between 1 and 10 (Mehra and Prescott, 1985). In all models, the risk price of the market is significantly positive and has a magnitude of approximately 5. However, only Regression (4) shows a significant negative price of risk of the shocks to the state variable, particularly the MPK spread. This result is consistent with the results in the Fama-Macbeth regressions. Thus, these findings satisfy the third restriction.

In conclusion, the MPK spread predicts changes in economic growth and aggregate stock returns. Shocks to the MPK spread, exacerbating capital misallocation, represent bad news for investors whose marginal utility depends on long-run consumption growth. Hence, consistent with the ICAPM framework, the MPK spread is a state variable, and shocks to the MPK spread are a priced risk factor.

7 Robustness

In this section, I check the robustness of the main findings. In brief, the main results are robust to using alternative definitions of superstars, additional test portfolios in the Fama-MacBeth regressions, value-weighted capital misallocation, separating the type of capital, subsample periods, and annual frequency data.

7.1 Alternative definitions of superstar firms

In this section, I follow the common method to identify superstars as a number of largest firms based on their market value (Bae, Bailey, and Kang, 2021; Schlingemann and Stulz, 2022). One disadvantage of this method is that we cannot identify exactly the number of superstars each quarter. The number of listed firms in the US stock market increased up to the 2000s and has reduced considerably ever since, so it is difficult to fix the number of superstars in the economy.

[Table 10 about here.]

Yet I show that essentially the top 5% firms by their markups in respective industries are important for the price of risk of misallocation shocks. First, in the top 10, 20, and 50 market cap firms, the MPK spread component is significantly and negatively priced, consistent with the main result because these firms are identical to superstars defined by markup. As the superstar portfolio includes more firms, the price of risk of MPK spread reduces and becomes less significant. After the superstar portfolio includes the largest 1,000 firms, the MPK spread component is no longer priced but the misallocation within the superstar portfolio is, implying that the presence of superstars deters capital reallocation to other firms in the portfolio.

Second, the price of risk for misallocation shocks is no longer significantly priced when I exclude all superstars defined by markup. In contrast, the price of risk for misallocation shocks is lower but does not disappear if I exclude the top 10, 20, or 50 firms by market cap. Thus, these results show that the difference between the MPK of the top 5% firms by their markups in respective industries and the MPK of other firms drives the price of risk of misallocation shocks[8].

Besides, Table A2 shows no results when we equally split the sample into the top and bottom half by markup, when we randomly select 50 firms 500 times, and when we select the bottom 50 firms by markup.

7.2 Predictability of risk factors

Consistently, if a state variable predicts future economic growth and stock market returns, then shocks or innovation in the state variable should also predict these variables since they carry the same information. Thus, I run the same predictive regressions using shocks to the aggregate capital misallocation and shocks to the MPK spread.

[Table 11 about here.]

Panel A of Table 11 reports the results of predicting per capita real consumption growth (nondurable and services) in k quarters. The predictive variables zt are shocks to the aggregate misallocation and the MPK spread. The columns show results for $k = 1, 4, 8, 12$ and 20 quarters. In all quarters forward, higher shocks to the MPK spread predict lower changes in per capita real consumption growth. The coefficient is the most significant at 8 and 12 quarters forward, with an adjusted R-squared of 6-7% in Regression (6) and (8). The aggregate misallocation shocks on the other hand have a statistically significant power in 4, 8, and 12 quarters but the economic significance is almost close to zero and has a counter-intuitive sign since higher misallocation as in the literature predicts lower economic growth hence consumption growth (David, Hopenhayn, and Venkateswaran, 2016).

Panel B reports the results of predicting industrial production growth. In 8,12, and 20 quarters forward, higher shocks to the MPK spread also predict lower changes in industrial production growth. Panel C reports the results of predicting employment growth. Although the aggregate misallocation shocks have predictive power in 8 and 12 quarters ahead, the sign is not economically intuitive. Shocks to the MPK spread on the other hand predict negative changes in employment growth.

Finally, Panel D reports the results of predicting stock market excess returns. Shocks to the MPK spread negatively predict the future stock market returns in 4 and 12 quarters. The

[8] In unreported results, I show that the main results are robust to using the top 5 firms by markup within industries instead of the top 5%. The results are less strong but remain significant when I remove the restriction that the markup share of superstars must rise over the 12 quarters. Besides, the results are robust to using a period of 1, 4, or 8 quarters.

coefficient is significant at the 5% level for 4 quarters and 1% level for 20 quarters. The in-sample R-squared is approximately 4.1% for 4 quarters and 2.0% for 20 quarters. The out-of-sample R-squared is positive and is approximately 0.7% and 1.6%.

7.3 Additional test portfolios

This section shows the robustness of the main results by using a different set of test portfolios. Table 12 reports the pricing results in the cross-section of 202 portfolios used in Giglio and Xiu (2021): 25 size × book-to-market, 17 Fama-French industry, 25 operating profitability and investment, 23 size and residual variance, 25 size and net issuance, 25 size and accruals, 25 size and momentum, and 25 size and beta.

[Table 12 about here.]

Table 12 reports results. The price of risks of the aggregate misallocation shocks loses significance when included in the CAPM and Fama and French (1992, 1993) three-factor model. Yet, in all models, only the shocks to the MPK spread display a negative price of risk, with a statistical significance of less than 1%. Although all intercepts are significant, misallocation shocks and the component as macroeconomic risk factors are non-return based and nontradable, so we cannot emphasize the significance of the intercepts unless they are implied from a theoretical model.

7.4 Value-weighted capital misallocation

The Appendix derives the general formula for the subsample decomposition of the value-weighted variance. The value-weighted capital misallocation has the form

$$\sigma^2_{mpk,w} = \underbrace{\frac{N}{N-1}\sum_{k=1}^{K}\frac{N_k-1}{N_k}\Omega_k\sigma^2_{mpk,w,k}}_{\text{Within-group misallocation}} + \underbrace{\frac{N}{N-1}\sum_{k=1}^{K}\Omega_k(\mu_{mpk,w,k}-\mu_{mpk,w})^2}_{\text{Between-group misallocation}}$$

where $\Omega_k = \sum_{i\in k} w_i$ is the total weight for each portfolio, and w_i is the weight of each stock. I normalize the weights so that $\sum_{k=1}^{K}\Omega_k = 1$. Furthermore, $\mu_{mpk,w} = \sum_{i=1}^{N} w_i mpk_i$ is the value-weighted mean MPK in the whole sample, and $\mu_{mpk,w,k} = \sum_{i\in k}\frac{w_i}{\Omega_k}mpk_i$ is the value-weighted mean MPK in each portfolio.

In the case when $k = 2$, the value-weighted capital misallocation has the form

$$\sigma^2_{mpk,w} = \underbrace{\frac{N}{N-1}\frac{N_0-1}{N_0}\Omega_0\sigma^2_{mpk,w,0}}_{\text{Misallocation among non-superstars}} + \underbrace{\frac{N}{N-1}\frac{N_*-1}{N_*}\Omega_*\sigma^2_{mpk,w,*}}_{\text{Misallocation among superstars}}$$
$$+ \underbrace{\frac{N}{N-1}\left[\Omega_0(\mu_{mpk,w,0}-\mu_{mpk,w})^2 + \Omega_*(\mu_{mpk,w,*}-\mu_{mpk,w})^2\right]}_{\text{MPK spread}}$$

Table 13 reports results using Giglio and Xiu (2021)'s 202 test portfolios. When the model includes the market, shocks to the aggregate capital misallocation are significantly and negatively priced. However, the significance vanishes when the model includes the Fama and French (1992, 1993) three factors and momentum factor. Consistently with the main finding, shocks to the MPK spread carry a negative price of risk. Thus, the pricing power of misallocation shocks between superstar firms and other firms is robust to the cross-sectional measure for aggregate capital misallocation.

[Table 13 about here.]

7.5 Physical capital versus intangible capital

With a rising trend of physical capital among superstars, in this section, I inspect whether any specific type of capital could drive capital misallocation and may affect the main results. In the same cross-section with Table 1, when I estimate the misallocation shocks and the components using physical capital, the magnitude of the price of risk inflates, but the statistical significance remains weak. When the misallocation shocks only consider intangible capital, then the price of risk is no longer priced, but the negative size reserves. Importantly, in both types of capital, the price of risk of shocks to the MPK spread remains negative and strongly significant. These results imply that the dispersion in the mean tangible and intangible MPK between superstars and non-superstars is equally important. Thus, no particular type of capital drives the main findings.

[Table 14 about here.]

7.6 Pre-2000s and post-2000s subsamples

Two trends that may affect superstars differently between these two periods are (1) the composition of superstars and (2) the decline in number of listed firms. Before the 2000s, superstar firms are mainly firms in the manufacturing industries with high tangible capital. After the 2000s, many superstar firms are in the tech and service industry with high intangible capital (Schlingemann and Stulz, 2022). Thus, there is an increasing market concentration towards firms in riskier industries in the later subsample.

On the market-wide, the number of listed firms has declined after the 2000s (Doidge, Karolyi, and Stulz, 2017). This trend may also affect the markup of superstars in the public market so I inspect the pricing power of shocks to capital misallocation in each subsample.

[Table 15 about here.]

In general, the long-short portfolio yields a negative expected return and the decreasing trend in expected returns across the beta-sorted portfolios remains across the subsamples. One interesting result is that before the 2000s when superstars were mainly in the manufacturing industries, the significance of the results was weak. Furthermore, the economic magnitude is also lower, compared to the expected returns in the post-2000s subsample. These results cast on the rising importance of superstars in driving the price of risk of misallocation shocks.

7.7 Annual frequency

The main results in the paper use the quarterly frequency. Table 16 reports replication of the sample using the annual frequency. There is a stronger pricing power for the price of risk of the aggregate misallocation shocks. The pricing of shocks to the MPK spread is robust to the annual frequency. Interestingly, the Fama-French model could explain 52% of the variation in the portfolio returns, indicated by the adjusted R-squared. When including shocks to the MPK spread, the adjusted R-squared improves to 63.7%. Table A3 in the Appendix shows the same set of results for annual frequency, using intangible capital from Peters and Taylor (2017) instead of the estimated method from Eisfeldt and Papanikolaou (2013). These results also confirm the robustness of our main findings that the MPK spread drives the price of risk of capital misallocation, implying that superstars influence asset prices via the channel of capital misallocation.

[Table 16 about here.]

8 Conclusion

The findings in this paper imply that superstar firms are an important friction that drives the price of risk of capital misallocation shocks. Using a cross-sectional measure for MPK dispersion, I decompose the capital misallocation into three components: the misallocation within the superstar portfolio, the misallocation within the non-superstar portfolio, and the MPK spread accounting for the dispersion in mean MPKs across the two portfolios.

In the cross-section of stock returns, I find that shocks to the MPK spread are significantly and negatively priced. Stocks with negative exposures to the shocks to this component carry higher risk premia, while stocks with positive exposures carry lower risk premia. Besides, adding the MPK spread-mimicking portfolio also improves the mean-variance efficiency of other portfolios. In the time series, the MPK spread negatively predicts in the long run consumption growth, industrial production growth, employment growth, and future stock market returns. Whereas, in the short run, the MPK spread predicts lower aggregate innovation growth and innovation growth among non-superstars.

These findings are intutitive. In an efficient market, capital flows towards its most productive uses, i.e. firms with the highest MPK would attract more investment. When superstar firms dominate this capital inflow, it may not always be due to their superior productivity or innovation. If these firms' higher MPKs result from market distortions, such as barriers to entry for competitors, then the higher MPK reflects an inefficiency rather than a pure productivity advantage. This misallocation can lead to slower economic growth by preventing capital from reaching potentially innovative but smaller competitors.

Efficiency in capital allocation is an important concept for economic growth; hence, shocks to capital misallocation capture a macroeconomic asset pricing factor. As the literature highlights markups are an important source of capital misallocation and the rise of superstars leads to higher capital misallocation. This paper highlights the role of superstars in shaping the price of risk associated with capital misallocation by preventing the optimal reallocation of production capital to other firms in the economy. One future work is to model and test the mechanism of how superstar firms deter innovation growth of other firms, resulting in the pricing power and predictability power of misallocation shocks between superstars and non-superstars.

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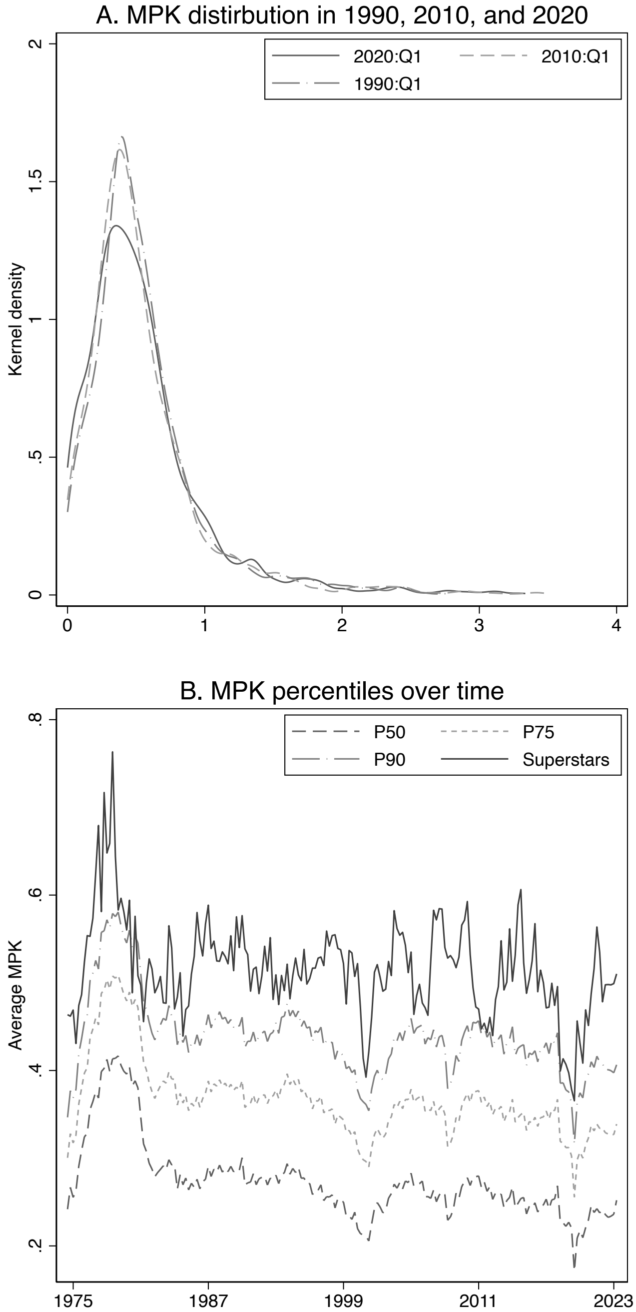
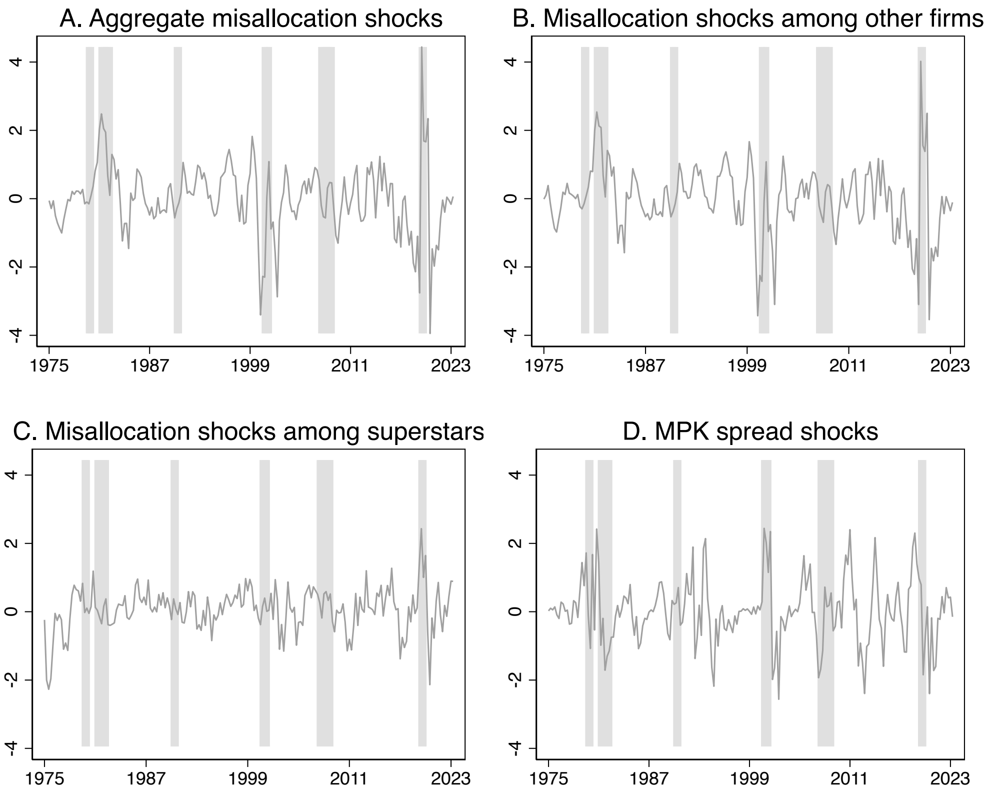
Figure 1: MPK distribution over time



Description. This figure plots MPK distribution across all firms in each year. Panel A plots the distribution density in 1990, 2010, and 2020. Panel B plots different moments of the distribution of average MPK from 1975:Q1 to 2023:Q4, compared to the average MPK of superstars. Firm-level MPK equals the log output-to-capital ratio. I use sales as output and net property, plant, and equipment (ppentq) as physical capital plus intangible capital estimated from Eisfeldt and Papanikolaou (2013).

Figure 2: Capital misallocation shocks against NBER recessions



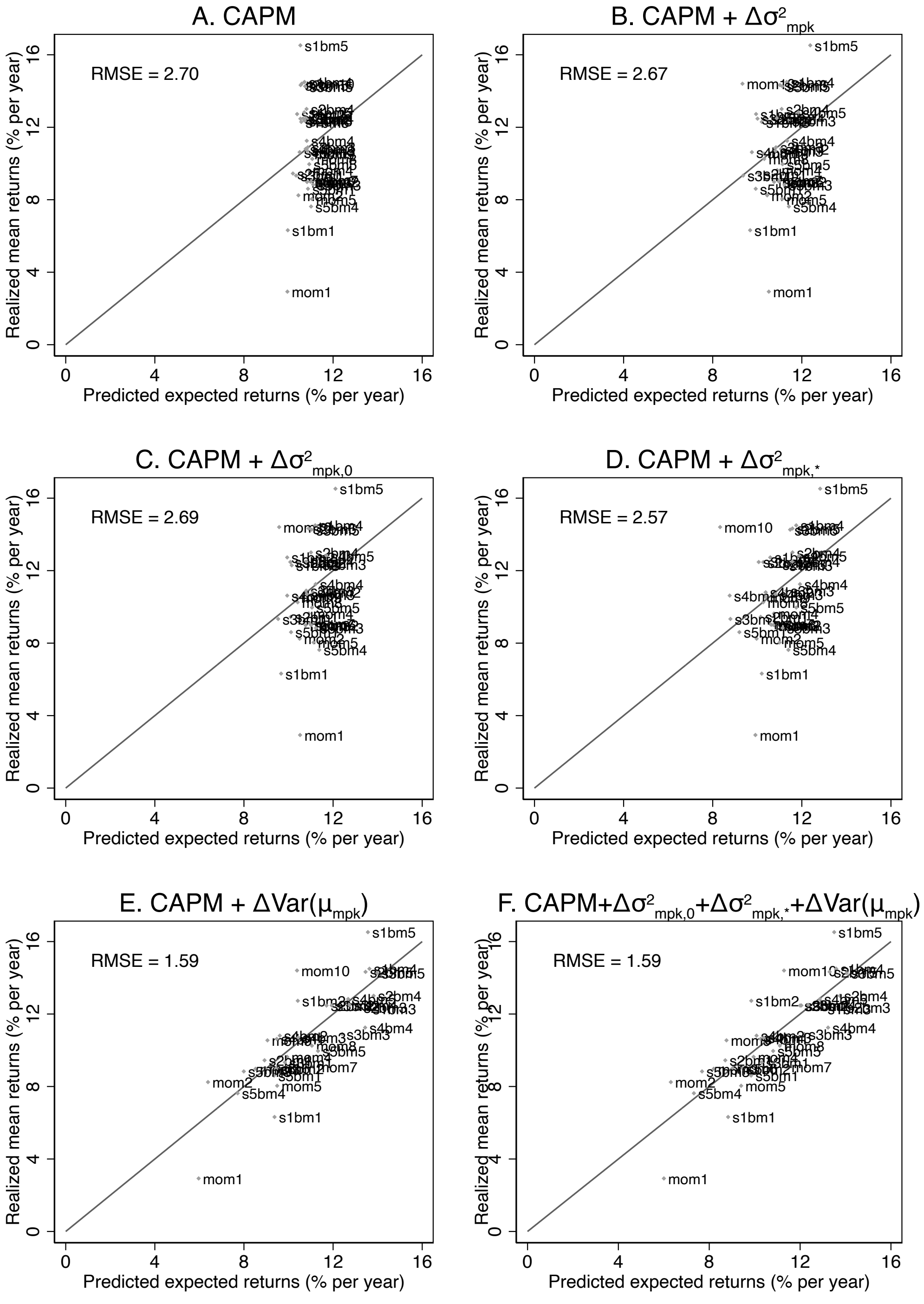
Description. This figure plots the aggregate misallocation shocks $\Delta\sigma^2_{mpk,t}$, misallocation shocks to non-superstars $\Delta\sigma^2_{mpk,t0}$, misallocation shocks to superstars $\Delta\sigma^2_{mpk,t*}$, and shocks to the MPK spread $\Delta\,\mathrm{Var}(\mu_{mpk,k})$. The sample is from 1975:Q1 to 2023:Q4. In each quarter, capital misallocation $\sigma^2_{mpk,t}$ is the cross-sectional dispersion of MPK across firms. The misallocation shocks are the annual changes in capital misallocation:

$$\Delta\sigma^2_{mpk,t} = \sigma^2_{mpk,t} - \sigma^2_{mpk,t-4},$$

whose level can be decomposed into:

$$\sigma^2_{mpk} = \underbrace{\frac{N_0 - 1}{N-1}\sigma^2_{mpk,0}}_{\text{Misallocation among non-superstars}} + \underbrace{\frac{N_* - 1}{N-1}\sigma^2_{mpk,*}}_{\text{Misallocation among superstars}} + \underbrace{\frac{N_0 N_*}{N(N-1)}(\mu_{mpk,0} - \mu_{mpk,*})^2}_{\text{MPK spread}}$$

Figure 3: Realized versus predicted mean returns



Description. This figure shows the cross-sectional asset pricing tests from the CAPM. Test portfolios include 25 size $\times$ book-to-market portfolios and 10 momentum portfolios. Each panel plots the realized mean excess returns of the portfolios against the mean excess returns predicted by the CAPM/Fama-French three-factor model with the aggregate misallocation shocks/shocks to the MPK spread. The sample runs from 1975:Q1 to 2023:Q4. Returns are shown in percent per year.

Table 1: Cross-sectional asset pricing tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Pricing 25 size×book-to-market and 10 momentum portfolios									
λ_0 (%)	12.090	10.792	10.894	11.410	14.116	13.060	12.552	14.469	13.969
	(3.67)***	(3.25)***	(3.28)***	(3.47)***	(4.26)***	(4.15)***	(4.01)***	(4.42)***	(4.43)***
	[3.67]***	[2.99]***	[3.05]***	[3.14]***	[2.52]**	[2.90]***	[3.07]***	[2.63]***	[2.57]**
MKT	-0.257	-0.057	-0.056	-0.319	-1.192	-0.773	-0.610	-1.254	-1.093
	(-0.25)	(-0.05)	(-0.05)	(-0.31)	(-1.17)	(-0.79)	(-0.62)	(-1.23)	(-1.10)
	[-0.22]	[-0.04]	[-0.04]	[-0.25]	[-0.66]	[-0.50]	[-0.43]	[-0.69]	[-0.60]
$\Delta\sigma^2_{mpk}$		-0.435				0.502	0.343	0.373	
		(-0.99)				(1.36)	(0.97)	(0.88)	
		[-0.90]				[0.94]	[0.73]	[0.52]	
$\Delta\sigma^2_{mpk,0}$			-0.410			0.591			-0.033
			(-0.87)			(1.56)			(-0.10)
			[-0.80]			[1.08]			[-0.06]
$\Delta\sigma^2_{mpk,*}$				-0.353			-0.495		0.204
				(-1.40)			(-1.99)**		(0.91)
				[-1.25]			[-1.50]		[0.52]
$\Delta\,\mathrm{Var}(\mu_{mpk,k})$					-1.078			-1.066	-1.036
					(-3.54)***			(-3.88)***	(-3.71)***
					[-2.09]**			[-2.29]**	[-2.13]**
R^2	0.012	0.064	0.050	0.131	0.668	0.200	0.148	0.669	0.688
Adj. R^2	-0.018	0.006	-0.009	0.077	0.647	0.122	0.066	0.637	0.647
RMSE	2.701	2.669	2.689	2.572	1.590	2.508	2.588	1.613	1.592

Fama-Macbeth t-statistics in parentheses. Shanken t-statistics in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the prices of risk with Fama and MacBeth (1973) and Shanken t-statistics for the 25 size × book-to-market, 10 momentum, 25 size×investment, and 25 size×operating profitability portfolios. The sample runs from 1975:Q1 to 2023:Q4. Returns and risk premia are reported in percent per year (quarterly percentages multiplied by four).

Table 1: Cross-sectional asset pricing tests - continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B: Pricing 25 size×book-to-market, 25 size×investment, 25 size×operating profitability portfolios									
λ_0 (%)	8.642	8.574	8.539	9.789	9.187	9.680	9.909	8.998	10.599
	(2.82)***	(2.88)***	(2.86)***	(3.17)***	(3.01)***	(3.13)***	(3.19)***	(3.02)***	(3.38)***
	[2.45]**	[2.51]**	[2.50]**	[2.64]***	[2.44]**	[2.51]**	[2.49]**	[2.44]**	[2.42]**
MKT	0.166	0.183	0.192	-0.121	0.014	-0.091	-0.151	0.059	-0.345
	(0.17)	(0.19)	(0.20)	(-0.12)	(0.01)	(-0.09)	(-0.15)	(0.06)	(-0.35)
	[0.13]	[0.14]	[0.15]	[-0.09]	[0.01]	[-0.07]	[-0.11]	[0.04]	[-0.23]
SMB	0.668	0.667	0.667	0.722	0.661	0.740	0.749	0.656	0.747
	(1.75)*	(1.74)*	(1.74)*	(1.90)*	(1.73)*	(1.95)*	(1.98)**	(1.71)*	(1.97)**
	[1.16]	[1.16]	[1.16]	[1.22]	[1.10]	[1.23]	[1.23]	[1.09]	[1.16]
HML	1.054	1.051	1.049	1.064	0.958	1.053	1.037	0.936	0.897
	(2.23)**	(2.23)**	(2.22)**	(2.25)**	(2.04)**	(2.23)**	(2.20)**	(1.99)**	(1.91)*
	[1.49]	[1.49]	[1.48]	[1.46]	[1.30]	[1.42]	[1.37]	[1.27]	[1.12]
UMD	3.057	3.006	2.964	2.940	3.390	2.394	2.333	3.239	2.521
	(2.90)***	(3.02)***	(2.98)***	(2.75)***	(3.18)***	(2.35)**	(2.30)**	(3.20)***	(2.47)**
	[2.30]**	[2.38]**	[2.35]**	[2.11]**	[2.39]**	[1.73]*	[1.66]*	[2.38]**	[1.65]
$\Delta\sigma^2_{mpk}$		-0.051				-0.157	-0.174	-0.055	
		(-0.32)				(-0.96)	(-1.05)	(-0.34)	
		[-0.26]				[-0.72]	[-0.78]	[-0.26]	
$\Delta\sigma^2_{mpk,0}$			-0.069			-0.216			-0.261
			(-0.42)			(-1.25)			(-1.48)
			[-0.34]			[-0.95]			[-1.01]
$\Delta\sigma^2_{mpk,*}$				0.260			0.406		0.424
				(1.48)			(2.05)**		(2.12)**
				[1.19]			[1.57]		[1.49]
$\Delta\,\mathrm{Var}(\mu_{mpk,k})$					-0.443			-0.462	-0.426
					(-2.89)***			(-3.03)***	(-2.85)***
					[-2.21]**			[-2.31]**	[-1.94]*
R^2	0.719	0.720	0.720	0.737	0.737	0.744	0.751	0.740	0.780
Adj. R^2	0.703	0.699	0.700	0.718	0.718	0.722	0.729	0.717	0.757
RMSE	1.273	1.281	1.280	1.242	1.240	1.232	1.216	1.242	1.151

Fama-Macbeth t-statistics in parentheses. Shanken t-statistics in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Exposure to misallocation shocks in the size $\times$ book-to-market portfolios

Panel A: Loading on $\Delta\sigma^2_{mpk}$										
	β					$t(\beta)$				
	Low	2	3	4	High	Low	2	3	4	High
Small	-0.220	-0.335	-0.666	-3.174	-5.842	-0.041	-0.076	-0.145	-0.652	-0.985
2	-0.647	-1.099	-3.184	-2.498	-2.959	-0.134	-0.250	-0.719	-0.534	-0.529
3	1.237	-0.140	-1.845	-2.488	-3.073	0.269	-0.035	-0.467	-0.537	-0.567
4	0.273	-2.662	-2.317	-3.399	-5.468	0.073	-0.735	-0.613	-0.715	-1.114
Big	0.507	-2.237	-3.021	-3.660	-3.272	0.174	-0.825	-1.021	-1.003	-0.694
Panel B: Loading on $\Delta\sigma^2_{mpk,0}$										
	β					$t(\beta)$				
	Low	2	3	4	High	Low	2	3	4	High
Small	0.971	0.678	0.418	-2.144	-4.515	0.177	0.153	0.091	-0.444	-0.771
2	0.411	-0.240	-2.320	-1.524	-1.853	0.084	-0.055	-0.527	-0.329	-0.337
3	1.929	0.641	-0.960	-1.506	-2.159	0.417	0.163	-0.244	-0.329	-0.406
4	0.848	-1.959	-1.527	-2.358	-4.421	0.222	-0.539	-0.406	-0.503	-0.908
Big	0.954	-1.578	-2.483	-2.914	-2.423	0.325	-0.575	-0.840	-0.804	-0.518
Panel C: Loading on $\Delta\sigma^2_{mpk,*}$										
	β					$t(\beta)$				
	Low	2	3	4	High	Low	2	3	4	High
Small	-7.608	-6.667*	-7.897**	-7.387**	-8.365*	-1.599	-1.673	-2.153	-1.961	-1.845
2	-6.447	-6.946*	-7.139**	-6.877*	-7.681*	-1.538	-1.916	-1.967	-1.882	-1.850
3	-5.878	-6.773**	-5.761*	-6.445*	-7.388*	-1.447	-2.012	-1.724	-1.787	-1.795
4	-5.252	-4.536	-4.652	-6.766**	-6.383*	-1.519	-1.428	-1.474	-1.979	-1.774
Big	-4.117	-3.042	-1.537	-2.283	-5.030	-1.594	-1.317	-0.590	-0.861	-1.336
Panel D: Loading on $\Delta\,\mathrm{Var}(\mu_{mpk,k})$										
	β					$t(\beta)$				
	Low	2	3	4	High	Low	2	3	4	High
Small	-12.973**	-11.059**	-11.839**	-12.092**	-16.284**	-2.539	-2.449	-2.560	-2.338	-2.333
2	-11.703**	-9.488**	-10.191**	-11.290**	-12.863**	-2.442	-2.368	-2.358	-2.423	-2.070
3	-6.934*	-8.291**	-10.171***	-11.427**	-10.713*	-1.739	-2.274	-2.700	-2.542	-1.718
4	-5.955	-8.478**	-9.350**	-12.357***	-13.146**	-1.544	-2.453	-2.541	-2.717	-2.507
Big	-4.536*	-7.993***	-7.024**	-9.558**	-10.299**	-1.649	-2.811	-2.346	-2.412	-2.156

Description. This table reports the factor loadings on misallocation shocks and the components for each of the 25 size $\times$ book-to-market portfolios, i.e. the betas from the first stage of Fama-MacBeth regressions. Particularly, for each test portfolio i, I estimate the factor loadings using time-series regression of the excess returns against the risk factor(s): $R^e_{it} = c_i + \sum_k \beta_{ik} f_{kt} + u_{it}$. The sample runs from 1975:Q1 to 2023:Q4.

Table 3: Exposure to shocks to the MPK spread (value-weighted results)

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5–Q1
Panel A: Expected return						
Ret–rf	11.633***	5.243***	3.707***	2.062***	6.816***	-4.818***
	(6.52)	(5.95)	(5.87)	(4.88)	(5.45)	(-2.64)
Panel B: CAPM						
MKT	1.220***	0.983***	0.915***	0.988***	1.182***	-0.038
	(23.05)	(46.49)	(38.53)	(39.35)	(28.79)	(-0.63)
α_{CAPM}	0.594	0.843	1.258*	-1.617**	-3.213**	-3.807**
	(0.41)	(1.16)	(1.79)	(-2.08)	(-2.57)	(-2.12)
Panel C: FF3 + UMD						
MKT	1.149***	0.980***	0.927***	0.997***	1.094***	-0.055
	(20.50)	(36.01)	(34.89)	(34.31)	(24.06)	(-0.82)
SMB	0.174**	-0.033	-0.083**	-0.045	0.205***	0.031
	(2.25)	(-0.73)	(-2.03)	(-0.89)	(2.76)	(0.32)
HML	-0.191**	-0.016	0.002	-0.047	-0.181***	0.010
	(-2.46)	(-0.46)	(0.06)	(-1.25)	(-3.87)	(0.11)
UMD	0.005	-0.038	-0.043	0.034	-0.052	-0.056
	(0.09)	(-1.27)	(-1.48)	(1.09)	(-0.91)	(-0.87)
$\alpha_{FF3+UMD}$	1.329	1.253	1.647**	-1.673**	-2.056	-3.384*
	(0.83)	(1.51)	(2.27)	(-2.09)	(-1.59)	(-1.68)
Panel D: FF5						
MKT	1.131***	0.997***	0.961***	1.019***	1.086***	-0.045
	(21.48)	(35.80)	(38.03)	(37.63)	(23.46)	(-0.66)
SMB	0.132*	-0.022	-0.045	-0.029	0.191**	0.059
	(1.82)	(-0.49)	(-1.09)	(-0.60)	(2.53)	(0.62)
HML	-0.231**	-0.066	-0.064	-0.166***	-0.139*	0.093
	(-2.48)	(-1.50)	(-1.55)	(-4.02)	(-1.84)	(0.81)
RMW	-1.044**	0.003	0.618***	0.466**	-0.605**	0.439
	(-2.50)	(0.02)	(3.54)	(2.19)	(-2.11)	(0.84)
CMA	0.589	0.513*	0.506*	0.821***	-0.097	-0.686
	(1.17)	(1.71)	(1.97)	(3.35)	(-0.19)	(-1.07)
α_{FF5}	2.419	0.569	0.103	-2.455***	-1.694	-4.113**
	(1.64)	(0.71)	(0.15)	(-3.14)	(-1.38)	(-2.06)

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports value-weighted average excess returns and alphas in annual percentage for portfolios sorted on exposure to shocks to the MPK spread. For each stock, I regress the quarterly excess returns either on misallocation shocks or on the decomposed misallocation shocks by a rolling window of 20 quarters (with a minimum of 12 quarters available). Each quarter, I sort stocks into quintiles based on their misallocation-beta, lagging by one quarter. I hold and rebalance the portfolio every quarter. The sample runs from 1975:Q1 to 2023:Q4.

Table 4: Post-formation portfolio exposure

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5–Q1
Panel A: Value-weighted portfolios						
MKT	5.124***	4.116***	3.454***	3.817***	4.549***	-0.575**
	(24.58)	(43.55)	(37.05)	(40.69)	(27.94)	(-2.51)
$\Delta\,\mathrm{Var}(\mu_{mpk,k})$	-2.665**	0.252	-0.780	0.592	0.827	3.493**
	(-2.19)	(0.35)	(-1.16)	(0.92)	(0.77)	(2.23)
α	-0.078	-0.186	0.327	0.765	-0.471	-0.394
	(-0.05)	(-0.27)	(0.50)	(1.00)	(-0.42)	(-0.20)
Panel B: Equally weighted portfolios						
MKT	5.843***	4.553***	4.444***	4.545***	5.243***	-0.599***
	(20.62)	(21.93)	(22.25)	(19.91)	(18.32)	(-3.51)
$\Delta\,\mathrm{Var}(\mu_{mpk,k})$	-5.307***	-1.915	-1.764	-1.301	-2.804	2.503**
	(-2.74)	(-1.43)	(-1.44)	(-1.04)	(-1.54)	(2.16)
α	3.412	3.387**	2.906**	3.606**	3.313*	-0.099
	(1.59)	(2.15)	(2.13)	(2.41)	(1.69)	(-0.07)

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the betas from the regression of portfolio returns, whose portfolios are sorted on the stock exposure to shocks to the MPK spread, against the market and shocks to the MPK spread. The sample runs from 1975:Q1 to 2023:Q4.

Table 5: Portfolio spanning tests

Panel A: Benchmark = Long-short returns to $\Delta\sigma^2_{mpk}$-mimicking portfolios			
Test portfolio = Returns to	$\Delta\sigma^2_{mpk,0}$	$\Delta\sigma^2_{mpk,*}$	$\Delta\,\mathrm{Var}(\mu_{mpk,k})$
Jensen alpha	-0.003	0.004	-0.044**
	(-0.49)	(0.37)	(-2.45)
Panel B: Benchmark = Long-short returns to $\Delta\,\mathrm{Var}(\mu_{mpk,k})$-mimicking portfolios			
Test portfolio = Returns to	$\Delta\sigma^2_{mpk,0}$	$\Delta\sigma^2_{mpk,*}$	$\Delta\sigma^2_{mpk}$
Jensen alpha	-0.001	0.004	0.005
	(-0.03)	(0.39)	(0.23)

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the spanning test alphas and the corresponding t-statistics. Panel A shows the time-series regressions of the returns to the aggregate misallocation shocks on returns to each decomposed shock. Panel B shows the regressions of the returns to shocks to the MPK spread on the returns to misallocation shocks to superstars, non-superstars, and all firms. The sample runs from 1975:Q1 to 2023:Q4.

Table 6: Predicting proxies for economic growth

	$k=1$				$k=4$				$k=8$				$k=12$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: Per capita real consumption growth																
σ^2_{mpk}	-0.091				0.067				0.035				-0.166			
	(-0.59)				(0.36)				(0.09)				(-0.32)			
	[-0.59]				[0.32]				[0.08]				[-0.32]			
$\sigma^2_{mpk,0}$		-0.086				0.080				0.053				-0.151		
		(-0.56)				(0.41)				(0.13)				(-0.28)		
		[-0.56]				[0.37]				[0.12]				[-0.28]		
$\sigma^2_{mpk,*}$			-0.697				-0.550				-1.077				-1.832	
			(-1.13)				(-1.16)				(-0.99)				(-1.14)	
			[-1.12]				[-1.10]				[-0.96]				[-1.13]	
$\mathrm{Var}(\mu_{mpk,k})$				-0.271				-0.750				-0.756				-0.333
				(-3.39)***				(-3.24)***				(-2.59)***				(-0.87)
				[-3.38]***				[-3.00]***				[-2.64]***				[-0.88]
R^2	0.006	0.005	0.057	0.039	0.001	0.001	0.010	0.089	0.000	0.000	0.022	0.050	0.002	0.002	0.043	0.007
RMSE	1.008	1.008	0.982	0.991	1.855	1.855	1.847	1.772	2.508	2.508	2.480	2.444	3.058	3.058	2.995	3.051
Panel B: Industrial production growth																
σ^2_{mpk}	-0.278				-0.524				-0.914				-1.363			
	(-1.20)				(-1.03)				(-0.72)				(-0.78)			
	[-1.20]				[-0.93]				[-0.69]				[-0.77]			
$\sigma^2_{mpk,0}$		-0.272				-0.522				-0.923				-1.402		
		(-1.17)				(-0.99)				(-0.70)				(-0.78)		
		[-1.16]				[-0.89]				[-0.67]				[-0.76]		
$\sigma^2_{mpk,*}$			-1.458				-1.964				-2.350				-2.054	
			(-1.73)*				(-1.39)				(-0.93)				(-0.67)	
			[-1.72]*				[-1.29]				[-0.91]				[-0.67]	
$\mathrm{Var}(\mu_{mpk,k})$				-0.282				-1.176				-2.423				-1.662
				(-1.57)				(-2.19)**				(-3.38)***				(-1.70)*
				[-1.56]				[-2.13]**				[-3.34]***				[-1.71]*
R^2	0.020	0.017	0.081	0.014	0.012	0.011	0.025	0.040	0.017	0.016	0.016	0.079	0.026	0.026	0.009	0.027
RMSE	1.753	1.755	1.697	1.759	4.288	4.290	4.260	4.225	6.345	6.348	6.347	6.139	7.559	7.561	7.628	7.558
Panel C: Employment growth																
σ^2_{mpk}	-0.093				0.148				0.294				0.260			
	(-0.64)				(1.04)				(0.83)				(0.54)			
	[-0.64]				[0.94]				[0.80]				[0.53]			
$\sigma^2_{mpk,0}$		-0.089				0.163				0.317				0.282		
		(-0.62)				(1.10)				(0.87)				(0.56)		
		[-0.62]				[1.00]				[0.83]				[0.55]		
$\sigma^2_{mpk,*}$			-0.585				-0.429				-0.501				-0.560	
			(-1.01)				(-1.01)				(-0.58)				(-0.50)	
			[-1.00]				[-0.94]				[-0.56]				[-0.49]	
$\mathrm{Var}(\mu_{mpk,k})$				-0.153				-0.497				-0.887				-0.585
				(-2.30)**				(-2.49)**				(-4.04)***				(-2.24)**
				[-2.28]**				[-2.38]**				[-3.98]***				[-2.28]**
R^2	0.007	0.006	0.041	0.013	0.007	0.008	0.009	0.056	0.016	0.017	0.007	0.096	0.009	0.010	0.006	0.032
RMSE	0.994	0.995	0.977	0.991	1.538	1.537	1.537	1.500	2.114	2.112	2.123	2.026	2.459	2.458	2.463	2.431

t-ratio of Hodrick (1992) with k-1 lags in parentheses. t-ratio of Newey-West (1987) with k-1 lags in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the results of the following predictive regression: $Q_{t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k}$, where $Q \in \{CG, IP, E\}$. The macroeconomic data to construct this measure are obtained from the Bureau of Economic Analysis. The predictive variables z_t are aggregate misallocation, misallocation among non-superstars, misallocation among superstars, and the MPK spread. The sample runs from 1975:Q1 to 2022:Q4.

Table 7: Predicting innovation growth

	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$		$k=6$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Aggregate innovation growth												
σ^2_{mpk}	-0.001		0.007		0.019		0.037		0.047		0.065	
	(-0.06)		(0.22)		(0.50)		(0.82)		(0.91)		(1.11)	
	[-0.06]		[0.20]		[0.47]		[0.79]		[0.87]		[1.09]	
Var($\mu_{mpk,k}$)		-6.516		-7.089		-12.314		-10.875		-8.159		-4.687
		(-2.23)**		(-1.91)*		(-2.46)**		(-2.27)**		(-1.10)		(-0.48)
		[-2.22]**		[-1.77]*		[-2.37]**		[-2.19]**		[-1.09]		[-0.48]
R^2	0.000	0.013	0.001	0.009	0.004	0.023	0.014	0.018	0.020	0.009	0.035	0.003
RMSE	0.025	0.025	0.033	0.032	0.036	0.036	0.036	0.036	0.038	0.038	0.040	0.040
Panel B: Innovation growth among non-superstars												
σ^2_{mpk}	-0.002		0.009		0.025		0.045		0.054		0.075	
	(-0.08)		(0.28)		(0.63)		(0.95)		(0.98)		(1.19)	
	[-0.08]		[0.25]		[0.60]		[0.91]		[0.94]		[1.16]	
Var($\mu_{mpk,k}$)		-9.215		-10.281		-18.665		-15.838		-14.617		-10.575
		(-2.50)**		(-2.37)**		(-3.18)***		(-2.92)***		(-1.68)*		(-0.95)
		[-2.49]**		[-2.20]**		[-3.09]***		[-2.83]***		[-1.68]*		[-0.95]
R^2	0.000	0.019	0.001	0.015	0.005	0.039	0.014	0.026	0.019	0.020	0.032	0.010
RMSE	0.030	0.029	0.038	0.038	0.042	0.041	0.043	0.043	0.045	0.045	0.048	0.048
Panel C: Innovation growth among superstars												
σ^2_{mpk}	0.004		0.011		0.022		0.040		0.058		0.075	
	(0.16)		(0.28)		(0.39)		(0.55)		(0.68)		(0.80)	
	[0.15]		[0.24]		[0.35]		[0.52]		[0.66]		[0.79]	
Var($\mu_{mpk,k}$)		0.767		0.005		1.727		-2.111		2.893		6.101
		(0.25)		(0.00)		(0.31)		(-0.34)		(0.42)		(0.70)
		[0.25]		[0.00]		[0.30]		[-0.34]		[0.41]		[0.67]
R^2	0.000	0.000	0.001	0.000	0.004	0.000	0.010	0.000	0.018	0.001	0.026	0.003
RMSE	0.028	0.028	0.038	0.038	0.041	0.041	0.044	0.044	0.049	0.050	0.053	0.053

t-ratio of Hodrick (1992) with k-1 lags in parentheses. t-ratio of Newey-West (1987) with k-1 lags in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the results of the following predictive regression:

$$R_{t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k},$$

where $I_{t:t+k}$ is the innovation growth in k quarters. The predictive variables z_t are the aggregate misallocation and the MPK spread. The predictive variables z_t are the aggregate misallocation and the MPK spread. The columns show results for $k = 1, 2, 3, 4$ and 5 quarters. I construct the innovation proxy I_t as the natural logarithm of one plus the number of patent applications divided by the firm market cap. The number of patent is from Kogan, Papanikolaou, Seru, and Stoffman (2017). The sample runs from 1975:Q1 to 2022:Q4.

Table 8: Predicting aggregate stock returns

	$k=1$				$k=4$				$k=8$				$k=12$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
σ^2_{mpk}	0.676				1.304				1.660				2.038			
	(1.44)				(1.95)*				(1.51)				(1.28)			
	[1.43]				[1.61]				[1.33]				[1.18]			
$\sigma^2_{mpk,0}$		0.729				1.396				1.777				2.181		
		(1.49)				(2.02)**				(1.57)				(1.32)		
		[1.48]				[1.67]*				[1.38]				[1.22]		
$\sigma^2_{mpk,*}$			-1.056				-1.398				-1.561				-2.028	
			(-0.76)				(-0.60)				(-0.43)				(-0.41)	
			[-0.76]				[-0.51]				[-0.39]				[-0.38]	
Var($\mu_{mpk,k}$)				-1.084				-1.654				-2.613				-2.815
				(-2.43)**				(-2.66)***				(-2.53)**				(-1.87)*
				[-2.42]**				[-2.24]**				[-2.26]**				[-1.75]*
R^2_{IS}	0.008	0.009	0.003	0.018	0.013	0.014	0.002	0.018	0.013	0.014	0.002	0.028	0.015	0.016	0.002	0.024
R^2_{OOS}	0.018	0.019	0.015	0.002	0.023	0.024	0.014	0.003	0.020	0.021	0.011	-0.005	0.017	0.018	0.014	-0.011
RMSE	6.622	6.620	6.639	6.590	10.082	10.078	10.137	10.058	12.822	12.817	12.896	12.728	14.973	14.967	15.068	14.906

t-ratio of Hodrick (1992) with k-1 lags in parentheses. t-ratio of Newey-West (1987) with k-1 lags in square brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the results of the following predictive regression:

$$R^e_{mkt,t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k},$$

where $R^e_{mkt,t:t+k}$ is the stock market excess returns in k quarters. Stock market returns are the value-weighted CRSP returns in excess of the risk-free rate. The predictive variables z_t are aggregate misallocation, misallocation among non-superstars, misallocation among superstars, and the MPK spread. The sample runs from 1975:Q1 to 2022:Q4.

Table 9: Factor risk premiums for empirical risk factors

	(1)	(2)	(3)	(4)
Panel A: 25 size×book-to-market portfolios				
MKT				
γ	5.945***	5.823***	5.945***	5.343***
	(10.49)	(9.95)	(10.81)	(8.85)
$\Delta\sigma^2_{mpk}$				
γ	0.098*			
	(1.81)			
$\Delta\sigma^2_{mpk,0}$				
γ		0.115**		
		(2.03)		
$\Delta\sigma^2_{mpk,*}$				
γ			-0.066*	
			(-1.75)	
Δ Var($\mu_{mpk,k}$)				
γ				-0.256***
				(-5.38)
R^2_{OLS}	0.661	0.663	0.666	0.490
MAE	0.021	0.020	0.022	0.018
Panel B: 25 size×momentum portfolios				
MKT				
γ	5.409***	5.596***	5.902***	5.399***
	(7.82)	(8.39)	(9.71)	(9.18)
$\Delta\sigma^2_{mpk}$				
γ	0.154**			
	(2.52)			
$\Delta\sigma^2_{mpk,0}$				
γ		0.129**		
		(2.34)		
$\Delta\sigma^2_{mpk,*}$				
γ			0.012	
			(0.22)	
Δ Var($\mu_{mpk,k}$)				
γ				-0.273***
				(-7.28)
R^2_{OLS}	0.659	0.663	0.466	0.610
MAE	0.018	0.020	0.022	0.020

GMM robust t-statistics in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the estimation from the first-stage GMM with equally weighted errors. The test portfolio includes 25 size×book-to-market portfolios in Panel A and 25 size×momentum portfolios in Panel B. The coefficient γ represents the price of risk for the corresponding factor. The sample runs from 1975:Q1 to 2022:Q4.

Table 10: Pricing portfolios by alternative definition of superstars

			Top 50 firms sorted on market cap			Top 50 firms sorted on sale		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
λ_0 (%)	12.090	10.893	10.978	9.870	14.968	10.838	12.166	14.435
	(3.67)***	(3.26)***	(3.28)***	(2.89)***	(4.51)***	(3.21)***	(3.74)***	(4.51)***
	[3.67]***	[3.14]***	[3.18]***	[2.33]**	[3.49]***	[3.09]***	[3.70]***	[3.53]***
MKT	-0.257	-0.049	-0.057	0.073	-1.089	-0.027	-0.342	-0.931
	(-0.25)	(-0.05)	(-0.05)	(0.07)	(-1.10)	(-0.03)	(-0.34)	(-0.95)
	[-0.22]	[-0.04]	[-0.05]	[0.05]	[-0.77]	[-0.02]	[-0.29]	[-0.67]
$\Delta\sigma^2_{mpk}$		-0.289						
		(-0.74)						
		[-0.70]						
$\Delta\sigma^2_{mpk,0}$			-1.189			-1.267		
			(-0.65)			(-0.69)		
			[-0.62]			[-0.65]		
$\Delta\sigma^2_{mpk,*}$				-0.182			-0.034	
				(-1.55)			(-0.54)	
				[-1.24]			[-0.51]	
Δ Var$(\mu_{mpk,k})$					-0.147			-0.154
					(-2.30)**			(-2.67)***
					[-1.76]*			[-2.05]**
R^2	0.012	0.044	0.038	0.140	0.129	0.040	0.035	0.144
Adj. R^2	-0.018	-0.015	-0.022	0.086	0.074	-0.020	-0.026	0.091
RMSE	2.701	2.698	2.707	2.560	2.576	2.704	2.712	2.553

Fama-Macbeth t-statistics in parentheses. Shanken t-statistics in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the prices of risk with Fama and MacBeth (1973) and Shanken t-statistics for the 25 size $\times$ book-to-market and 10 momentum portfolios. The sample runs from 1975:Q2 to 2023:Q4. Returns and risk premia are reported in percent per year (quarterly percentages multiplied by four). For robustness, I identify superstars as the top 50 firms sorted on market cap or sales each quarter.

Table 11: Predicting economic growth using risk factors

	k = 1		k = 4		k = 8		k = 12		k = 20	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Per capita real consumption growth										
$\Delta\sigma^2_{mpk}$	-0.193		0.305		0.648		0.840		0.856	
	(-0.83)		(1.91)*		(2.61)***		(2.32)**		(1.40)	
	[-0.82]		[2.12]**		[2.59]**		[2.35]**		[1.40]	
Δ Var($\mu_{mpk,k}$)		-0.191		-0.687		-0.855		-0.935		-0.669
		(-2.38)**		(-2.59)***		(-2.86)***		(-2.90)***		(-1.63)
		[-2.37]**		[-2.39]**		[-2.90]***		[-2.98]***		[-1.66]*
R^2	0.037	0.021	0.028	0.081	0.069	0.070	0.071	0.058	0.038	0.018
RMSE	0.992	1.000	1.830	1.779	2.420	2.418	2.951	2.972	3.715	3.754
Panel B: Industrial production growth										
$\Delta\sigma^2_{mpk}$	-0.255		0.189		0.698		0.603		0.322	
	(-0.79)		(0.41)		(1.16)		(0.72)		(0.29)	
	[-0.78]		[0.39]		[1.17]		[0.71]		[0.29]	
Δ Var($\mu_{mpk,k}$)		0.014		-0.217		-1.523		-1.518		-1.168
		(0.09)		(-0.35)		(-2.14)**		(-2.00)**		(-1.78)*
		[0.09]		[-0.34]		[-2.14]**		[-2.04]**		[-1.82]*
R^2	0.021	0.000	0.002	0.001	0.012	0.034	0.006	0.024	0.001	0.010
RMSE	1.752	1.771	4.309	4.310	6.360	6.288	7.638	7.567	9.166	9.126
Panel C: Employment growth										
$\Delta\sigma^2_{mpk}$	-0.221		0.059		0.412		0.547		0.276	
	(-1.05)		(0.36)		(2.04)**		(2.41)**		(0.89)	
	[-1.05]		[0.36]		[2.08]**		[2.42]**		[0.88]	
Δ Var($\mu_{mpk,k}$)		-0.021		-0.217		-0.632		-0.654		-0.430
		(-0.21)		(-0.84)		(-2.22)**		(-2.41)**		(-1.77)*
		[-0.21]		[-0.80]		[-2.22]**		[-2.47]**		[-1.78]*
R^2	0.050	0.000	0.002	0.012	0.038	0.053	0.046	0.043	0.008	0.016
RMSE	0.972	0.997	1.543	1.535	2.089	2.073	2.413	2.417	2.634	2.624
Panel D: Stock market excess returns										
$\Delta\sigma^2_{mpk}$	0.950		2.343		0.607		-2.511		-0.794	
	(1.67)*		(1.51)		(0.36)		(-1.23)		(-0.19)	
	[1.67]*		[1.51]		[0.35]		[-1.24]		[-0.19]	
Δ Var($\mu_{mpk,k}$)		-0.876		-3.961		-1.646		-3.120		-6.777
		(-1.14)		(-2.26)**		(-0.77)		(-1.25)		(-2.93)***
		[-1.14]		[-2.34]**		[-0.77]		[-1.26]		[-2.95]***
R^2_{IS}	0.021	0.010	0.025	0.041	0.001	0.004	0.009	0.009	0.000	0.020
R^2_{OOS}	0.043	0.015	0.044	0.007	0.011	-0.003	0.019	0.005	-0.025	0.016
RMSE	6.579	6.615	14.894	14.772	20.873	20.843	25.205	25.203	36.449	36.080

t-ratio of Hodrick (1992) with k-1 lags in parentheses. t-ratio of Newey-West (1987) with k-1 lags in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the results of the following predictive regression: $Q_{t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k}$, where $Q \in \{CG, IP, E, R^e_{mkt}\}$. The macroeconomic data to construct this measure are obtained from the Bureau of Economic Analysis. Stock market returns are the value-weighted CRSP returns in excess of risk-free rate. The predictive variables z_t are shocks to the aggregate misallocation and the MPK spread.

Table 12: Pricing Giglio and Xiu (2021)'s 202 portfolios

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Models including MKT factor									
λ_0 (%)	10.479	9.847	9.950	9.652	10.988	9.789	9.738	10.633	10.465
	(4.25)***	(3.93)***	(3.99)***	(3.80)***	(4.49)***	(3.90)***	(3.87)***	(4.34)***	(4.22)***
	[4.25]***	[3.73]***	[3.83]***	[3.17]***	[3.10]***	[3.14]***	[3.17]***	[3.09]***	[3.07]***
MKT	0.092	0.169	0.166	0.029	-0.336	-0.033	0.005	-0.275	-0.291
	(0.10)	(0.19)	(0.19)	(0.03)	(-0.39)	(-0.04)	(0.01)	(-0.32)	(-0.34)
	[0.09]	[0.15]	[0.15]	[0.02]	[-0.24]	[-0.03]	[0.00]	[-0.20]	[-0.22]
$\Delta\sigma^2_{mpk}$		-0.345				-0.076	-0.108	-0.027	
		(-1.68)*				(-0.47)	(-0.66)	(-0.16)	
		[-1.51]				[-0.35]	[-0.51]	[-0.11]	
$\Delta\sigma^2_{mpk,0}$			-0.304			0.010			0.103
			(-1.53)			(0.06)			(0.64)
			[-1.38]			[0.05]			[0.44]
$\Delta\sigma^2_{mpk,*}$				-0.491			-0.515		-0.311
				(-2.16)**			(-2.19)**		(-1.48)
				[-1.77]*			[-1.77]*		[-1.06]
$\Delta\,\mathrm{Var}(\mu_{mpk,k})$					-0.960			-0.889	-0.808
					(-3.51)***			(-3.70)***	(-4.02)***
					[-2.39]**			[-2.59]**	[-2.84]***
R^2	0.001	0.064	0.046	0.209	0.340	0.238	0.211	0.357	0.386
Adj. R^2	-0.004	0.055	0.037	0.201	0.333	0.226	0.199	0.347	0.374
RMSE	2.524	2.449	2.472	2.252	2.057	2.216	2.255	2.036	1.994

Fama-Macbeth t-statistics in parentheses. Shanken t-statistics in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the prices of risk with Fama and MacBeth (1973) and Shanken t-statistics for the 25 size $\times$ book-to-market, 17 Fama-French industry, 25 operating profitability and investment, 23 size and residual variance, 25 size and net issuance, 25 size and accruals, 25 size and momentum, and 25 size and beta portfolios. The sample runs from 1975:Q1 to 2023:Q4.

Table 12: Pricing Giglio and Xiu (2021)'s 202 portfolios - continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B: Models including MKT, SMB, HML, and UMD factors									
λ_0 (%)	7.550	7.314	7.279	7.555	7.541	7.077	7.154	7.371	7.107
	(3.82)***	(3.88)***	(3.88)***	(3.73)***	(3.81)***	(3.74)***	(3.80)***	(3.93)***	(3.77)***
	[3.59]***	[3.63]***	[3.62]***	[3.51]***	[3.45]***	[3.48]***	[3.54]***	[3.55]***	[3.35]***
MKT	0.478	0.537	0.545	0.477	0.461	0.591	0.574	0.505	0.564
	(0.61)	(0.70)	(0.71)	(0.60)	(0.59)	(0.77)	(0.74)	(0.66)	(0.73)
	[0.46]	[0.52]	[0.53]	[0.46]	[0.43]	[0.57]	[0.56]	[0.48]	[0.53]
SMB	0.630	0.625	0.624	0.630	0.628	0.616	0.619	0.624	0.614
	(1.66)*	(1.64)	(1.64)	(1.66)*	(1.65)	(1.62)	(1.63)	(1.64)	(1.62)
	[1.16]	[1.14]	[1.14]	[1.16]	[1.13]	[1.12]	[1.13]	[1.12]	[1.09]
HML	0.966	0.994	0.994	0.967	0.937	0.992	0.993	0.959	0.956
	(1.96)*	(2.02)**	(2.02)**	(1.96)*	(1.90)*	(2.02)**	(2.02)**	(1.95)*	(1.94)*
	[1.39]	[1.43]	[1.43]	[1.39]	[1.32]	[1.42]	[1.43]	[1.35]	[1.34]
UMD	1.575	1.618	1.619	1.576	1.622	1.614	1.614	1.650	1.646
	(2.82)***	(2.89)***	(2.89)***	(2.82)***	(2.90)***	(2.88)***	(2.88)***	(2.95)***	(2.94)***
	[1.97]*	[2.01]**	[2.01]**	[1.97]*	[1.98]**	[2.00]**	[2.00]**	[2.01]**	[1.99]**
$\Delta\sigma^2_{mpk}$		0.082				0.084	0.083	0.100	
		(0.51)				(0.52)	(0.51)	(0.63)	
		[0.44]				[0.44]	[0.44]	[0.52]	
$\Delta\sigma^2_{mpk,0}$			0.091			0.100			0.126
			(0.56)			(0.62)			(0.79)
			[0.49]			[0.53]			[0.65]
$\Delta\sigma^2_{mpk,*}$				-0.022			-0.060		-0.116
				(-0.18)			(-0.53)		(-1.07)
				[-0.16]			[-0.45]		[-0.87]
Δ Var($\mu_{mpk,k}$)					-0.325			-0.320	-0.348
					(-2.29)**			(-2.23)**	(-2.51)**
					[-1.91]*			[-1.86]*	[-2.06]**
R^2	0.528	0.532	0.533	0.528	0.542	0.534	0.533	0.544	0.546
Adj. R^2	0.519	0.520	0.521	0.516	0.530	0.519	0.519	0.530	0.529
RMSE	1.748	1.744	1.744	1.752	1.727	1.746	1.748	1.727	1.728

Fama-Macbeth t-statistics in parentheses. Shanken t-statistics in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Pricing Giglio and Xiu (2021)'s 202 portfolios using value-weighted misallocation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Models including MKT factor									
λ_0 (%)	10.479	10.494	14.534	13.911	13.919	13.948	13.411	13.374	14.375
	(4.25)***	(4.22)***	(5.83)***	(5.55)***	(5.65)***	(5.84)***	(5.68)***	(5.55)***	(5.97)***
	[4.25]***	[3.34]***	[4.87]***	[4.66]***	[3.50]***	[4.78]***	[4.64]***	[3.63]***	[4.22]***
MKT	0.092	-0.149	-1.223	-1.097	-1.146	-1.139	-0.976	-1.039	-1.310
	(0.10)	(-0.17)	(-1.47)	(-1.30)	(-1.35)	(-1.38)	(-1.19)	(-1.23)	(-1.58)
	[0.09]	[-0.12]	[-1.05]	[-0.94]	[-0.77]	[-0.97]	[-0.83]	[-0.73]	[-0.99]
$\Delta\sigma^2_{mpk}$		-0.769				-0.434	-0.509	-0.326	
		(-2.50)**				(-1.94)*	(-2.19)**	(-1.33)	
		[-1.95]*				[-1.53]	[-1.73]*	[-0.85]	
$\Delta\sigma^2_{mpk,0}$			0.609			0.297			0.384
			(2.26)**			(1.46)			(1.86)*
			[1.84]*			[1.15]			[1.28]
$\Delta\sigma^2_{mpk,*}$				-0.613			-0.646		-0.361
				(-2.29)**			(-2.37)**		(-1.43)
				[-1.88]*			[-1.89]*		[-0.99]
Δ Var($\mu_{mpk,k}$)					-1.266			-1.048	-0.876
					(-3.57)***			(-3.57)***	(-3.84)***
					[-2.19]**			[-2.31]**	[-2.64]***
R^2	0.001	0.127	0.210	0.256	0.300	0.300	0.263	0.343	0.376
Adj. R^2	-0.004	0.118	0.202	0.249	0.293	0.289	0.251	0.334	0.363
RMSE	2.524	2.366	2.250	2.183	2.118	2.124	2.179	2.056	2.011

Fama-Macbeth t-statistics in parentheses. Shanken t-statistics in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the prices of risk with Fama and MacBeth (1973) and Shanken t-statistics for the 25 size $\times$ book-to-market, 17 Fama-French industry, 25 operating profitability and investment, 23 size and residual variance, 25 size and net issuance, 25 size and accruals, 25 size and momentum, and 25 size and beta portfolios. The sample runs from 1975:Q1 to 2023:Q4.

Table 13: Pricing Giglio and Xiu (2021)'s 202 portfolios using value-weighted misallocation - continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Models including MKT, SMB, HML, and UMD factors									
λ_0 (%)	7.550	7.473	7.272	7.330	7.838	7.322	7.130	7.783	7.485
	(3.82)***	(3.71)***	(3.92)***	(3.87)***	(3.87)***	(3.97)***	(3.85)***	(3.86)***	(4.05)***
	[3.59]***	[3.48]***	[3.68]***	[3.63]***	[3.29]***	[3.72]***	[3.59]***	[3.29]***	[3.45]***
MKT	0.478	0.372	0.412	0.395	0.253	0.405	0.443	0.270	0.333
	(0.61)	(0.47)	(0.54)	(0.51)	(0.32)	(0.53)	(0.58)	(0.34)	(0.43)
	[0.46]	[0.36]	[0.41]	[0.39]	[0.23]	[0.40]	[0.43]	[0.24]	[0.31]
SMB	0.630	0.548	0.561	0.566	0.622	0.555	0.570	0.617	0.635
	(1.66)*	(1.45)	(1.49)	(1.52)	(1.66)*	(1.48)	(1.53)	(1.65)	(1.71)*
	[1.16]	[1.01]	[1.04]	[1.05]	[1.09]	[1.03]	[1.05]	[1.08]	[1.12]
HML	0.966	0.932	0.917	0.933	0.916	0.917	0.893	0.899	0.865
	(1.96)*	(1.87)*	(1.84)*	(1.87)*	(1.84)*	(1.84)*	(1.80)*	(1.82)*	(1.75)*
	[1.39]	[1.32]	[1.30]	[1.32]	[1.23]	[1.30]	[1.26]	[1.21]	[1.17]
UMD	1.575	1.646	1.641	1.660	1.731	1.635	1.624	1.709	1.690
	(2.82)***	(2.93)***	(2.92)***	(2.95)***	(3.07)***	(2.91)***	(2.89)***	(3.04)***	(3.00)***
	[1.97]*	[2.04]**	[2.03]**	[2.06]**	[2.02]**	[2.02]**	[2.01]**	[2.00]**	[1.98]**
$\Delta\sigma^2_{mpk}$		-0.136				-0.132	-0.119	-0.058	
		(-0.76)				(-0.74)	(-0.67)	(-0.32)	
		[-0.67]				[-0.65]	[-0.59]	[-0.26]	
$\Delta\sigma^2_{mpk,0}$			-0.051			-0.052			0.083
			(-0.27)			(-0.28)			(0.46)
			[-0.24]			[-0.25]			[0.37]
$\Delta\sigma^2_{mpk,*}$				0.040			0.014		0.024
				(0.23)			(0.08)		(0.14)
				[0.20]			[0.07]		[0.11]
$\Delta\,\mathrm{Var}(\mu_{mpk,k})$					-0.530			-0.509	-0.500
					(-2.89)***			(-2.76)***	(-2.72)***
					[-2.33]**			[-2.23]**	[-2.20]**
R^2	0.528	0.528	0.528	0.529	0.550	0.529	0.533	0.552	0.556
Adj. R^2	0.519	0.515	0.516	0.517	0.539	0.514	0.518	0.538	0.540
RMSE	1.748	1.753	1.752	1.751	1.711	1.756	1.748	1.712	1.709

Fama-Macbeth t-statistics in parentheses. Shanken t-statistics in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Pricing tangible versus intangible misallocation shocks

		Tangible capital				Intangible capital			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
λ_0 (%)	12.090	10.964	11.798	13.468	10.224	12.225	13.150	12.183	17.843
	(3.67)***	(3.11)***	(3.33)***	(4.01)***	(3.10)***	(3.66)***	(3.94)***	(3.69)***	(5.67)***
	[3.67]***	[3.05]***	[3.33]***	[3.03]***	[1.71]*	[3.65]***	[3.55]***	[2.63]***	[3.73]***
MKT	-0.257	-0.024	-0.194	-0.965	-0.102	-0.283	-0.497	-0.598	-1.777
	(-0.25)	(-0.02)	(-0.18)	(-0.94)	(-0.10)	(-0.27)	(-0.47)	(-0.59)	(-1.87)*
	[-0.22]	[-0.02]	[-0.15]	[-0.65]	[-0.05]	[-0.23]	[-0.38]	[-0.39]	[-1.13]
$\Delta\sigma^2_{mpk}$		-0.203				0.069			
		(-0.49)				(0.13)			
		[-0.47]				[0.13]			
$\Delta\sigma^2_{mpk,0}$			-0.041				0.443		
			(-0.10)				(0.88)		
			[-0.09]				[0.78]		
$\Delta\sigma^2_{mpk,*}$				-0.710				-0.897	
				(-2.21)**				(-2.00)**	
				[-1.66]*				[-1.42]	
Δ Var($\mu_{mpk,k}$)					-1.168				-0.961
					(-3.52)***				(-2.82)***
					[-1.93]*				[-1.84]*
R^2	0.012	0.024	0.013	0.259	0.529	0.012	0.031	0.195	0.191
Adj. R^2	-0.018	-0.037	-0.049	0.213	0.499	-0.050	-0.029	0.145	0.141
RMSE	2.701	2.727	2.742	2.375	1.894	2.743	2.716	2.475	2.482

Fama-Macbeth t-statistics in parentheses. Shanken t-statistics in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the prices of risk with Fama and MacBeth (1973) and Shanken t-statistics for the 25 size × book-to-market and 10 momentum portfolios. I use sales as output and net property, plant, and equipment (ppentq) as physical capital plus intangible capital estimated from Eisfeldt and Papanikolaou (2013). The sample runs from 1975:Q2 to 2023:Q4. Returns and risk premia are reported in percent per year (quarterly percentages multiplied by four).

Table 15: Exposure to shocks to the MPK spread - subsamples

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5–Q1
Panel A: Pre-2000s						
Ret–rf	10.971**	10.566***	9.888***	9.995***	7.050*	-3.922*
	(2.56)	(2.85)	(2.90)	(2.95)	(1.83)	(-1.86)
α_{CAPM}	0.212	0.768	0.889	1.316	-3.161	-3.373
	(0.10)	(0.64)	(0.73)	(0.95)	(-1.65)	(-1.06)
α_{FF3}	2.004	0.551	1.126	0.414	-1.249	-3.253
	(0.95)	(0.39)	(0.86)	(0.26)	(-0.67)	(-1.05)
α_{FF5}	2.977	-0.409	-0.807	-2.250	-3.554	-6.531*
	(1.28)	(-0.27)	(-0.66)	(-1.56)	(-1.66)	(-1.80)
Panel E: Post-2000s						
Ret–rf	11.099**	9.968***	10.548***	8.465**	5.755	-5.344***
	(2.36)	(2.64)	(2.97)	(2.25)	(1.28)	(-2.83)
α_{CAPM}	2.060	2.538*	3.371***	1.127	-2.876	-4.936**
	(1.00)	(1.93)	(3.31)	(0.71)	(-1.46)	(-2.44)
α_{FF3}	1.876	2.416*	3.531***	1.318	-2.856	-4.731***
	(0.96)	(1.84)	(3.67)	(0.88)	(-1.45)	(-2.57)
α_{FF5}	3.657**	1.477	2.370**	-1.174	-3.357	-7.013**
	(2.06)	(1.10)	(2.32)	(-0.82)	(-1.52)	(-2.28)

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports value-weighted average excess returns and alphas in annual percentage for portfolios sorted on exposure to shocks to the MPK spread. Panel A reports the results for the subsample 1975:Q2–2000:Q4. Panel B reports the results for the subsample 2001:Q1–2023:Q4. For each stock, I regress the quarterly excess returns either on misallocation shocks or on the decomposed misallocation shocks by a rolling window of 20 quarters (with a minimum of 12 quarters available). Each quarter, I sort stocks into quintiles based on their misallocation-beta, lagging by one quarter. I hold and rebalance the portfolio every quarter.

Table 16: Cross-sectional asset pricing tests - annual frequency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
λ_0 (%)	21.248	21.022	20.335	20.741	24.741	19.322	20.304	24.218	23.201
	(7.74)***	(7.62)***	(7.60)***	(6.72)***	(8.15)***	(7.59)***	(6.73)***	(8.06)***	(7.03)***
	[6.05]***	[4.75]***	[4.56]***	[5.03]***	[4.20]***	[4.87]***	[5.00]***	[4.15]***	[3.86]***
MKT	-12.531	-12.336	-11.645	-13.558	-16.363	-10.691	-13.068	-15.715	-16.189
	(-3.54)***	(-3.45)***	(-3.31)***	(-3.46)***	(-4.31)***	(-3.14)***	(-3.39)***	(-4.16)***	(-3.93)***
	[-2.52]**	[-2.02]**	[-1.87]*	[-2.38]**	[-2.14]**	[-1.88]*	[-2.32]**	[-2.06]**	[-2.07]**
SMB	2.223	2.214	2.096	2.805	2.270	1.889	2.798	2.209	2.608
	(1.53)	(1.51)	(1.43)	(1.67)	(1.55)	(1.30)	(1.66)	(1.51)	(1.55)
	[0.94]	[0.80]	[0.74]	[1.00]	[0.71]	[0.70]	[1.00]	[0.69]	[0.75]
HML	2.976	3.269	3.449	3.030	3.540	3.689	3.128	3.788	3.714
	(1.68)*	(1.83)*	(1.94)*	(1.50)	(1.99)*	(2.07)**	(1.56)	(2.14)**	(1.86)*
	[1.04]	[0.97]	[1.00]	[0.91]	[0.91]	[1.12]	[0.94]	[0.98]	[0.90]
$\Delta\sigma^2_{mpk}$		0.945				0.829	0.231	0.566	
		(2.96)***				(2.75)***	(0.81)	(1.97)*	
		[1.80]*				[1.71]*	[0.57]	[0.99]	
$\Delta\sigma^2_{mpk,0}$			1.087			0.902			0.119
			(2.95)***			(2.85)***			(0.42)
			[1.74]*			[1.78]*			[0.22]
$\Delta\sigma^2_{mpk,*}$				-0.185			-0.177		-0.078
				(-0.81)			(-0.79)		(-0.36)
				[-0.56]			[-0.54]		[-0.19]
$\Delta\,\mathrm{Var}(\mu_{mpk,k})$					-1.311			-1.028	-1.037
					(-4.85)***			(-4.40)***	(-4.08)***
					[-2.44]**			[-2.20]**	[-2.17]**
R^2	0.494	0.505	0.512	0.550	0.543	0.525	0.551	0.555	0.631
Adj. R^2	0.465	0.465	0.473	0.514	0.506	0.476	0.505	0.510	0.584
RMSE	2.162	2.161	2.146	2.060	2.077	2.139	2.080	2.069	1.905

Fama-Macbeth t-statistics in parentheses. Shanken t-statistics in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the prices of risk with Fama and MacBeth (1973) and Shanken t-statistics for the 25 size $\times$ book-to-market, 10 momentum, 10 investment, and 10 operating profitability portfolios. The sample runs from 1975 to 2023. Returns and risk premia are reported in percent per year.

Appendix: Decomposing value-weighted capital misallocation

The general formula for the value-weighted variance, assuming no observation with zero weight, has the form

$$s_w^2 = \frac{N}{N-1} \sum_{i=1}^{N} w_i (x_i - \bar{x}_w)^2$$

where N is the number of observations, w_i is the weight for the observation x_i, $\bar{x}_w = \sum_{i=1}^{N} w_i x_i$ is the value-weighted mean of the sample.

Assume the sample splits into K portfolios, each with N_k observations and weights w_i such that $\sum_{i \in k} w_i = \Omega_k$ for each portfolio k. I normalize the weights so that $\sum_{i=1}^{N} w_i = 1$ and

$$\sum_{k=1}^{K} \Omega_k = \sum_{k=1}^{K} \sum_{i \in k} w_i = \sum_{i=1}^{N} w_i = 1.$$

For each portfolio k, the weighted variance $s_{w,k}^2$ and the weighted mean $\bar{x}_{w,k}$ are given by

$$s_{w,k}^2 = \frac{N_k}{N_k - 1} \sum_{i \in k} \frac{w_i}{\Omega_k} (x_i - \bar{x}_{w,k})^2$$
$$\bar{x}_{w,k} = \sum_{i \in k} \frac{w_i}{\Omega_k} x_i \iff \sum_{i \in k} w_i x_i = \Omega_k \bar{x}_{w,k}$$

Then total weighted mean $\bar{x}_w$ is of the form

$$\begin{aligned} \bar{x}_w &= \sum_{i=1}^{N} w_i x_i \\ &= \sum_{k=1}^{K} \sum_{i \in k} w_i x_i \\ &= \sum_{k=1}^{K} \Omega_k \bar{x}_{w,k} \end{aligned}$$

From the total weighted variance, we have

$$\begin{aligned} s_w^2 &= \frac{N}{N-1} \sum_{i=1}^{N} w_i (x_i - \bar{x}_w)^2 \\ &= \frac{N}{N-1} \sum_{k=1}^{K} \sum_{i \in k} w_i (x_i - \bar{x}_w)^2 \\ &= \frac{N}{N-1} \sum_{k=1}^{K} \sum_{i \in k} w_i (x_i - \bar{x}_{w,k} + \bar{x}_{w,k} - \bar{x}_w)^2 \\ &= \frac{N}{N-1} \sum_{k=1}^{K} \sum_{i \in k} w_i \left[(x_i - \bar{x}_{w,k})^2 + 2(x_i - \bar{x}_{w,k})(\bar{x}_{w,k} - \bar{x}_w) + (\bar{x}_{w,k} - \bar{x}_w)^2 \right] \end{aligned}$$

Consider the cross-term

$$\begin{aligned}
\sum_{k=1}^{K}\sum_{i\in k} w_i(x_i-\bar{x}_{w,k})(\bar{x}_{w,k}-\bar{x}_w) &= \sum_{k=1}^{K}(\bar{x}_{w,k}-\bar{x}_w)\sum_{i\in k} w_i(x_i-\bar{x}_{w,k}) \\
&= \sum_{k=1}^{K}(\bar{x}_{w,k}-\bar{x}_w)(\sum_{i\in k} w_i x_i-\bar{x}_{w,k}\sum_{i\in k} w_i) \\
&= \sum_{k=1}^{K}(\bar{x}_{w,k}-\bar{x}_w)(\Omega_k\bar{x}_{w,k}-\Omega_k\bar{x}_{w,k}) \\
&= 0
\end{aligned}$$

Thus,

$$s_w^2 = \frac{N}{N-1}\left[\underbrace{\sum_{k=1}^{K}\sum_{i\in k} w_i(x_i-\bar{x}_{w,k})^2}_{\text{Within-group variances}} + \underbrace{\sum_{k=1}^{K}\sum_{i\in k} w_i(\bar{x}_{w,k}-\bar{x}_w)^2}_{\text{Between-group variance}}\right]$$

The first term represents the within-group variances, and the second term represents the between-group variance, i.e. the weighted variance of the subsample means from the total mean. We can write the within-group variances as

$$\begin{aligned}
\sum_{k=1}^{K}\sum_{i\in k} w_i(x_i-\bar{x}_{w,k})^2 &= \sum_{k=1}^{K}\Omega_k\sum_{i\in k}\frac{w_i}{\Omega_k}(x_i-\bar{x}_{w,k})^2 \\
&= \sum_{k=1}^{K}\frac{N_k-1}{N_k}\Omega_k s_{w,k}^2
\end{aligned}$$

where $\frac{w_i}{\Omega_k}$ is the weight within each portfolio such that $\sum_{i\in k}\frac{w_i}{\Omega_k}=1$. For the between-group variance,

$$\begin{aligned}
\sum_{k=1}^{K}\sum_{i\in k} w_i(\bar{x}_{w,k}-\bar{x}_w)^2 &= \sum_{k=1}^{K}(\bar{x}_{w,k}-\bar{x}_w)^2\sum_{i\in k} w_i \\
&= \sum_{k=1}^{K}\Omega_k(\bar{x}_{w,k}-\bar{x}_w)^2
\end{aligned}$$

Combining both terms, we have:

$$s_w^2 = \frac{N}{N-1}\left[\sum_{k=1}^{K}\frac{N_k-1}{N_k}\Omega_k s_{w,k}^2 + \sum_{k=1}^{K}\Omega_k(\bar{x}_{w,k}-\bar{x}_w)^2\right]$$

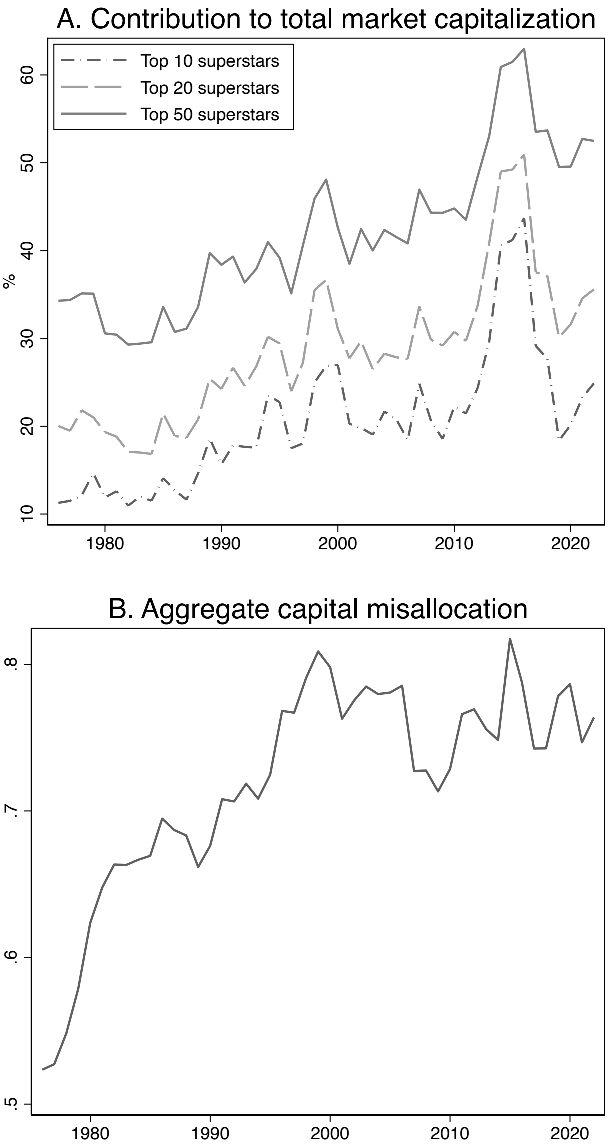
where $\Omega_k=\sum_{i\in k} w_i$, $\bar{x}_w=\sum_{i=1}^{N} w_i x_i$, and $\bar{x}_{w,k}=\sum_{i\in k}\frac{w_i}{\Omega_k}x_i$.

Given $K=2$, the formula simplifies to

$$s_w^2 = \frac{N}{N-1}\left[\frac{N_1-1}{N_1}\Omega_1 s_{w,1}^2 + \frac{N_2-1}{N_2}\Omega_2 s_{w,2}^2 + \Omega_1(\bar{x}_{w,1}-\bar{x}_w)^2 + \Omega_2(\bar{x}_{w,2}-\bar{x}_w)^2\right].$$

Online Appendix: Additional results

Figure A1: Market concentration and capital misallocation



Description. This figure shows the rising trend in market concentration and aggregate capital misallocation. Panel A plots the market cap of top 10, 20, and 50 superstar firms by size and market power over the total market cap in percentage. Panel B plots the dispersion in MPK across firms, where MPK is the log output-to-capital (measured by sale/cogs). The sample is at an annually from 1975 to 2023.

Table A1: Correlation between shocks

	$\Delta\sigma^2_{mpk}$	$\Delta\sigma^2_{mpk,0}$	$\Delta\sigma^2_{mpk,*}$	$\Delta\,\mathrm{Var}(\mu_{mpk,k})$
$\Delta\sigma^2_{mpk}$	1.00			
$\Delta\sigma^2_{mpk,0}$	0.99***	1.00		
$\Delta\sigma^2_{mpk,*}$	0.25***	0.14*	1.00	
$\Delta\,\mathrm{Var}(\mu_{mpk,k})$	-0.15**	-0.17**	0.10	1.00

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the correlation between the shocks. The sample is from 1975:Q1 to 2023:Q4. In each quarter, capital misallocation $\sigma^2_{mpk,t}$ is the cross-sectional dispersion of MPK across firms. The misallocation shocks are the annual changes in capital misallocation:

$$\Delta\sigma^2_{mpk,t} = \sigma^2_{mpk,t} - \sigma^2_{mpk,t-4},$$

whose level can be decomposed into:

$$\sigma^2_{mpk} = \underbrace{\frac{N_0 - 1}{N - 1}\sigma^2_{mpk,0}}_{\text{Misallocation among non-superstars}} + \underbrace{\frac{N_* - 1}{N - 1}\sigma^2_{mpk,*}}_{\text{Misallocation among superstars}} + \underbrace{\frac{N_0 N_*}{N(N-1)}(\mu_{mpk,0} - \mu_{mpk,*})^2}_{\text{MPK spread}}$$

Table A2: Significance of $\Delta\,\mathrm{Var}(\mu_{mpk,k})$ - simulation results

	Frequency	Percent
*** $p < 0.01$	2	.4
** $p < 0.05$	24	4.8
* $p < 0.10$	36	7.2
* $p < 1$	438	88
Total	500	100

Description. This table reports the significance of the price of risk of shocks to the MPK spread ($\Delta\,\mathrm{Var}(\mu_{mpk,k})$) in the second-stage Fama-MacBeth regression. Each simulation selects randomly 50 firms to the superstar portfolio.

Table A3: Cross-sectional asset pricing tests - alternative measure for intangible capital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
λ_0 (%)	20.904	19.552	19.635	20.890	19.656	20.172	20.208	17.806	18.174
	(6.96)***	(7.43)***	(7.47)***	(7.24)***	(6.75)***	(7.57)***	(7.61)***	(7.31)***	(7.64)***
	[5.49]***	[6.14]***	[6.18]***	[5.69]***	[4.44]***	[5.65]***	[5.81]***	[4.53]***	[4.81]***
MKT	-11.685	-9.675	-9.761	-10.864	-9.621	-10.051	-10.137	-7.748	-8.049
	(-2.93)***	(-2.69)**	(-2.72)***	(-2.86)***	(-2.54)**	(-2.78)***	(-2.81)***	(-2.26)**	(-2.37)**
	[-2.09]**	[-1.95]*	[-1.97]*	[-2.02]*	[-1.54]	[-1.86]*	[-1.91]*	[-1.29]	[-1.36]
SMB	2.648	2.375	2.381	2.544	2.855	2.560	2.497	2.840	2.862
	(1.62)	(1.45)	(1.45)	(1.55)	(1.73)*	(1.56)	(1.52)	(1.72)*	(1.73)*
	[1.02]	[0.93]	[0.93]	[0.97]	[0.96]	[0.94]	[0.93]	[0.91]	[0.93]
HML	2.787	2.578	2.545	2.383	2.133	2.739	2.713	2.598	2.650
	(1.13)	(1.05)	(1.03)	(0.95)	(0.85)	(1.11)	(1.10)	(1.05)	(1.08)
	[0.71]	[0.67]	[0.67]	[0.60]	[0.47]	[0.67]	[0.68]	[0.56]	[0.58]
$\Delta\sigma^2_{mpk}$		-0.260				-0.381	-0.371	-0.144	
		(-0.79)				(-1.11)	(-1.08)	(-0.46)	
		[-0.61]				[-0.78]	[-0.78]	[-0.27]	
$\Delta\sigma^2_{mpk,0}$			-0.223			-0.352			-0.172
			(-0.70)			(-1.05)			(-0.55)
			[-0.53]			[-0.74]			[-0.33]
$\Delta\sigma^2_{mpk,*}$				-0.101			-0.133		-0.048
				(-0.77)			(-1.01)		(-0.35)
				[-0.53]			[-0.68]		[-0.20]
Δ Var($\mu_{mpk,k}$)					-0.463			-0.492	-0.458
					(-3.83)***			(-3.92)***	(-3.64)***
					[-2.36]**			[-2.30]**	[-2.16]**
R^2	0.568	0.559	0.557	0.563	0.629	0.591	0.578	0.672	0.673
Adj. R^2	0.542	0.524	0.522	0.528	0.599	0.549	0.535	0.639	0.632
RMSE	1.814	1.851	1.854	1.842	1.698	1.800	1.829	1.612	1.626

Fama-Macbeth t-statistics in parentheses. Shanken t-statistics in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the prices of risk with Fama and MacBeth (1973) and Shanken t-statistics for the 25 size $\times$ book-to-market, 10 momentum, 25 size and operating profitability, and 25 size and investment portfolios. I obtain intangible capital from Peters and Taylor (2017), accessed via WRDS. The sample runs from 1975 to 2022.

Table A4: Exposure to shocks to the MPK spread (equally weighted results)

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5–Q1
Panel A: Expected return						
Ret–rf	16.965***	13.699***	12.935***	12.607***	14.025***	-2.940**
	(4.25)	(4.35)	(4.26)	(3.93)	(3.68)	(-2.56)
Panel B: CAPM						
MKT	1.403***	1.138***	1.115***	1.171***	1.332***	-0.072*
	(18.73)	(21.34)	(21.07)	(21.50)	(19.49)	(-1.92)
α_{CAPM}	4.712**	3.464**	2.990**	2.357	2.466	-2.245*
	(2.32)	(2.28)	(2.09)	(1.57)	(1.28)	(-1.91)
Panel C: FF3 + UMD						
MKT	1.091***	0.952***	0.941***	0.966***	1.029***	-0.062
	(21.56)	(30.84)	(32.38)	(33.46)	(27.10)	(-1.42)
SMB	1.189***	0.825***	0.772***	0.854***	1.144***	-0.045
	(14.76)	(16.25)	(16.24)	(18.39)	(18.21)	(-0.60)
HML	-0.013	0.147***	0.136***	0.109***	0.007	0.020
	(-0.18)	(4.20)	(4.36)	(2.82)	(0.13)	(0.36)
UMD	-0.158*	-0.097**	-0.089**	-0.126**	-0.177**	-0.020
	(-1.80)	(-2.52)	(-2.02)	(-2.30)	(-2.47)	(-0.42)
$\alpha_{FF3+UMD}$	6.504***	3.955***	3.442***	3.257***	4.323***	-2.180*
	(4.37)	(4.75)	(4.44)	(3.65)	(3.18)	(-1.82)
Panel D: FF5						
MKT	1.108***	0.988***	0.986***	1.021***	1.065***	-0.043
	(19.57)	(31.72)	(34.85)	(34.28)	(24.84)	(-0.97)
SMB	1.187***	0.860***	0.818***	0.907***	1.171***	-0.015
	(15.67)	(17.31)	(18.57)	(23.47)	(17.71)	(-0.22)
HML	-0.045	0.087*	0.052	0.006	-0.032	0.013
	(-0.45)	(1.68)	(1.08)	(0.12)	(-0.42)	(0.15)
RMW	-1.286***	0.126	0.471**	0.364**	-0.672**	0.614
	(-2.87)	(0.64)	(2.11)	(2.11)	(-2.40)	(1.45)
CMA	1.017*	0.717***	0.809***	1.085***	0.964**	-0.054
	(1.94)	(2.78)	(3.20)	(3.72)	(2.09)	(-0.13)
α_{FF5}	6.104***	2.397***	1.430*	0.861	2.933**	-3.172**
	(4.37)	(2.85)	(1.79)	(1.15)	(2.51)	(-2.39)

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports equally weighted average excess returns and alphas in annual percentage for portfolios sorted on exposure to shocks to the MPK spread. For each stock, I regress the quarterly excess returns either on misallocation shocks or on the decomposed misallocation shocks by a rolling window of 20 quarters (with a minimum of 12 quarters available). Each quarter, I sort stocks into quintiles based on their misallocation-beta, lagging by one quarter. I hold and rebalance the portfolio every quarter. The sample runs from 1975:Q1 to 2023:Q4.

Table A5: Characteristics of stocks in the MPK spread-mimicking portfolios

	Low	Q2	Q3	Q4	High	High–Low	t(High–Low)
$\beta_{\Delta\,\mathrm{Var}(\mu_{mpk,k})}$	-0.592	-0.198	-0.022	0.169	0.513	1.105	(2.43)
Market cap	17,492.180	38,355.184	49,901.367	29,264.824	25,961.316	8,469.136	(3.36)
Markup ratio	1.785	1.680	1.682	1.825	1.934	0.148	(4.54)
Book-to-market	0.501	0.490	0.474	0.478	0.461	-0.039	(-1.94)
Innovation	19.908	29.970	36.518	18.421	18.042	-1.866	(-1.73)
Duration	62.301	80.425	81.964	79.883	64.740	2.439	(2.35)
Investment	2,179.251	6,231.840	12,381.994	6,100.768	4,392.167	2,212.916	(4.32)
Physical capital	3,754.690	9,973.484	9,830.880	7,848.565	4,537.075	782.385	(2.29)
Intangible capital	1,812.195	2,899.301	2,930.864	2,621.818	2,197.016	384.821	(4.26)

Description. This table reports the value-weighted average characteristics of stocks in each MPK spread-mimicking portfolio. The sample runs from 1975:Q1 to 2023:Q4.

Table A6: Predicting aggregate patent ratio

	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta\sigma^2_{mpk}$	-0.039		0.048		-0.074		-0.033		-0.008	
	(-0.61)		(0.53)		(-0.58)		(-0.25)		(-0.04)	
	[-0.60]		[0.49]		[-0.57]		[-0.24]		[-0.04]	
Δ Var$(\mu_{mpk,k})$		-6.769		-8.501		-4.824		-5.373		-4.901
		(-4.27)***		(-4.05)***		(-2.70)***		(-2.20)**		(-1.86)*
		[-4.19]***		[-4.52]***		[-2.65]**		[-2.60]**		[-2.02]**
R^2	0.003	0.154	0.003	0.145	0.005	0.032	0.001	0.030	0.000	0.018
RMSE	0.021	0.019	0.027	0.025	0.033	0.033	0.038	0.038	0.045	0.045

t-ratio of Hodrick (1992) with k-1 lags in parentheses. t-ratio of Newey-West (1987) with k-1 lags in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Description. This table reports the results of the following predictive regression:

$$I_{t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k},$$

where $I_{t:t+k}$ is the innovation growth in k quarters. The predictive variables z_t are shocks to the aggregate misallocation and the MPK spread. The columns show results for $k = 1, 4, 8, 12$ and 20 quarters. Following Bae, Bailey, and Kang (2021), I construct the innovation proxy I_t as the natural logarithm of one plus the number of patent applications divided by the population. The number of patents granted each year is from the US Patent Trademark Office (USPTO) and the US population is from the U.S. Bureau of Economic Analysis (BEA). The aggregate patent ratio equals = log(1 + # patents/population). The sample is at an annual frequency from 1975 to 2020.