Market Concentration, Capital Misallocation, and Asset Pricing*

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Abstract

Superstar firms, which dominate stock markets through their large size and high markups, can distort efficient capital allocation. This paper empirically studies the asset pricing implications of superstar firms through the channel of capital misallocation, measured as the cross-sectional dispersion in the marginal product of capital (MPK). I decompose this measure into misallocation (1) among superstars, (2) among other firms, and (3) between these two groups. I find that only changes in the third component, termed the "MPK spread", are negatively priced in the cross-section of stock returns. Stocks with negative exposure to these changes outperform stocks with positive exposure by 4.8% per year. In the long run, a higher MPK spread predicts lower economic growth and aggregate stock returns, while in the short run, it predicts lower innovation growth. Consistent with the ICAPM framework, capital misallocation between superstar and non-superstar firms is a key state variable, and its changes capture a macroeconomic risk factor.

JEL classification: E22, G11, G12, G14.

Keywords: Superstar firms, capital misallocation, economic growth, cross-sectional asset pricing.

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1 Introduction

In recent decades, the US stock markets have become increasingly concentrated. Not only did the number of listed firms decline by 50% between 1996 and 2012 (Doidge, Karolyi, and Stulz, 2017), but also a few numbers of highly successful firms, so-called "superstar" firms, have dominated the market (Kwon, Ma, and Zimmermann, 2024). These developments have led to several macroeconomic and corporate consequences, such as the decline in aggregate labor share (e.g., Autor, Dorn, Katz, Patterson, and Van Reenen, 2020) and contribution to GDP (e.g., Schlingemann and Stulz, 2022). However, little is known about the implications for asset pricing.

This paper shows the asset pricing consequences of superstar firms through the channel of capital misallocation. Bae, Bailey, and Kang (2021) find that stock market concentration is associated with capital misallocation as it impedes competition and innovation. As higher capital misallocation hinders economic growth (David, Hopenhayn, and Venkateswaran, 2016; Dou, Ji, Tian, and Wang, 2023), capital misallocation could be a candidate state variable that predicts changes in investment opportunities in the Intertemporal CAPM (ICAPM) framework.

My paper finds that capital misallocation between superstar and non-superstar firms is a key state variable and its changes capture a macroeconomic risk factor. Using the quarterly data of US-listed firms from Compustat from 1975:Q1 to 2023:Q4, I measure capital misallocation as the cross-sectional dispersion in the firm-level marginal product of capital (MPK) (David and Venkateswaran, 2019) and David, Schmid, and Zeke (2022). I decompose this measure into three components: (1) misallocation among superstar firms, (1) misallocation among non-superstar firms, and (3) misallocation between these two groups referred to as "MPK spread". I construct changes in the aggregate misallocation and each component and show three key results.

First, only changes in the MPK spread, indicating capital misallocation between superstar and non-superstar firms, are a priced risk factor. In different cross-sections of stock returns, changes in the MPK spread carry a negative price of risk, implying that stocks with negative exposure to the changes earn a higher expected return. These stocks depreciate when changes in the MPK spread rise, making them more risky. In contrast, stocks with positive exposure to these changes earn a lower expected return. Their returns tend to increase when changes in the MPK spread rise, making them a hedge. The long-short portfolio sorted on individual stock exposure to changes in the MPK spread, referred to as the MPK spread-mimicking portfolio, earns an expected return of -4.8% per year.

Second, in contrast, changes in the aggregate capital misallocation and the other components do not carry significant prices of risk. A spanning test analysis confirms the dominance of the MPK spread over other components. Specifically, only the MPK spread-mimicking portfolio spans the portfolio exposed to changes in aggregate misallocation. Whereas, the portfolios exposed to changes in aggregate misallocation and other components do not span the MPK spread-mimicking portfolio.

Third, only the MPK spread is a key state variable as it predicts future economic growth. In the long term, a higher MPK spread predicts lower consumption growth, industrial production growth, and employment growth. In the short term, a higher MPK spread predicts lower aggregate innovation growth and innovation growth of non-superstar firms. In contrast, aggregate capital misallocation as well as the other components do not yield any predictive power. Therefore, only capital misallocation between superstar and non-superstar firms is a candidate state variable.

Consistent with the ICAPM, the MPK spread satisfies three restrictions proposed by Maio and Santa-Clara (2012). First, the MPK spread as a state variable negatively forecasts changes in investment opportunities, proxied by the aggregate stock returns. Second, changes in the MPK spread as a factor earn a negative price of risk in cross-sectional tests, consistent with the sign of forecast. Third, in the multi-factor model that includes market and changes in the MPK spread as the factors, 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 spread in the mean productive use of production capital between superstar and non-superstar firms discourages long-run economic growth. Thus, changes in capital misallocation between superstar and non-superstar firms represent negative news to investors whose marginal utility depends on consumption growth risks. In the ICAPM framework, these changes capture a macroeconomic risk factor, highlighting superstar firms' role in shaping the risk premium associated with capital misallocation.

Following Autor, Dorn, Katz, Patterson, and Van Reenen (2020) and Cheng, Vyas, Wittenberg-Moerman, and Zhao (2024), I identify superstar firms as the top 5% firms in their industries based on market capitalization and market power. I estimate firm-level market power as markup, proxied by the ratio of sales to the cost of goods sold, using the method from

De Loecker, Eeckhout, and Unger (2020)[1]. I measure firm-level MPK as the log ratio of output-to-capital. Capital includes both tangible capital (net property, plant, and equipment) and intangible capital estimated from Eisfeldt and Papanikolaou (2013) and Eisfeldt, Kim, and Papanikolaou (2020). Aggregate capital misallocation is then the dispersion in MPK across firms in each quarter. A time series of the changes in misallocation shows that periods of high capital misallocation coincide with recessions, consistent with the countercyclical pattern of capital misallocation documented in the literature (e.g., Eisfeldt and Rampini, 2006; Bloom, 2009; Bachmann and Bayer, 2014; Kehrig, 2015; David, Schmid, and Zeke, 2022).

To test the role of superstar firms, I examine the pricing of changes in aggregate misallocation, misallocation among superstar firms, misallocation among non-superstar firms, and the MPK spread. The cross-sectional Fama-MacBeth regressions show that changes in the MPK spread are significantly and negatively priced in the cross-section of 25 size$\times$book-to-market, 10 momentum, 25 size$\times$investment, 25 size$\times$operating profitability portfolios. This finding is robust to using Giglio and Xiu (2021)'s 202 portfolios. Whereas, the pricing of changes in aggregate misallocation and the other two components are not robust and consistent across different models and test portfolios.

Next, I create mimicking portfolios to examine individual stock exposure to changes in aggregate misallocation and each component. For each stock, I regress the quarterly excess returns on the changes using a rolling window of 20 quarters. Then I sort stocks into quintiles based on their beta estimates in each quarter. The value-weighted portfolios show that the average excess returns decrease as the stock exposure to changes in 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 when I construct an equally weighted portfolio.

Finally, to test whether the aggregate misallocation or its components is a state variable, I run the standard predictive regression of several future macroeconomic variables on the lagged aggregate misallocation and its components. I find that only the MPK spread predicts negative

[1] Additionally, I also impose the condition that superstar firms have to increase their markup shares within their industries compared to the previous 12 quarters (3 years).

per capita real consumption growth (nondurables and services), industrial production growth, employment growth, and stock market returns in the next 4 to 12 quarters (1 to 3 years). The MPK spread also predicts negative aggregate innovation growth, especially innovation growth of non-superstar firms in the next 1 to 5 quarters. Thus, only 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 or sales show that the top 50 firms confirm the results in the cross-sectional asset pricing tests and predictability. Besides, the results are robust to using different industry classifications, a value-weighted measure for misallocation, separating misallocation by tangible and intangible capital, the pre-2000s and post-2000s subsamples, and using annual frequency.

The contribution of this paper is threefold. First, I link the macroeconomic consequences of superstars to asset pricing. Second, I propose capital misallocation between superstars and non-superstars as a state variable and its changes 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, resulting in higher capital misallocation, could prevent innovation growth and deter economic growth, consistent with Bae, Bailey, and Kang (2021) and Kung and Schmid (2015). Investors are willing to pay a sizeable premium to eliminate such long-run uncertainty about economic growth.

Related literature. My paper contributes to three strands of literature. First, the literature has documented several macroeconomic consequences of superstar firms. For example, Autor, Dorn, Katz, Patterson, and Van Reenen (2020) argue that the rise of superstar firms leads to a decline in the aggregate labor share.[2] Schlingemann and Stulz (2022) argue that the market capitalization of listed firms has become less informative about firms' contribution to aggregate output.[3] Gutierrez and Philippon (2019) also find that the contribution of superstar firms to aggregate productivity growth has also decreased. My paper contributes to this literature by linking one consequence of superstar firms to asset pricing.

[2]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 aggregate labor share. Gutierrez and Philippon (2020) also find that the contribution of superstar firms to aggregate labor productivity has decreased.

[3]This is due to the decline in the manufacturing industry oriented in tangible capital and the shift towards the service industry which favors intangible capital.

Particularly, there has been evidence that superstar firms deter efficient capital allocation. For instance, Bae, Bailey, and Kang (2021) find that a concentrated stock market is less likely to allocate capital to firms that could use capital more efficiently. Su (2022) also shows that capital misallocation increases when the economy includes superstar firms.[4] De Loecker, Eeckhout, and Unger (2020) and De Loecker and Eeckhout (2021) show that economic activity is more reallocated toward superstar firms. Neuhann and Sockin (2024) suggest that financial market concentration can dampen efficient capital allocation. [5] Based on this evidence, my paper shows that changes in capital misallocation between superstar firms and non-superstar firms capture an asset pricing factor.

Second, several papers have shown that markups are an important source of capital misallocation. Peters (2020) finds that older firms improve their productivity away from competitors, raising the markups that they can optimally charge on their existing products, consistent with the superstar phenomenon. Capital misallocation rises as a result of a decline in creative destruction.[6] 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.[7]

Furthermore, capital misallocation is an important deterrent to economic growth (Eisfeldt and Rampini, 2006, 2008; Eisfeldt and Shi, 2018). My paper adds to the literature by looking at different components of an empirical measure of capital misallocation. I find that only the component that captures the misallocation between superstar firms and the rest of the firms negatively predicts proxies for economic growth. Other components do not have predictive power for economic growth.

Third, recent papers document asset pricing implications of superstar firms and market con-

[4]When firms face uncertainty in their product quality, superstar firms become riskier as they face more volatile fluctuations in their markups.

[5]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. Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez (2017) also document an increase in capital misallocation in South Europe and observe that firms with higher net worth, but not necessarily higher productivity, attract more capital, causing productivity losses.

[6]Creative destruction is the extent to which new firms replace older firms to maintain competition in the market

[7]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 the reallocation of labor and capital toward 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.

centration. For example, Emery and Koëter (2024) show that rising stock market concentration increases the size premium. Cheng, Vyas, Wittenberg-Moerman, and Zhao (2024) show in product markets that firms with high exposure to superstars experience weaker financial performance and higher risk. Hou and Robinson (2006) shows at the industry level that firms in more concentrated industries earn lower expected returns. My paper finds evidence for market-wide concentration and that stocks negatively (positively) exposed to changes in misallocation between superstar and non-superstar firms earn a higher (lower) expected return.

The mechanism of my paper is closely related to Dou, Ji, Tian, and Wang (2023) who show that changes in 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.[8] The source of friction that drives misallocation is financial constraints, while my paper studies size and market power as the main sources of friction.

Finally, my paper examines the effect of capital misallocation on risk premia. Whereas, 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 countercyclicality of the capital misallocation between superstar and non-superstar firms.

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

2 Data

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

[8] Changes in misallocation are a risk factor as capital misallocation influences the investors' stochastic discount factor (SDF) through its effect on consumption growth.

2.1 Sample and variable construction

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:Q1 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,

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

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).

Following David, Schmid, and Zeke (2022) and David, Hopenhayn, and Venkateswaran (2016), I compute the firm-level MPK as the log ratio of output to lagged capital.[9] I use sales as output and net property, plant, and equipment (ppentq) as tangible capital plus intangible capital estimated from Eisfeldt and Papanikolaou (2013). I exclude firm-quarter observations

[9]Changes in capital misallocation capture the recessions better when we take the lagged capital.

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.

In the main analysis, the test portfolios for the Fama-MacBeth regressions include 25 size and 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 portfolios sorted by size and book-to-market ratio, 17 industry portfolios, 25 portfolios sorted by operating profitability and investment, 25 portfolios sorted by size and variance, 35 portfolios sorted by size and net issuance, 25 portfolios sorted by size and accruals, 25 portfolios sorted by size and beta, and 25 portfolios sorted by size and momentum. I retrieve all factor data at a quarterly frequency and annual frequency for a robust check from Kenneth French's data library[10].

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 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)[11]. 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).

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)

[10] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[11] https://www.uspto.gov/web/offices/ac/ido/oeip/taf/h_at.htm

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, Dorn, Katz, Patterson, and Van Reenen (2020)'s discussion that superstars are firms *increasingly dominating* their industries, leading to rising 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 ($0.85 \times$ 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 (2024) 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 ($0.85 \times$ saleq/cogsq $\times$ market cap).[12] Finally, I also impose the condition that superstar firms have to increase their markup shares within their industries compared to the previous 12 quarters (3 years) to follow that intuition from Autor, Dorn, Katz, Patterson, and Van Reenen (2020) that superstars *increasingly dominate* the market.[13]

2.3 Capital misallocation

In the absence of any friction, MPK should equalize across firms. The MPK dispersion can help to measure capital misallocation because it is proportional to aggregate TFP loss (Midrigan and Xu, 2014). 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

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

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.

[12] Cheng, Vyas, Wittenberg-Moerman, and Zhao (2024) 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.

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

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 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.

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

$$\Delta\sigma^2_{mpk,t} = \sigma^2_{mpk,t} - \sigma^2_{mpk,t-4}. \tag{3}$$

[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.

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 the case of two groups (superstar firms and non-superstar firms), the aggregate MPK dispersion can be decomposed into

$$\begin{aligned}\underbrace{\sigma^2_{mpk}}_{\text{Total misallocation (Misall}_{\text{total}})} &= \underbrace{\frac{N_0 - 1}{N - 1}\sigma^2_{mpk,0}}_{\text{Misallocation within non-superstars (Misall}_{\text{rest}})} \\ &+ \underbrace{\frac{N_* - 1}{N - 1}\sigma^2_{mpk,*}}_{\text{Misallocation within superstars (Misall}_{\text{top}})} + \underbrace{\frac{N_0 N_*}{N(N-1)}(\mu_{mpk,0} - \mu_{mpk,*})^2}_{\text{MPK spread}}\end{aligned} \tag{4}$$

Section A0.1 in the Appendix shows the derivation. Intuitively, 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 changes in misallocation into

$$\Delta \text{Misall}_{\text{total}} = \Delta \text{Misall}_{\text{rest}} + \Delta \text{Misall}_{\text{top}} + \Delta \text{MPK spread} \tag{5}$$

[Figure 2 about here.]

Figure 2 plots the time series of the aggregate misallocation and its components. Periods of high misallocation tend to coincide with the NBER recessions, implying the countercyclicality of capital misallocation. Consistent with David, Schmid, and Zeke (2022), MPK dispersion rises during economic downturns. The MPK spread, i.e. the misallocation between superstars and non-superstars, particularly displays clear 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. 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.

3 Asset pricing results

Bae, Bailey, and Kang (2021) show that stock market concentration is associated with capital misallocation as it impedes competition and innovation. As higher capital misallocation indicates slower economic growth (David, Hopenhayn, and Venkateswaran, 2016; Dou, Ji, Tian, and Wang, 2023), capital misallocation could be a candidate state variable that predicts changes in investment opportunities under the Intertemporal CAPM (ICAPM) framework.

In this section, I show the cross-sectional asset pricing results of changes in 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 changes.

3.1 Cross-sectional analysis

In this section, I examine whether the changes in aggregate misallocation 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)

$$R^e_{it} = \alpha_i + \sum_k \beta_{ik} f_{kt} + u_{it}, \tag{6}$$

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

$$R^e_{it} = \lambda_{0,t} + \sum_k \lambda_{kt} \hat{\beta}_{ik} + \varepsilon_{i,t}. \tag{7}$$

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 changes in aggregate misallocation and its components. Table 1 reports results for the second-stage regressions. Panel A shows that results in the cross-section of 25 size $\times$ 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 changes in aggregate misallocation, the changes in aggregate misallocation have a negative price of risk, although not significant.

[Table 1 about here.]

When the model includes changes in each component as a separate factor, Model (5), (8), and (9) show that changes in 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 changes 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 $\times$ investment and 25 size $\times$ operating profitability portfolios. While the significance of the price of risk of other decomposed changes is not robust to different t-ratios, the significance of the price of risk of changes in the MPK spread remains consistent.

Intuitively, a positive change in 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, changes in 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 changes in 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 changes. These results confirm an important role of superstars in asset pricing: The negative price of risk of capital changes in misallocation 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 changes in misallocation 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 exposure to the changes in aggregate misallocation and changes in 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 changes in the MPK spread. In other words, value stocks should have lower betas for changes in 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 changes in aggregate misallocation, 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 changes in misallocation in the non-superstar portfolio show no significant betas. Thus, these two factors are seemingly spurious factors. In Panel C, the changes in misallocation in the superstar portfolio, most betas are negative and large but weakly significant. Only changes in 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 changes than growth stocks.

3.2 Factor-mimicking Portfolios

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

$$R_{it}^e = \alpha_i + \beta_{it}\Delta z_t + \varepsilon_{it}, \quad t = t-20 \rightarrow t. \quad z \in \{\text{Misall}_{\text{total}}, \text{Misall}_{\text{rest}}, \text{Misall}_{\text{top}}, \text{MPK spread}\} \tag{8}$$

The stock's exposure to the changes in misallocation 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 changes in 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 changes in the MPK spread. The expected return reduces when misallocation increases, i.e. a positive change in 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 changes in 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 changes in 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 changes in aggregate misallocation and changes in the misallocation within each portfolio. Yet, the results are insignificant. These results strengthen the mechanism for the negative price of risk of the changes in the MPK spread.

Table A2 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 changes in the MPK spread.

Table A3 reports the value-weighted average characteristic of the stocks in each quintile portfolio. The results show that, on average, stocks negatively exposed to changes in 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 changes (Quintile 5). Thus, non-superstar firms tend to be negatively exposed to changes in the MPK spread. Whereas, superstar firms tend to be positively exposed to theses changes. Consistently, non-superstar firms tend to be risky, and superstar firms tend to provide a hedge during economic downturns against changes in 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 changes in 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.

3.3 Spanning tests

Next, I study the diversification benefits of each portfolio. This section tests whether the portfolio exposed to changes in 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 changes in aggregate misallocation. The Jensen measure is significantly different from zero for the portfolio exposed to changes in the MPK spread as the test asset. Therefore, adding the portfolio exposed to changes in the MPK spread to the portfolio exposed to the changes in aggregate misallocation 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 changes in the MPK spread. The portfolio exposed to changes in the MPK spread prices all benchmark portfolios. Hence, Adding the portfolio exposed to changes in the MPK spread improves the mean-variance efficiency of the portfolio exposed to the changes in the aggregate misallocation and other portfolios.

4 Predicting 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:

$$\Delta CG_{t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k}, \quad z \in \{\text{Misall}_{\text{total}}, \text{Misall}_{\text{rest}}, \text{Misall}_{\text{top}}, \text{MPK spread}\} \tag{9}$$

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:

$$\Delta IP_{t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k} \tag{10}$$

where $IP_{t:t+k}$ is the industrial production growth in k quarters. From 4 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:

$$\Delta E_{t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k} \tag{11}$$

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, changes in the MPK spread also robustly predict negative economic growth. Table 11 reports the same set of regressions when changes in aggregate misallocation and the MPK spread act as predictors. Changes in the MPK spread negatively predict consumption growth, industrial growth, and employment growth. Although the changes in aggregate misallocation 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).

Intuitively, the predictability results support the mechanism that superstar firms attract more capital disproportionally due to their market power rather than their productivity. If the driving factor is productivity, it would be considered good news for the economy, making it unclear why it would be associated with negative outcomes such as slower economic growth, and declining employment. Therefore, the results suggest that the observed effects are not tied to productive efficiency but rather to the influence of market power, which could negatively impact these economic indicators.

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:

$$\Delta I_{t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k} \tag{12}$$

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 changes do no carry a significantly negative price of risk. Therefore, only the MPK spread is a good candidate state variable.

4.1 Consistency with the ICAPM

In this section, I examine whether changes in 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:

$$R^e_{mkt,t:t+k} = \alpha + \beta z_t + \epsilon_{t:t+k} \tag{13}$$

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 (13) 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 $t+k$:

$$\hat{R}^e_{mkt,t:t+k} = \hat{\alpha}_t + \hat{\beta}_t z_t, \tag{14}$$

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

$$R^2_{OOS} = 1 - \frac{\sum_{t=80}^{T-k}(R_{mkt,t:t+k} - \hat{R}_{mkt,t:t+k})^2}{\sum_{t=80}^{T-k}(R_{mkt,t:t+k} - k\bar{R}_{mkt,1:t})^2}, \tag{15}$$

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 changes in 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

$$\mathbb{E}(R^e_{i,t+1}) = \gamma_m \text{ Cov}(R^e_{i,t+1}, MKT_{t+1}) + \gamma_z \text{ Cov}(R^e_{i,t+1}, \Delta z_{t+1}) \tag{16}$$

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:

$$g_T(\mathbf{b}) \equiv \frac{1}{T}\sum_{t=0}^{T-1} \begin{pmatrix} R^e_{i,t+1} - \gamma_m R^e_{i,t+1}(MKT_{t+1} - \mu_m) \\ -\gamma_z R^e_{i,t+1}(\Delta z_{t+1} - \mu_z) \\ MKT_{t+1} - \mu_m \\ \Delta z_{t+1} - \mu_z \end{pmatrix} = 0, \quad i = 1, \ldots, N. \tag{17}$$

The first factor in this model is the market with unconditional mean μ_m. The second factor is the changes in the state variable z, where $z \in \{\text{Misall}_{\text{total}}, \text{Misall}_{\text{rest}}, \text{Misall}_{\text{top}}, \text{MPK spread}\}$. To test the goodness of fit, I construct the mean absolute pricing error (MAE)

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} |\hat{\alpha}_i|, \tag{18}$$

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:

$$R^2_{\text{OLS}} = 1 - \frac{\text{Var}_N(\hat{\alpha}_i)}{\text{Var}_N(\bar{R}_i)}, \tag{19}$$

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 changes in 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. Changes in 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 changes in the MPK spread are a priced risk factor.

5 Robustness tests

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

5.1 Alternative definitions of superstar firms

To identify superstar firms, I adopt a widely used approach that defines them as the largest firms based on market capitalization or sales (Bae, Bailey, and Kang, 2021; Schlingemann and Stulz, 2022). While the number of listed firms in the U.S. stock market increased substantially before the 2000s and has since declined, the concentration of superstar firms within the top decile of market capitalization and sales distribution has remained relatively stable.

[Table 10 about here.]

Table 10 shows that the pricing results are robust to defining superstar firms as the 50 firms sorted by market cap and sales. The MPK spread is negatively priced, although the significance is relatively weaker. Yes, it is consistent with the main findings as the top 50 superstar firms sorted by market cap or sales are nearly identical to superstar firms identified by markup shares.

The main mechanism driving the MPK spread in this paper is the markup of superstar firms. Ayyagari, Demirgüç-Kunt, and Maksimovic (2024) find that markups are positively related to a greater probability of being a star firm. However, another potential friction contributing to capital misallocation could be financial constraints. To investigate this alternative, I estimate firm-level financial constraints using two standard proxies: the Kaplan and Zingales (1997) index (KZ index) and the Whited and Wu (2006) index (WW index). Higher values of these indices correspond to greater financial constraints. Accordingly, I redefine superstar firms as the bottom 5% within their industries based on financial constraints. Results reported in Table A5 indicate that the price of risk of the MPK spread is not significant under this alternative definition, suggesting that financial constraints do not drive my asset pricing results.

Additionally, I test the robustness of these findings by splitting the sample into top and bottom halves based on markup. When I randomly select 50 firms from each half and repeat this process 500 times, the results indicate that only 4.8% of the changes in the MPK spread are statistically significant at the 5% level (see Table A1). This simulation supports the conclusion that essentially superstar firms' markup drives the MPK spread.

5.2 Predictability of risk factors

Consistently, if a state variable predicts future economic growth and stock market returns, then changes in the state variable should also predict these variables since they carry the same information. Thus, I run the same predictive regressions using changes in the aggregate capital misallocation and changes in 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 changes in 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 changes in 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 changes in aggregate misallocation 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 changes in the MPK spread also predict lower changes in industrial production growth. Panel C reports the results of predicting employment growth. Although the changes in aggregate misallocation have predictive power in 8 and 12 quarters ahead, the sign is not economically intuitive. Changes in 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. Changes in the MPK spread negatively predict the future stock market returns in 4 and 12 quarters. The 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%.

5.3 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 portfolios sorted by size and book-to-market ratio, 17 industry portfolios, 25 portfolios sorted by operating profitability and investment, 25 portfolios sorted by size and variance, 35 portfolios sorted by size and net issuance, 25 portfolios sorted by size and accruals, 25 portfolios sorted by size and beta, and 25 portfolios sorted by size and momentum.

[Table 12 about here.]

Table 12 reports results. The price of risks of the changes in aggregate misallocation loses significance when included in the CAPM and Fama and French (1992, 1993) three-factor model. Yet, in all models, only the changes in the MPK spread display a negative price of risk, with a statistical significance of less than 1%. Although all intercepts are significant, changes in aggregate misallocation and its components 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.

5.4 Industry classification

First, to examine whether the main results are driven by firms in leading industries, I re-estimate the pricing model after excluding technology firms, identified by the two-digit SIC code "73". The results, reported in Table A6, indicate that the MPK spread remains significantly negatively priced in all models. These findings confirm that superstar firms are not necessarily concentrated in leading industries such as technology. Thus, the effects documented in the paper are not driven solely by the dominance of firms in these industries.

Second, in Table A7, I assess the robustness of the main results using the 300-industry classification from Hoberg and Phillips (2016), which provides a more granular delineation of industry boundaries based on product market similarities. The results show that the MPK spread remains significantly negatively priced, consistent with the main findings. This suggests that the main conclusions are not sensitive to the choice of industry classification.

5.5 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

$$\sigma^2_{mpk,w} = \underbrace{\frac{N}{N-1}\sum_{k=1}^{K}\frac{N_k-1}{N_k}\Omega_k\sigma^2_{mpk,w,k}}_{\text{Within-group misallocation}} + \underbrace{\frac{N}{N-1}\sum_{k=1}^{K}\Omega_k(\mu_{mpk,w,k}-\mu_{mpk,w})^2}_{\text{Between-group misallocation}} \tag{20}$$

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

$$\begin{aligned}\sigma^2_{mpk,w} = & \underbrace{\frac{N}{N-1}\frac{N_0-1}{N_0}\Omega_0\sigma^2_{mpk,w,0}}_{\text{Misallocation among non-superstars}} + \underbrace{\frac{N}{N-1}\frac{N_*-1}{N_*}\Omega_*\sigma^2_{mpk,w,*}}_{\text{Misallocation among superstars}} \\ & + \underbrace{\frac{N}{N-1}\left[\Omega_0(\mu_{mpk,w,0}-\mu_{mpk,w})^2 + \Omega_*(\mu_{mpk,w,*}-\mu_{mpk,w})^2\right]}_{\text{MPK spread}}\end{aligned} \tag{21}$$

Table 13 reports results using Giglio and Xiu (2021)'s 202 test portfolios. When the model includes the market, changes in 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, changes in the MPK spread carry a negative price of risk. Thus, the pricing power of changes in misallocation between superstar firms and other firms is robust to the cross-sectional measure for aggregate capital misallocation.

[Table 13 about here.]

5.6 Tangible capital versus intangible capital

With a rising trend of intangible 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 changes in aggregate misallocation and its components using physical capital, the magnitude of the price of risk inflates, but the statistical significance remains weak. When the changes in misallocation 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 changes in 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.]

5.7 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 changes in 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 changes in misallocation.

5.8 Annual frequency

The main results in the paper use the quarterly frequency. Table A9 reports replication of the sample using the annual frequency. There is a stronger pricing power for the price of risk of the changes in aggregate misallocation. The pricing of changes in 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 changes in the MPK spread, the adjusted R-squared improves to 63.7%. Table A8 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.

6 Conclusion

This paper shows the asset pricing consequence of superstar firms. Specifically, I propose a new state variable in the ICAPM framework: capital misallocation between superstar and non-superstar firms. Using a measure of cross-sectional MPK dispersion, I decompose capital misallocation into three components: the misallocation within the superstar portfolio, the misallocation within the non-superstar portfolio, and the MPK spread. The MPK spread captures the dispersion in mean MPKs across the two portfolios.

In the cross-section of stock returns, I find that changes in the MPK spread are significantly and negatively priced. Stocks with negative exposure to the changes in this component carry higher risk premia, while stocks with positive exposure 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 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 economically intuitive. In an efficient market, capital flows towards its most productive uses. Yet, if superstar firms' MPKs are driven by market distortions, such as market power that raises barriers to competitor entry, the higher MPK reflects an inefficiency rather than a pure productivity advantage. Such misallocation can dampen economic growth by restricting capital access to smaller, potentially innovative competitors. Therefore, capital misallocation between superstar and non-superstar firms emerges as a state variable, with changes in this misallocation capturing a priced risk factor.

While the literature highlights the rise of superstars and the rise in capital misallocation, this paper highlights the role of superstars in shaping the price of risk associated with capital misallocation. One direction for future work is to model and test the innovation channel through which superstar firms deter innovation growth of other firms, resulting in the pricing power and predictability power of changes in misallocation between superstar and non-superstar firms.

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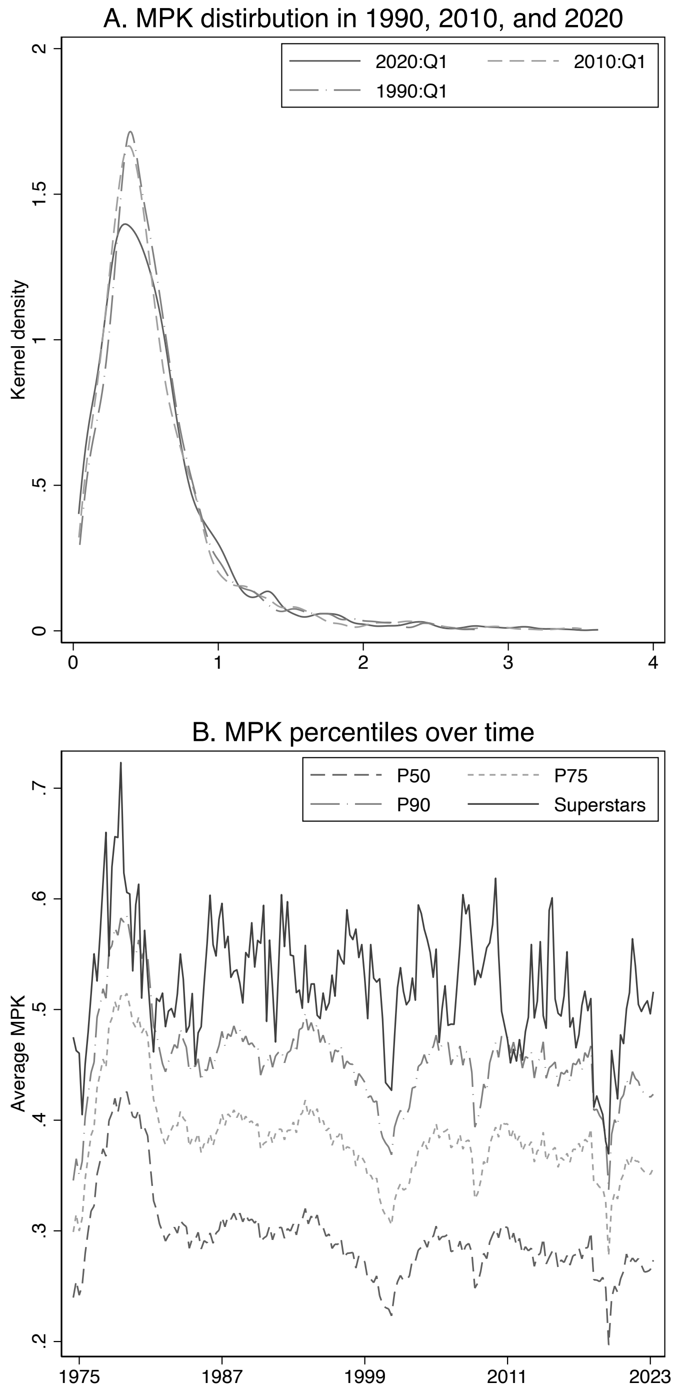
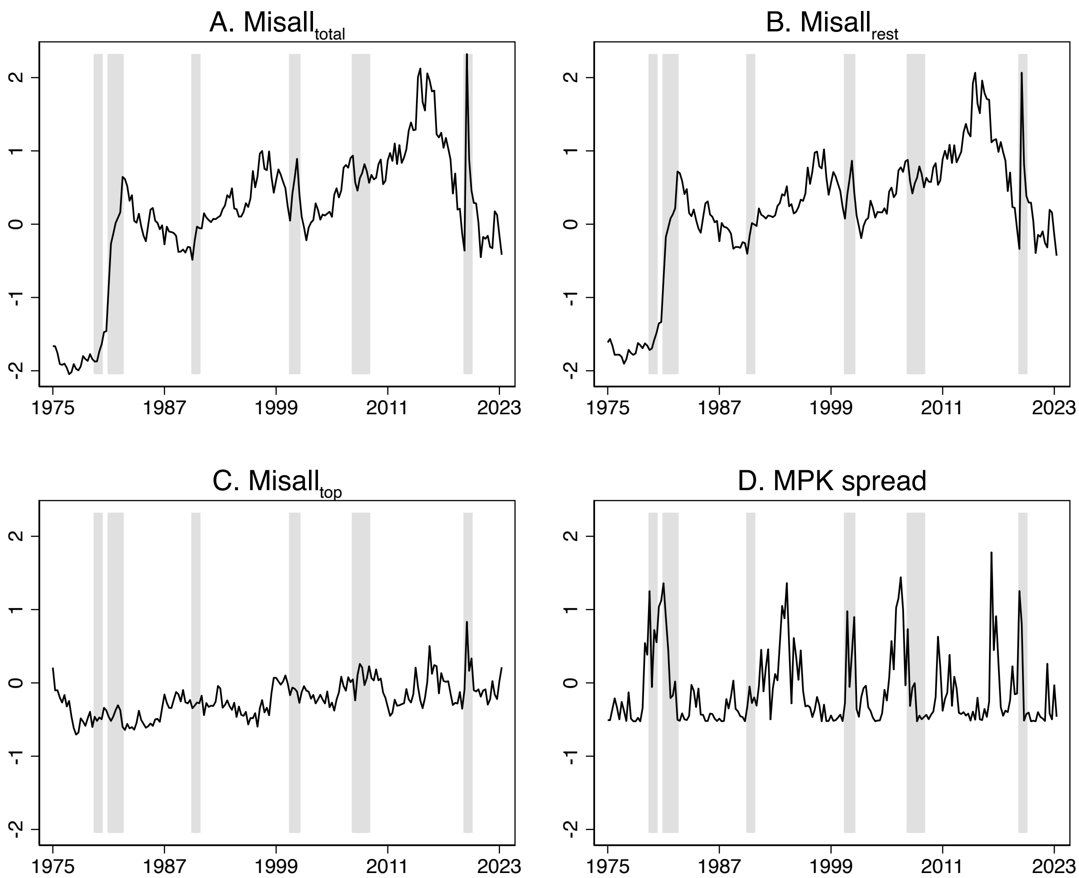
Figure 1: MPK distribution over time



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 is the 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).

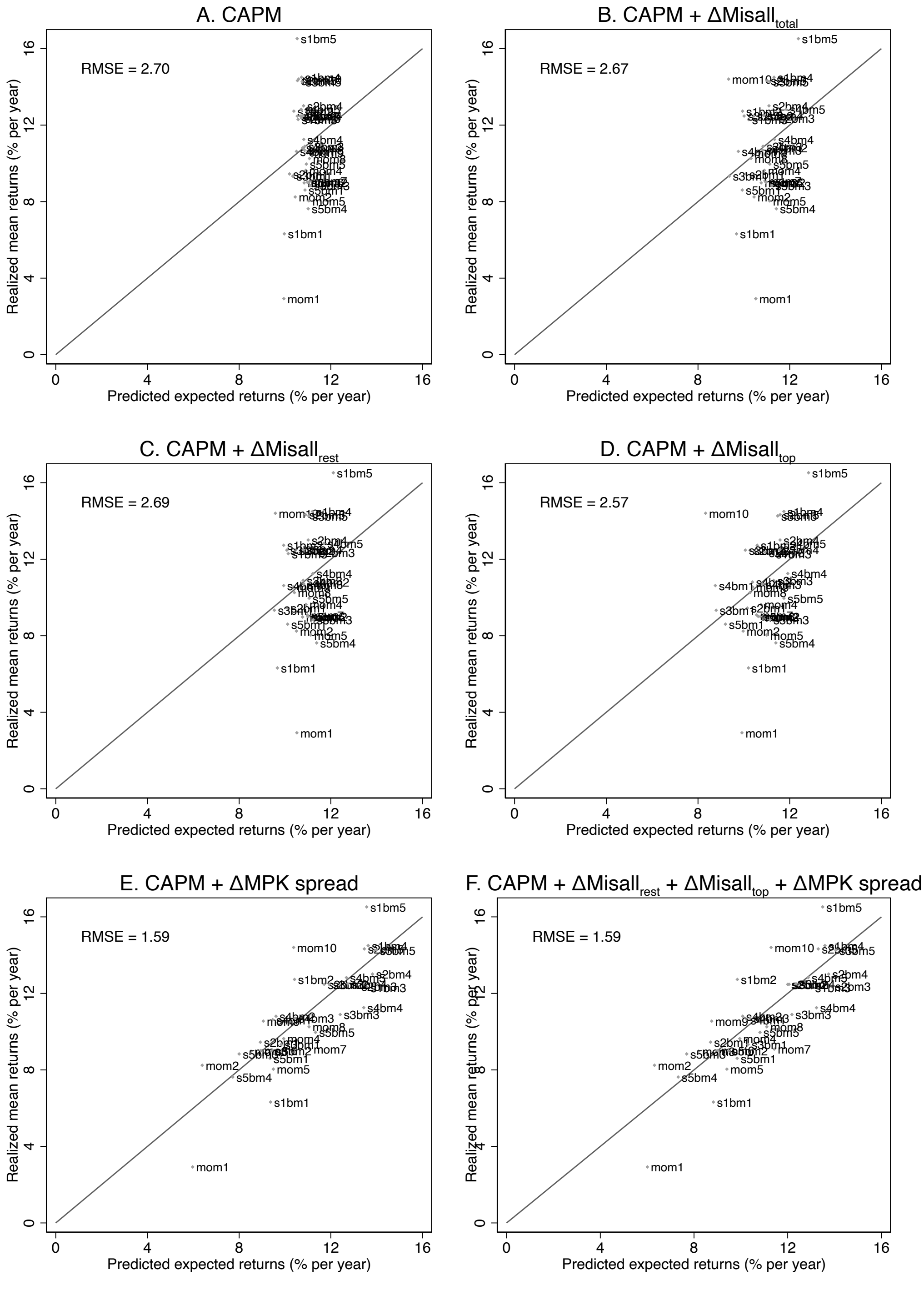
Figure 2: Capital misallocation against NBER recessions



Description. This figure plots the aggregate misallocation, misallocation to non-superstars, misallocation to superstars, and the MPK spread. 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 aggregate misallocation is be decomposed into:

$$\underbrace{\sigma^2_{mpk}}_{\text{Total misallocation (Misall}_{\text{total}})} = \underbrace{\frac{N_0 - 1}{N-1}\sigma^2_{mpk,0}}_{\text{Misallocation within non-superstars (Misall}_{\text{rest}})} + \underbrace{\frac{N_* - 1}{N-1}\sigma^2_{mpk,*}}_{\text{Misallocation within superstars (Misall}_{\text{top}})} + \underbrace{\frac{N_0 N_*}{N(N-1)}(\mu_{mpk,0} - \mu_{mpk,*})^2}_{\text{MPK spread}}$$

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 with the changes in aggregate misallocation and its components. The sample runs from 1975:Q1 to 2023:Q4. Returns are 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									
Constant	12.090	10.792	10.895	11.405	14.109	13.051	12.544	14.467	13.972
	(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]***	[2.62]***	[2.56]**
MKT	-0.257	-0.057	-0.056	-0.318	-1.191	-0.771	-0.608	-1.253	-1.094
	(-0.25)	(-0.05)	(-0.05)	(-0.31)	(-1.17)	(-0.78)	(-0.62)	(-1.23)	(-1.10)
	[-0.22]	[-0.04]	[-0.04]	[-0.25]	[-0.65]	[-0.50]	[-0.43]	[-0.69]	[-0.60]
ΔMisall$_{\text{total}}$		-0.435				0.501	0.342	0.374	
		(-0.99)				(1.36)	(0.97)	(0.89)	
		[-0.90]				[0.94]	[0.73]	[0.52]	
ΔMisall$_{\text{rest}}$			-0.410			0.590			-0.034
			(-0.87)			(1.56)			(-0.10)
			[-0.80]			[1.08]			[-0.06]
ΔMisall$_{\text{top}}$				-0.353			-0.494		0.205
				(-1.40)			(-1.99)**		(0.91)
				[-1.25]			[-1.50]		[0.52]
ΔMPK spread					-1.077			-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	0.646
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									
Constant	8.642	8.574	8.539	9.785	9.186	9.676	9.904	8.998	10.594
	(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	-0.120	0.014	-0.090	-0.149	0.059	-0.344
	(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	0.739	0.749	0.657	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]	[1.13]
UMD	3.057	3.006	2.964	2.940	3.390	2.395	2.335	3.239	2.522
	(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]
ΔMisall$_{total}$		-0.051				-0.157	-0.174	-0.055	
		(-0.32)				(-0.96)	(-1.05)	(-0.34)	
		[-0.26]				[-0.72]	[-0.78]	[-0.26]	
ΔMisall$_{rest}$			-0.069			-0.216			-0.261
			(-0.42)			(-1.25)			(-1.48)
			[-0.34]			[-0.95]			[-1.01]
ΔMisall$_{top}$				0.260			0.405		0.423
				(1.48)			(2.05)**		(2.12)**
				[1.19]			[1.57]		[1.49]
ΔMPK spread					-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	0.738	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	1.152

Fama-Macbeth t-statistics in parentheses

Shanken t-statistics in square brackets

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

Table 2: Exposure in the 25 size $\times$ book-to-market portfolios

Panel A: Loading on $\Delta Misall_{total}$

	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 $\Delta Misall_{rest}$

	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 $\Delta Misall_{top}$

	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 ΔMPK spread

	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 changes in aggregate misallocation and its 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 changes in the MPK spread (value-weighted results)

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5–Q1
Panel A: Expected return						
R^e	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 changes in the MPK spread. For each stock, I regress the quarterly excess returns either on changes in misallocation or each component 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)
ΔMPK spread	-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)
ΔMPK spread	-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 changes in the MPK spread, against the market and changes in the MPK spread. The sample runs from 1975:Q1 to 2023:Q4.

Table 5: Portfolio spanning tests

Panel A: Benchmark = Long-short returns to ΔMisall$_{total}$-mimicking portfolios			
Test portfolio = Returns to	ΔMisall$_{rest}$	ΔMisall$_{top}$	ΔMPK spread
Jensen alpha	-0.003	0.004	-0.044**
	(-0.49)	(0.37)	(-2.45)
Panel B: Benchmark = Long-short returns to ΔMPK spread-mimicking portfolios			
Test portfolio = Returns to	ΔMisall$_{rest}$	ΔMisall$_{top}$	ΔMisall$_{total}$
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 changes in aggregate misallocation on returns to each component. Panel B shows the regressions of the returns to changes in the MPK spread on the returns to changes in misallocation in superstars, non-superstars, and all firms. The sample runs from 1975:Q1 to 2023:Q4.

Table 6: Predicting proxies for economic growth

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

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

	Misall$_{\text{total}}$			Misall$_{\text{rest}}$			Misall$_{\text{top}}$			MPK spread		
	$\hat{\beta}$	R^2	RMSE	$\hat{\beta}$	R^2	RMSE	$\hat{\beta}$	R^2	RMSE	$\hat{\beta}$	R^2	RMSE
Panel A: Aggregate innovation growth												
$k=1$	-0.001	0.000	0.025	-0.002	0.000	0.025	0.488	0.005	0.025	-6.516	0.013	0.025
	(-0.06)			(-0.08)			(0.90)			(-2.23)**		
	[-0.06]			[-0.08]			[0.89]			[-2.22]**		
$k=2$	0.007	0.001	0.033	0.006	0.000	0.033	0.868	0.009	0.032	-7.089	0.009	0.032
	(0.22)			(0.19)			(1.14)			(-1.91)*		
	[0.20]			[0.17]			[1.01]			[-1.77]*		
$k=3$	0.019	0.004	0.036	0.018	0.003	0.036	1.210	0.015	0.036	-12.314	0.023	0.036
	(0.50)			(0.48)			(1.25)			(-2.46)**		
	[0.47]			[0.45]			[1.17]			[-2.37]**		
$k=4$	0.037	0.014	0.036	0.036	0.013	0.036	1.653	0.028	0.036	-10.875	0.018	0.036
	(0.82)			(0.80)			(1.38)			(-2.27)**		
	[0.79]			[0.77]			[1.32]			[-2.19]**		
$k=5$	0.047	0.020	0.038	0.046	0.019	0.038	2.133	0.041	0.037	-8.159	0.009	0.038
	(0.91)			(0.88)			(1.41)			(-1.10)		
	[0.87]			[0.85]			[1.36]			[-1.09]		
$k=6$	0.065	0.035	0.040	0.064	0.033	0.040	2.850	0.066	0.039	-4.687	0.003	0.040
	(1.11)			(1.08)			(1.58)			(-0.48)		
	[1.09]			[1.06]			[1.55]			[-0.48]		
Panel B: Innovation growth of non-superstar firms												
$k=1$	-0.002	0.000	0.030	-0.003	0.000	0.030	0.538	0.004	0.030	-9.215	0.019	0.029
	(-0.08)			(-0.11)			(0.82)			(-2.50)**		
	[-0.08]			[-0.11]			[0.82]			[-2.49]**		
$k=2$	0.009	0.001	0.038	0.009	0.001	0.038	0.772	0.005	0.038	-10.281	0.015	0.038
	(0.28)			(0.25)			(0.91)			(-2.37)**		
	[0.25]			[0.23]			[0.81]			[-2.20]**		
$k=3$	0.025	0.005	0.042	0.025	0.004	0.042	0.901	0.006	0.042	-18.665	0.039	0.041
	(0.63)			(0.61)			(0.82)			(-3.18)***		
	[0.60]			[0.58]			[0.78]			[-3.09]***		
$k=4$	0.045	0.014	0.043	0.044	0.013	0.043	1.313	0.012	0.043	-15.838	0.026	0.043
	(0.94)			(0.93)			(0.97)			(-2.92)***		
	[0.91]			[0.89]			[0.93]			[-2.83]***		
$k=5$	0.055	0.019	0.045	0.054	0.018	0.045	1.790	0.020	0.045	-14.617	0.020	0.045
	(0.99)			(0.97)			(1.06)			(-1.68)*		
	[0.95]			[0.93]			[1.03]			[-1.68]*		
$k=6$	0.075	0.032	0.047	0.075	0.031	0.047	2.400	0.032	0.047	-10.575	0.010	0.048
	(1.20)			(1.18)			(1.19)			(-0.95)		
	[1.17]			[1.16]			[1.17]			[-0.95]		
Panel C: Innovation growth of superstar firms												
$k=1$	0.004	0.000	0.026	0.005	0.000	0.026	0.283	0.002	0.026	0.767	0.000	0.026
	(0.16)			(0.20)			(0.41)			(0.25)		
	[0.15]			[0.19]			[0.41]			[0.25]		
$k=2$	0.011	0.001	0.038	0.011	0.001	0.038	1.315	0.018	0.036	0.005	0.000	0.038
	(0.28)			(0.29)			(1.11)			(0.00)		
	[0.24]			[0.24]			[0.95]			[0.00]		
$k=3$	0.022	0.004	0.041	0.019	0.003	0.041	2.201	0.037	0.041	1.727	0.000	0.041
	(0.39)			(0.32)			(1.31)			(0.31)		
	[0.35]			[0.29]			[1.19]			[0.30]		
$k=4$	0.040	0.010	0.044	0.038	0.009	0.044	2.762	0.050	0.044	-2.111	0.000	0.044
	(0.55)			(0.51)			(1.32)			(-0.34)		
	[0.52]			[0.48]			[1.22]			[-0.34]		
$k=5$	0.058	0.018	0.049	0.056	0.016	0.049	2.745	0.040	0.049	2.893	0.001	0.050
	(0.68)			(0.63)			(1.13)			(0.42)		
	[0.66]			[0.61]			[1.09]			[0.41]		
$k=6$	0.075	0.026	0.053	0.074	0.025	0.053	3.290	0.051	0.051	6.101	0.003	0.053
	(0.80)			(0.75)			(1.23)			(0.70)		
	[0.79]			[0.74]			[1.21]			[0.67]		

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

	Misall$_{\text{total}}$				Misall$_{\text{rest}}$				Misall$_{\text{top}}$				MPK spread			
	$\hat{\beta}$	R^2_{IS}	R^2_{OOS}	RMSE	$\hat{\beta}$	R^2_{IS}	R^2_{OOS}	RMSE	$\hat{\beta}$	R^2_{IS}	R^2_{OOS}	RMSE	$\hat{\beta}$	R^2_{IS}	R^2_{OOS}	RMSE
$k = 1$	0.676	0.008	0.018	6.622	0.729	0.009	0.019	6.620	-1.056	0.003	0.015	6.639	-1.084	0.018	0.002	6.590
	(1.44)				(1.49)				(-0.76)				(-2.43)**			
	[1.43]				[1.48]				[-0.76]				[-2.42]**			
$k = 4$	1.304	0.013	0.023	10.082	1.396	0.014	0.024	10.078	-1.398	0.002	0.014	10.137	-1.654	0.018	0.003	10.058
	(1.95)*				(2.02)**				(-0.60)				(-2.66)***			
	[1.61]				[1.67]*				[-0.51]				[-2.24]**			
$k = 8$	1.660	0.013	0.020	12.822	1.777	0.014	0.021	12.817	-1.561	0.002	0.011	12.896	-2.613	0.028	-0.005	12.728
	(1.51)				(1.57)				(-0.43)				(-2.53)**			
	[1.33]				[1.38]				[-0.39]				[-2.26]**			
$k = 12$	2.038	0.015	0.017	14.973	2.181	0.016	0.018	14.967	-2.028	0.002	0.014	15.068	-2.815	0.024	-0.011	14.906
	(1.28)				(1.32)				(-0.41)				(-1.87)*			
	[1.18]				[1.22]				[-0.38]				[-1.75]*			

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)
ΔMisall$_{\text{total}}$				
γ	0.098*			
	(1.81)			
ΔMisall$_{\text{rest}}$				
γ		0.115**		
		(2.03)		
ΔMisall$_{\text{top}}$				
γ			-0.066*	
			(-1.75)	
ΔMPK spread				
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)
ΔMisall$_{\text{total}}$				
γ	0.154**			
	(2.52)			
ΔMisall$_{\text{rest}}$				
γ		0.129**		
		(2.34)		
ΔMisall$_{\text{top}}$				
γ			0.012	
			(0.22)	
ΔMPK spread				
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 35 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)
Constant	12.090	10.792	10.978	9.870	14.968	10.838	12.166	14.435
	(3.67)***	(3.25)***	(3.28)***	(2.89)***	(4.51)***	(3.21)***	(3.74)***	(4.51)***
	[3.67]***	[2.99]***	[3.18]***	[2.33]**	[3.49]***	[3.09]***	[3.70]***	[3.53]***
MKT	-0.257	-0.057	-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]
ΔMisall$_{\text{total}}$		-0.435						
		(-0.99)						
		[-0.90]						
ΔMisall$_{\text{rest}}$			-1.189			-1.267		
			(-0.65)			(-0.69)		
			[-0.62]			[-0.65]		
ΔMisall$_{\text{top}}$				-0.182			-0.034	
				(-1.55)			(-0.54)	
				[-1.24]			[-0.51]	
ΔMPK spread					-0.147			-0.154
					(-2.30)**			(-2.67)***
					[-1.76]*			[-2.05]**
R^2	0.012	0.064	0.038	0.140	0.129	0.040	0.035	0.144
Adj. R^2	-0.018	0.006	-0.022	0.086	0.074	-0.020	-0.026	0.091
RMSE	2.701	2.669	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:Q1 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

	ΔMisall$_{\text{total}}$			ΔMisall$_{\text{rest}}$			ΔMisall$_{\text{top}}$			ΔMPK spread		
	$\hat{\beta}$	R^2	RMSE	$\hat{\beta}$	R^2	RMSE	$\hat{\beta}$	R^2	RMSE	$\hat{\beta}$	R^2	RMSE
Panel A: Per-capita real consumption growth												
$k=1$	-0.193	0.037	0.992	-0.172	0.030	0.996	-0.349	0.067	0.976	-0.191	0.021	1.000
	(-0.83)			(-0.77)			(-1.37)			(-2.38)**		
	[-0.82]			[-0.76]			[-1.36]			[-2.37]**		
$k=4$	0.305	0.028	1.830	0.322	0.031	1.827	-0.207	0.007	1.850	-0.687	0.081	1.779
	(1.91)*			(2.07)**			(-1.18)			(-2.59)***		
	[2.12]**			[2.27]**			[-1.27]			[-2.39]**		
$k=8$	0.648	0.069	2.420	0.681	0.076	2.411	-0.272	0.007	2.499	-0.855	0.070	2.418
	(2.61)***			(2.86)***			(-0.81)			(-2.86)***		
	[2.59]**			[2.84]***			[-0.79]			[-2.90]***		
$k=12$	0.840	0.071	2.951	0.885	0.079	2.939	-0.420	0.010	3.046	-0.935	0.058	2.972
	(2.32)**			(2.60)***			(-0.88)			(-2.90)***		
	[2.35]**			[2.64]***			[-0.87]			[-2.98]***		
Panel B: Industrial production growth												
$k=1$	-0.255	0.021	1.752	-0.219	0.016	1.757	-0.605	0.066	1.711	0.014	0.000	1.771
	(-0.79)			(-0.70)			(-1.69)*			(0.09)		
	[-0.78]			[-0.70]			[-1.68]*			[0.09]		
$k=4$	0.189	0.002	4.309	0.272	0.004	4.305	-1.266	0.049	4.206	-0.217	0.001	4.310
	(0.41)			(0.57)			(-3.64)***			(-0.35)		
	[0.39]			[0.54]			[-3.52]***			[-0.34]		
$k=8$	0.698	0.012	6.360	0.868	0.019	6.338	-2.261	0.072	6.163	-1.523	0.034	6.288
	(1.16)			(1.56)			(-2.63)***			(-2.14)**		
	[1.16]			[1.57]			[-2.55]**			[-2.14]**		
$k=12$	0.603	0.006	7.638	0.833	0.011	7.618	-3.041	0.086	7.324	-1.518	0.024	7.567
	(0.72)			(1.10)			(-2.85)***			(-2.00)**		
	[0.71]			[1.10]			[-2.82]***			[-2.04]**		
Panel C: Employment growth												
$k=1$	-0.221	0.050	0.972	-0.206	0.044	0.975	-0.265	0.040	0.977	-0.021	0.000	0.997
	(-1.05)			(-1.03)			(-1.14)			(-0.21)		
	[-1.05]			[-1.02]			[-1.14]			[-0.21]		
$k=4$	0.059	0.002	1.543	0.073	0.002	1.542	-0.230	0.013	1.534	-0.217	0.012	1.535
	(0.36)			(0.43)			(-1.96)**			(-0.84)		
	[0.36]			[0.44]			[-2.32]**			[-0.80]		
$k=8$	0.412	0.038	2.089	0.442	0.044	2.083	-0.323	0.013	2.116	-0.632	0.053	2.073
	(2.04)**			(2.20)**			(-1.41)			(-2.22)**		
	[2.08]**			[2.26]**			[-1.37]			[-2.22]**		
$k=12$	0.547	0.046	2.413	0.594	0.054	2.403	-0.524	0.025	2.440	-0.654	0.043	2.417
	(2.41)**			(2.82)***			(-1.54)			(-2.41)**		
	[2.42]**			[2.84]***			[-1.52]			[-2.47]**		

t-ratio of Hodrick (1992) with $k-1$ lags in parentheses; Newey–West (1987) 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 changes in 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									
Constant	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]
$\Delta\text{Misall}_{\text{total}}$		-0.345				-0.076	-0.108	-0.027	
		(-1.68)*				(-0.47)	(-0.66)	(-0.16)	
		[-1.51]				[-0.35]	[-0.51]	[-0.11]	
$\Delta\text{Misall}_{\text{rest}}$			-0.304			0.010			0.103
			(-1.53)			(0.06)			(0.64)
			[-1.38]			[0.05]			[0.44]
$\Delta\text{Misall}_{\text{top}}$				-0.491			-0.515		-0.311
				(-2.16)**			(-2.19)**		(-1.48)
				[-1.77]*			[-1.77]*		[-1.06]
ΔMPK spread					-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 portfolios sorted by size and book-to-market ratio, 17 industry portfolios, 25 portfolios sorted by operating profitability and investment, 25 portfolios sorted by size and variance, 35 portfolios sorted by size and net issuance, 25 portfolios sorted by size and accruals, 25 portfolios sorted by size and beta, and 25 portfolios sorted by size and momentum. 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									
Constant	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]**
ΔMisall$_{\text{total}}$		0.082				0.084	0.083	0.100	
		(0.51)				(0.52)	(0.51)	(0.63)	
		[0.44]				[0.44]	[0.44]	[0.52]	
ΔMisall$_{\text{rest}}$			0.091			0.100			0.126
			(0.56)			(0.62)			(0.79)
			[0.49]			[0.53]			[0.65]
ΔMisall$_{\text{top}}$				-0.022			-0.060		-0.116
				(-0.18)			(-0.53)		(-1.07)
				[-0.16]			[-0.45]		[-0.87]
ΔMPK spread					-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									
Constant	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]
$\Delta\text{Misall}_{\text{total}}$		-0.769				-0.434	-0.509	-0.326	
		(-2.50)**				(-1.94)*	(-2.19)**	(-1.33)	
		[-1.95]*				[-1.53]	[-1.73]*	[-0.85]	
$\Delta\text{Misall}_{\text{rest}}$			0.609			0.297			0.384
			(2.26)**			(1.46)			(1.86)*
			[1.84]*			[1.15]			[1.28]
$\Delta\text{Misall}_{\text{top}}$				-0.613			-0.646		-0.361
				(-2.29)**			(-2.37)**		(-1.43)
				[-1.88]*			[-1.89]*		[-0.99]
ΔMPK spread					-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 25 portfolios sorted by size and book-to-market ratio, 17 industry portfolios, 25 portfolios sorted by operating profitability and investment, 25 portfolios sorted by size and variance, 35 portfolios sorted by size and net issuance, 25 portfolios sorted by size and accruals, 25 portfolios sorted by size and beta, and 25 portfolios sorted by size and momentum. 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									
Constant	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]**
ΔMisall$_{\text{total}}$		-0.136				-0.132	-0.119	-0.058	
		(-0.76)				(-0.74)	(-0.67)	(-0.32)	
		[-0.67]				[-0.65]	[-0.59]	[-0.26]	
ΔMisall$_{\text{rest}}$			-0.051			-0.052			0.083
			(-0.27)			(-0.28)			(0.46)
			[-0.24]			[-0.25]			[0.37]
ΔMisall$_{\text{top}}$				0.040			0.014		0.024
				(0.23)			(0.08)		(0.14)
				[0.20]			[0.07]		[0.11]
ΔMPK spread					-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

		Tangible capital				Intangible capital			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	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]
$\Delta \text{Misall}_{\text{total}}$		-0.203				0.069			
		(-0.49)				(0.13)			
		[-0.47]				[0.13]			
$\Delta \text{Misall}_{\text{rest}}$			-0.041				0.443		
			(-0.10)				(0.88)		
			[-0.09]				[0.78]		
$\Delta \text{Misall}_{\text{top}}$				-0.710				-0.897	
				(-2.21)**				(-2.00)**	
				[-1.66]*				[-1.42]	
ΔMPK spread					-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 $\times$ 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:Q1 to 2023:Q4. Returns and risk premia are reported in percent per year (quarterly percentages multiplied by four).

Table 15: Exposure to changes in the MPK spread - subsample periods

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5–Q1
Panel A: Pre-2000s						
R^e	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 B: Post-2000s						
R^e	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 changes in the MPK spread. Panel A reports the results for the subsample 1975:Q1–2000:Q4. Panel B reports the results for the subsample 2001:Q1–2023:Q4. For each stock, I regress the quarterly excess returns either on changes in misallocation or each component 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.

Appendix: Decomposing capital misallocation

A0.1 Equally weighted capital misallocation

In each quarter t, capital misallocation is given by the dispersion in firm-level (log) MPKs in the economy

$$\sigma^2_{mpk,t} = \frac{1}{N-1}\sum_{i=1}^{N}(mpk_{it} - \mu_{mpk,t})^2 \tag{22}$$

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

$$\sigma^2_{mpk} = \frac{1}{N-1}\sum_{i=1}^{N}(mpk_i - \mu_{mpk})^2 \tag{23}$$

$$= \frac{1}{N-1}\sum_{i=1}^{N} mpk_i^2 - 2\frac{N}{N-1}\mu^2_{mpk} + \frac{N}{N-1}\mu^2_{mpk} \tag{24}$$

Hence,

$$\sigma^2_{mpk} + \frac{N}{N-1}\mu^2_{mpk} = \frac{1}{N-1}\sum_{i=1}^{N} mpk_i^2 \tag{25}$$

$$\iff (N-1)\sigma^2_{mpk} + N\mu^2_{mpk} = \sum_{i=1}^{N} mpk_i^2 \tag{26}$$

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 (26) 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 (25) into

$$\sigma^2_{mpk} + \frac{N}{N-1}\mu^2_{mpk} = \frac{1}{N-1}\left[\sum_{i=1}^{N_1} mpk_i^2 + \sum_{i=1}^{N_2} mpk_i^2 + \ldots + \sum_{i=1}^{N_K} mpk_i^2\right] \tag{27}$$

$$\iff \sigma^2_{mpk} = \frac{1}{N-1}\sum_{k=1}^{K}(N_k - 1)\sigma^2_{mpk,k} + \frac{1}{N-1}\left[\sum_{k=1}^{K} N_k\mu^2_{mpk,k} - N\mu^2_{mpk}\right] \tag{28}$$

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

$$\mu_{mpk} = \frac{N_1\mu_{mpk,1} + N_2\mu_{mpk,2} + \ldots + N_K\mu_{mpk,K}}{N_1 + N_2 + \ldots + N_k} \tag{29}$$

$$= \frac{1}{N}\sum_{k=1}^{K} N_k\mu_{mpk,k} \tag{30}$$

$$\Rightarrow N\mu^2_{mpk} = \frac{1}{N}\left(\sum_{k=1}^{K} N_k\mu_{mpk,k}\right)^2 \tag{31}$$

Hence,

$$\sigma^2_{mpk} = \frac{1}{N-1}\sum_{k=1}^{K}(N_k-1)\sigma^2_{mpk,k} + \frac{1}{N-1}\left[\sum_{k=1}^{K} N_k\mu^2_{mpk,k} - \frac{1}{N}\left(\sum_{k=1}^{K} N_k\mu_{mpk,k}\right)^2\right] \tag{32}$$

$$= \frac{1}{N-1}\sum_{k=1}^{K}(N_k-1)\sigma^2_{mpk,k} + \frac{N}{N-1}\left[\underbrace{\frac{1}{N}\sum_{k=1}^{K} N_k\mu^2_{mpk,k}}_{\mathbb{E}(\mu^2_{mpk,k})} - \underbrace{\left(\frac{1}{N}\sum_{k=1}^{K} N_k\mu_{mpk,k}\right)^2}_{\mathbb{E}(\mu_{mpk,k})^2}\right] \tag{33}$$

(34)

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

$$\sigma^2_{mpk} = \underbrace{\sum_{k=1}^{K}\frac{N_k-1}{N-1}\sigma^2_{mpk,k}}_{\text{Within-group misallocation}} + \underbrace{\frac{N}{N-1}\mathrm{Var}(\mu_{mpk,k})}_{\text{Between-group misallocation}} \tag{35}$$

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 (35) simplifies to the case when

$K = 2$. Specifically,

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

Hence, we can rewrite Equation (35) in this case as

$$\sigma_{mpk}^2 = \underbrace{\frac{N_0 - 1}{N-1}\sigma_{mpk,0}^2}_{\text{Misallocation among non-superstars}} + \underbrace{\frac{N_* - 1}{N-1}\sigma_{mpk,*}^2}_{\text{Misallocation among superstars}} + \underbrace{\frac{N_0 N_*}{N(N-1)}(\mu_{mpk,0} - \mu_{mpk,*})^2}_{\text{MPK spread}} \tag{36}$$

A0.2 Value-weighted capital misallocation

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

$$s_w^2 = \frac{N}{N-1}\sum_{i=1}^{N} w_i (x_i - \bar{x}_w)^2 \tag{37}$$

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

$$\sum_{k=1}^{K}\Omega_k = \sum_{k=1}^{K}\sum_{i\in k} w_i = \sum_{i=1}^{N} w_i = 1. \tag{38}$$

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

$$s_{w,k}^2 = \frac{N_k}{N_k - 1}\sum_{i\in k}\frac{w_i}{\Omega_k}(x_i - \bar{x}_{w,k})^2 \tag{39}$$

$$\bar{x}_{w,k} = \sum_{i\in k}\frac{w_i}{\Omega_k}x_i \iff \sum_{i\in k} w_i x_i = \Omega_k \bar{x}_{w,k} \tag{40}$$

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

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

From the total weighted variance, we have

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

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

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

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,

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

Combining both terms, we have:

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

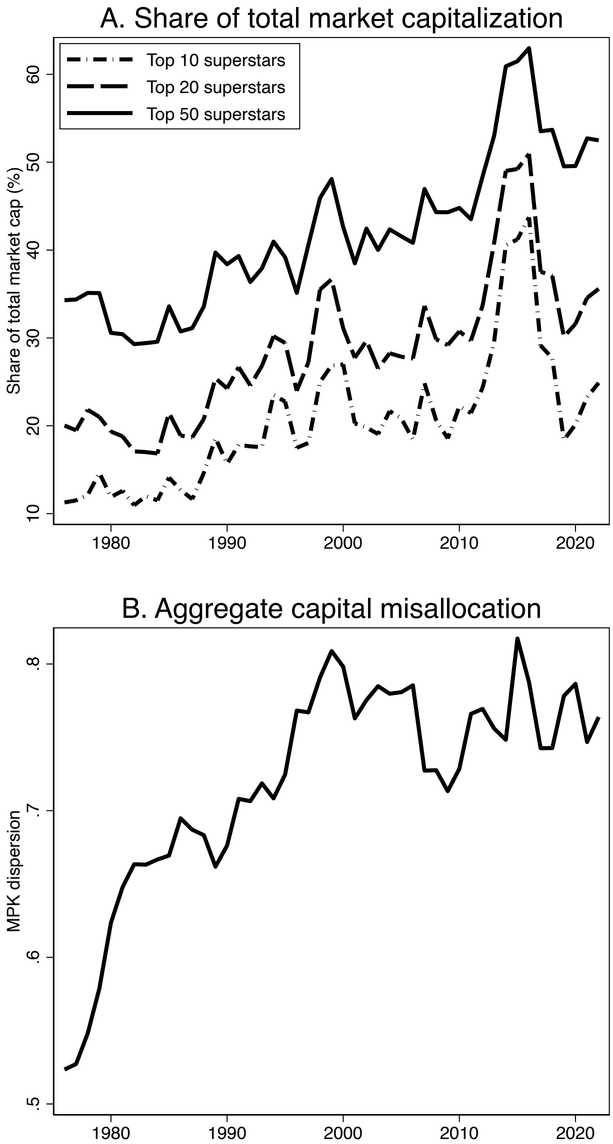
where $\Omega_k=\sum_{i\in k} w_i$, $\bar{x}_w=\sum_{i=1}^{N} w_i x_i$, and $\bar{x}_{w,k}=\sum_{i\in k}\frac{w_i}{\Omega_k}x_i$.

Given $K=2$, the formula simplifies to

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

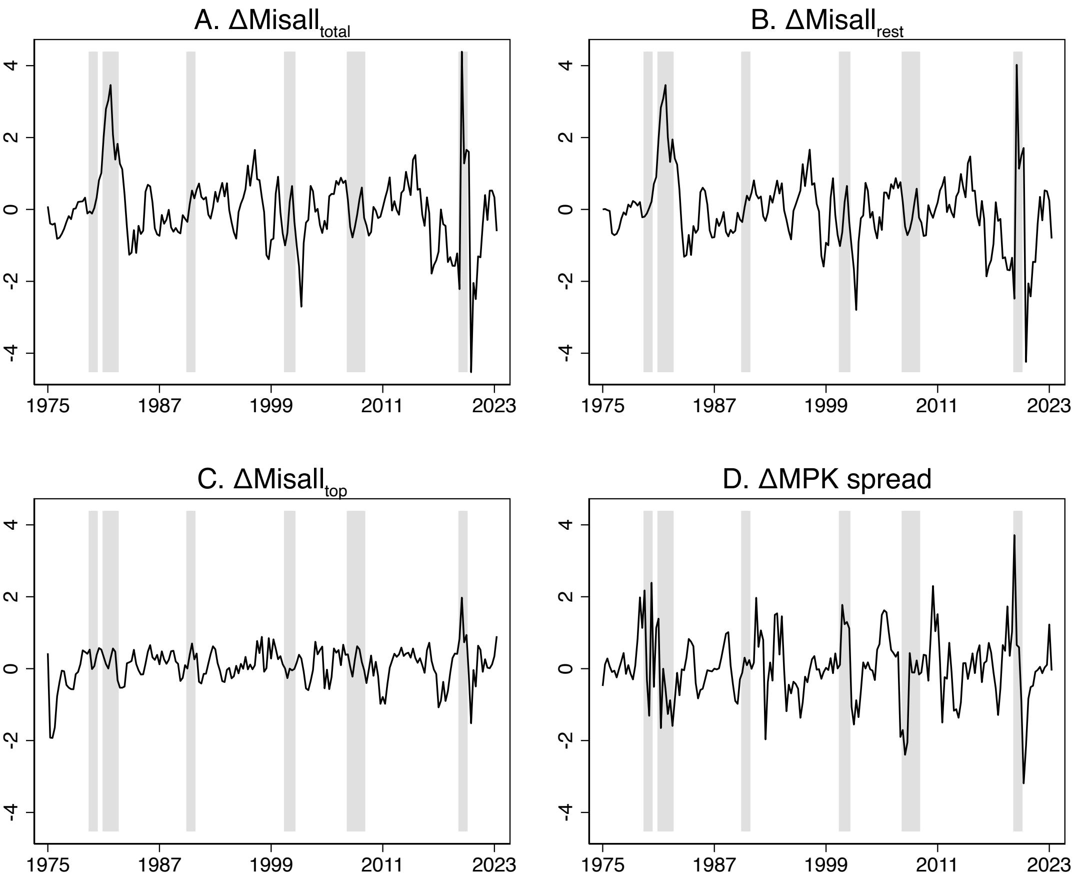
Online Appendix: Additional results

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 annual from 1975 to 2023.

Figure A2: Changes in capital misallocation against NBER recessions



Description. This figure plots the changes in aggregate misallocation $\Delta\sigma^2_{mpk,t}$, changes in misallocation in non-superstars $\Delta\sigma^2_{mpk,t0}$, changes in misallocation in superstars $\Delta\sigma^2_{mpk,t*}$, and changes in 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 changes in misallocation 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:

$$\underbrace{\sigma^2_{mpk}}_{\text{Total misallocation (Misall}_{\text{total}})} = \underbrace{\frac{N_0-1}{N-1}\sigma^2_{mpk,0}}_{\text{Misallocation within non-superstars (Misall}_{\text{rest}})} + \underbrace{\frac{N_*-1}{N-1}\sigma^2_{mpk,*}}_{\text{Misallocation within superstars (Misall}_{\text{top}})} + \underbrace{\frac{N_0N_*}{N(N-1)}(\mu_{mpk,0}-\mu_{mpk,*})^2}_{\text{MPK spread}}$$

Table A1: Significance of $\triangle$MPK spread - 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 changes in the MPK spread in the second-stage Fama-MacBeth regression. Each simulation selects randomly 50 firms to the superstar portfolio.

Table A2: Exposure to changes in the MPK spread (equally weighted results)

	Q1 (low)	Q2	Q3	Q4	Q5 (high)	Q5–Q1
Panel A: Expected return						
R^e	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 changes in the MPK spread. For each stock, I regress the quarterly excess returns either on changes in misallocation or on each component 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 A3: Characteristics of stocks in the MPK spread-mimicking portfolios

	Low	Q2	Q3	Q4	High	High–Low	t(High–Low)
$\beta_{\Delta\text{MPK spread}}$	-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 A4: Predicting aggregate patent ratio

	ΔMisall$_{\text{total}}$			ΔMisall$_{\text{rest}}$			ΔMisall$_{\text{top}}$			ΔMPK spread		
	$\hat{\beta}$	R^2	RMSE	$\hat{\beta}$	R^2	RMSE	$\hat{\beta}$	R^2	RMSE	$\hat{\beta}$	R^2	RMSE
$k=1$	-0.039	0.003	0.021	0.022	0.001	0.021	-0.373	0.002	0.021	-6.769	0.154	0.019
	(-0.61)			(0.36)			(-0.39)			(-4.27)***		
	[-0.60]			[0.36]			[-0.38]			[-4.19]***		
$k=2$	0.048	0.003	0.027	0.012	0.000	0.027	1.092	0.010	0.027	-8.501	0.145	0.025
	(0.53)			(0.13)			(0.84)			(-4.05)***		
	[0.49]			[0.13]			[0.90]			[-4.52]***		
$k=3$	-0.074	0.005	0.033	-0.104	0.009	0.033	-0.734	0.003	0.033	-4.824	0.032	0.033
	(-0.58)			(-0.69)			(-0.58)			(-2.70)***		
	[-0.57]			[-0.67]			[-0.53]			[-2.65]**		
$k=4$	-0.033	0.001	0.038	-0.006	0.000	0.038	1.724	0.013	0.038	-5.373	0.030	0.038
	(-0.25)			(-0.03)			(1.13)			(-2.20)**		
	[-0.24]			[-0.03]			[1.14]			[-2.60]**		
$k=5$	-0.008	0.000	0.045	-0.077	0.002	0.045	0.357	0.000	0.045	-4.901	0.018	0.045
	(-0.04)			(-0.33)			(0.21)			(-1.86)*		
	[-0.04]			[-0.33]			[0.21]			[-2.02]**		
$k=6$	-0.248	0.016	0.050	-0.264	0.018	0.050	0.792	0.001	0.051	-15.007	0.021	0.050
	(-0.86)			(-0.91)			(0.45)			(-2.34)**		
	[-0.84]			[-0.90]			[0.47]			[-2.06]**		

t-ratio of Hodrick (1992) with $k-1$ lags in parentheses; Newey–West (1987) 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 changes in 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 $= \log(1 + \#\ \text{patents/population})$. The sample is at an annual frequency from 1975 to 2020.

Table A5: Pricing 35 portfolios - Decomposition using financial constraints

			Kaplan-Zingales (KZ) Index			Whited-Wu (WW) Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	12.090	10.792	10.914	18.735	11.921	10.539	13.710	11.410
	(3.67)***	(3.25)***	(3.33)***	(5.02)***	(3.19)***	(3.10)***	(3.71)***	(3.43)***
	[3.67]***	[2.99]***	[2.98]***	[3.72]***	[3.19]***	[2.85]***	[3.46]***	[2.86]***
MKT	-0.257	-0.057	-0.124	-2.297	-0.208	0.015	-0.823	-0.109
	(-0.25)	(-0.05)	(-0.12)	(-2.01)**	(-0.19)	(0.01)	(-0.75)	(-0.11)
	[-0.22]	[-0.04]	[-0.10]	[-1.37]	[-0.17]	[0.01]	[-0.62]	[-0.08]
ΔMisall$_{\text{total}}$		-0.435						
		(-0.99)						
		[-0.90]						
ΔMisall$_{\text{rest}}$			-0.513			-0.445		
			(-1.22)			(-0.97)		
			[-1.08]			[-0.88]		
ΔMisall$_{\text{top}}$				0.879			-0.307	
				(2.17)**			(-1.10)	
				[1.59]			[-1.01]	
ΔMPK spread					-0.027			0.475
					(-0.08)			(1.35)
					[-0.07]			[1.12]
R^2	0.012	0.064	0.093	0.351	0.013	0.060	0.092	0.048
Adj. R^2	-0.018	0.006	0.036	0.310	-0.049	0.001	0.036	-0.011
RMSE	2.701	2.669	2.629	2.224	2.741	2.676	2.629	2.692

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 portfolios sorted by size and book-to-market ratio and 10 portfolios sorted by momentum. Superstar firms are in the bottom 5% in their industries by their financial constraints. As proxies for financial constraint, I use Kaplan and Zingales (1997)'s (KZ) index and Whited and Wu (2006)'s (WW) index. The higher the KZ index or the WW index, the higher the likelihood of financial constraint.

Table A6: Pricing 35 portfolios excluding tech industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	12.090	10.746	10.676	11.536	13.470	11.529	11.251	13.618	12.718
	(3.67)***	(3.26)***	(3.23)***	(3.53)***	(4.07)***	(3.75)***	(3.65)***	(4.23)***	(4.13)***
	[3.67]***	[2.99]***	[2.93]***	[3.38]***	[2.16]**	[3.55]***	[3.51]***	[2.21]**	[1.97]*
MKT	-0.257	-0.063	-0.032	-0.301	-0.901	-0.314	-0.225	-0.927	-0.627
	(-0.25)	(-0.06)	(-0.03)	(-0.30)	(-0.89)	(-0.32)	(-0.23)	(-0.92)	(-0.65)
	[-0.22]	[-0.05]	[-0.02]	[-0.25]	[-0.45]	[-0.26]	[-0.19]	[-0.46]	[-0.30]
ΔMisall$_{\text{total}}$		-0.441				-0.052	-0.164	0.284	
		(-1.12)				(-0.19)	(-0.62)	(0.72)	
		[-1.01]				[-0.17]	[-0.57]	[0.38]	
ΔMisall$_{\text{rest}}$			-0.480			-0.018			-0.198
			(-1.10)			(-0.06)			(-0.72)
			[-0.99]			[-0.06]			[-0.34]
ΔMisall$_{\text{top}}$				-0.235			-0.207		0.163
				(-1.08)			(-0.95)		(0.75)
				[-1.01]			[-0.89]		[0.35]
ΔMPK spread					-1.171			-1.188	-1.259
					(-3.63)***			(-4.20)***	(-4.40)***
					[-1.92]*			[-2.19]**	[-2.09]**
R^2	0.012	0.080	0.076	0.081	0.474	0.091	0.083	0.475	0.513
Adj. R^2	-0.018	0.023	0.018	0.024	0.442	0.003	-0.005	0.424	0.448
RMSE	2.701	2.647	2.653	2.645	2.001	2.673	2.684	2.032	1.988

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 portfolios sorted by size and book-to-market ratio and 10 portfolios sorted by momentum. Superstar firms are defined by the top 5% in their industries by the markup share, using two-digit SIC codes. In this analysis, I exclude the tech industries with the two-digit SIC code of "73".

Table A7: Pricing Giglio and Xiu (2021)'s 202 test portfolios - using Hoberg and Phillips (2016)'s 300 industry classification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	10.628	12.403	11.509	11.335	10.464	14.040	14.125	11.862	12.459
	(2.84)***	(3.14)***	(2.96)***	(3.04)***	(2.80)***	(3.54)***	(3.51)***	(3.05)***	(3.36)***
	[2.83]***	[2.84]***	[2.84]***	[2.87]***	[2.21]**	[2.88]***	[2.82]***	[2.44]**	[2.70]***
MKT	-0.569	-1.072	-0.810	-0.918	-1.204	-1.583	-1.769	-1.564	-1.696
	(-0.40)	(-0.74)	(-0.56)	(-0.65)	(-0.84)	(-1.11)	(-1.23)	(-1.07)	(-1.18)
	[-0.31]	[-0.55]	[-0.43]	[-0.49]	[-0.56]	[-0.76]	[-0.84]	[-0.73]	[-0.81]
ΔMisall$_{\text{total}}$		-0.480				-0.631	-0.589	-0.227	
		(-1.80)*				(-2.18)**	(-2.09)**	(-0.98)	
		[-1.49]				[-1.67]*	[-1.58]	[-0.72]	
ΔMisall$_{\text{rest}}$			-0.264			-0.468			-0.215
			(-1.29)			(-2.01)**			(-1.14)
			[-1.10]			[-1.53]			[-0.83]
ΔMisall$_{\text{top}}$				-0.123			-0.121		-0.136
				(-1.81)*			(-1.79)*		(-2.01)**
				[-1.43]			[-1.25]		[-1.41]
ΔMPK spread					-0.766			-0.643	-0.584
					(-2.99)***			(-2.90)***	(-2.66)***
					[-2.20]**			[-2.11]**	[-1.94]*
R^2	0.038	0.165	0.099	0.169	0.467	0.292	0.401	0.543	0.555
Adj. R^2	0.033	0.156	0.090	0.161	0.462	0.282	0.391	0.536	0.546
RMSE	3.440	3.214	3.338	3.205	2.567	2.966	2.730	2.382	2.357

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 portfolios sorted by size and book-to-market ratio, 17 industry portfolios, 25 portfolios sorted by operating profitability and investment, 25 portfolios sorted by size and variance, 35 portfolios sorted by size and net issuance, 25 portfolios sorted by size and accruals, 25 portfolios sorted by size and beta, and 25 portfolios sorted by size and momentum. Superstar firms are defined by the top 5% in their industries by the markup share, using 300 industry classification from Hoberg and Phillips (2016). The sample runs from 1975 to 2022.

Table A8: Cross-sectional asset pricing tests - alternative measure for intangible capital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	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]
ΔMisall$_{\text{total}}$		-0.260				-0.381	-0.371	-0.144	
		(-0.79)				(-1.11)	(-1.08)	(-0.46)	
		[-0.61]				[-0.78]	[-0.78]	[-0.27]	
ΔMisall$_{\text{rest}}$			-0.223			-0.352			-0.172
			(-0.70)			(-1.05)			(-0.55)
			[-0.53]			[-0.74]			[-0.33]
ΔMisall$_{\text{top}}$				-0.101			-0.133		-0.048
				(-0.77)			(-1.01)		(-0.35)
				[-0.53]			[-0.68]		[-0.20]
ΔMPK spread					-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 A9: Cross-sectional asset pricing tests - annual frequency

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	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]
ΔMisall$_{\text{total}}$		0.945				0.829	0.231	0.566	
		(2.96)***				(2.75)***	(0.81)	(1.97)*	
		[1.80]*				[1.71]*	[0.57]	[0.99]	
ΔMisall$_{\text{rest}}$			1.087			0.902			0.119
			(2.95)***			(2.85)***			(0.42)
			[1.74]*			[1.78]*			[0.22]
ΔMisall$_{\text{top}}$				-0.185			-0.177		-0.078
				(-0.81)			(-0.79)		(-0.36)
				[-0.56]			[-0.54]		[-0.19]
ΔMPK spread					-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.