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Displacement Risk and the Magnificent Seven

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ABSTRACT

This thesis explores the link between technological displacement risk, artificial intelligence-related innovation, and the returns of the largest, high-tech, American firms, the "Magnificent Seven" ("M7"). We suggest that AI innovation is inherently disruptive, gives rise to systematic technological displacement risk, and that its resulting effect on the cross-section of returns can be proxied using the residualized returns of the M7. Theory tells us that this effect varies across value and growth stocks, negatively affecting value stocks, while growth stocks partly hedge the risk associated with innovation activity, resulting in a lower realized value-growth premium as this activity increases. We test the effectiveness of our M7 displacement risk proxy using Fama-MacBeth-style cross-sectional regressions, evaluate its ability to estimate the value premium, and test its correlation with other value factors, as well as "AI" term searches. We find that the factor is not priced (using a t-statistic threshold of 3) in the cross-section when controlling for Fama-French 3-factors, but has the expected effect on value and growth stocks, improves value premium estimates and correlates with the HML and RMW factors, as well as "AI" term searches. The factor also fails to be priced in the cross-section when alternative portfolio sorts are tried, and when momentum, or the CMA and RMW factors are introduced to the model.

Keywords: Displacement risk, Magnificent Seven, Return cross-section, Asset pricing
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1 Introduction

In recent years, artificial intelligence (AI)[1] and its applications have been rapidly rolled out to the wider public, bringing with them the promise of productivity gains and growth, but also concerns of widespread labor automation and disruptive competition (Acemoglu and Restrepo 2019a; Acemoglu and Restrepo 2019b; Knesl 2023). At the same time, valuations of the largest American high-tech firms, the "Magnificent Seven",[2] have expanded rapidly following the release of flagship generative AI models like ChatGPT (*Figure 1*), while the difference in returns between value and growth stocks (the former having low price/earnings ratios, the latter, high) has shrunk considerably (*Figure 2*).

Tying all of these phenomena together is the idea of displacement risk, the risk associated with the disruption of incumbent firms' business models by new firms (Gârleanu, Kogan, and Panageas 2012). Following standard asset pricing theory, if technological displacement is a systematic risk factor, it ought to appear in the cross-section of stocks' returns, affecting both the difference in value and growth firms' returns and those of the Magnificent Seven (Ang 2014; Fama and French 1993). Value firms are generally more exposed to this risk, and thus carry a greater risk premium, having higher expected returns than growth firms (Gârleanu and Panageas 2025). However, in times when displacement risk is high, these firms' *realized* returns will be lower, due to them being more likely to be displaced by new firms. At the same time, growth firms, which tend to be more innovative and agile, act as hedges against displacement risk, earning a realized premium relative to value stocks.

We suggest that displacement risk is inherent to AI technology, particularly because its recent developments have tended towards automating labor, rather than significantly improving productivity or widening the scope of workers' tasks (Acemoglu and Restrepo 2019b). These developments can result in employment declines (Brynjolfsson, Chandar, and Chen 2025) and the disruption of firms with high shares of displaceable labor (Knesl 2023). Simultaneously, AI could disproportionately benefit a small number of "superstar" firms (Babina et al. 2024), while the rest face increased competitive pressure.

Furthermore, we suggest that the Magnificent Seven, as some of the most influential, most involved firms in AI innovation, can act as a proxy for innovative activity: displacement risk creates a hedging motive through investors' stochastic discount factor, which raises prices for those assets that pay off when displacement is high (Gârleanu, Kogan, and Panageas 2012). That is, we attribute a part of the Magnificent Seven's return variation to the increasing displacement risk, since they are seen by investors as a hedge against it. We thus utilize the residualized returns of the Magnificent Seven to create a displacement risk proxy, aiming to test its ability to price the cross-section of returns, explain the value-growth premium, and evaluate its relationship with other value factors.

We conduct three tests to evaluate whether the Magnificent Seven are a proxy for displacement risk, constructing 11 P/E sorted portfolios in order to compare their differential effects on value and growth stocks. The primary test involves running standard two-pass, cross-sectional

[1] An umbrella term for technologies such as large language models and image generators, as well as other, often more specialized applications of machine learning.

[2] Alphabet (Google), Amazon, Apple, Meta Platforms, Microsoft, Nvidia and Tesla.

regressions with our factor alongside the CAPM and the Fama-French 3-factor (FF3) models. Additional tests involve calculating the sum of squared errors of value premia estimates compared to the observed premia, and looking at the correlation between our factor and the Fama-French High-Minus-Low factor and search trend results for the term "AI". The first test evaluates whether our displacement risk proxy is priced and whether it has the theoretically implied (negative) sign effect. The second test aims to show that the factor has a value-growth effect in the data, by reducing estimation errors. The third test explores the correlation with known value factors and a proxy for AI dispersion.

We find that our proxy (1) has a negative, but statistically unpriced, factor premium in the cross-section, (2) reduces value premium estimation errors and (3) correlates negatively with HML, and positively with AI searches. The factor premium is also weak to robustness tests, such as the addition of extra Fama-French factors or testing on alternative portfolios. At the same time, however, the proxy's factor premium continues to correlate with known value factors even when losing statistical significance in the cross-section. This suggests that the residual simply loses pricing power as it becomes residualized by more factors, but that its underlying nature does not change. We also consider newer, augmented value factors as potential confounders in our analysis and find at least two that may explain our results, although we do not test this. We further discuss the limitations of our study and suggest alternative empirical methods that may be able to better isolate the AI displacement risk inherent to the Magnificent Seven.

In summary, our study explores a novel explanation of (a part of) Magnificent Seven stocks' returns, by connecting them to variation in displacement risk. Understanding the nature of these stocks' returns is important due to their sheer size and importance to the global economy. As such, presenting rational explanations for their valuations is particularly crucial for investors and the asset pricing literature. By extension, we explore the displacement risk inherent to AI-related technologies, assigning it an empirical proxy. This is likely to remain an important field of research, as there is considerable division surrounding the implications of the rapid development of AI-adjacent technologies. Ultimately, we conduct standard tests to evaluate our hypothesis and find some suggestive evidence for a displacement risk proxy component in the Magnificent Seven's returns. This component is, however, not sufficiently robust to be deemed priced in the cross-section. We believe that further research is needed to sufficiently isolate displacement risk in asset prices and more rigorously rule out potential confounders.

2 Literature Review

Our thesis relates primarily to three strands of economic literature. First, it relates to the literature on consumption-based asset pricing models. These models show how investors' marginal utility growth covaries with risky payoff streams. Our connection to this literature is in using the hedging implications arising from displacement risk and investigating what they mean for a specific subset of risky assets. Second, our thesis is connected to factor models in empirical asset pricing. These models can include e.g. statistical and macroeconomic risk factors, in both cases attempting to price assets' expected returns by measuring their exposure to a set of these factors. We extend this literature by proposing and testing a displacement risk proxy within this framework. Our thesis is also related to granularity and asset pricing, which helps us connect the movements of large firms to cross-sectional asset prices. Granularity theory allows for the price movements of large firms to have an effect on aggregates, whereas firms' idiosyncratic risk is generally regarded as unpriced in traditional asset pricing. Finally, our thesis is connected to the growing literature on AI and displacement. This includes both literature on theoretical effects as well as empirical studies on the effects on workers and firms. This literature gives us the academic relationship linking displacement risk and AI.

2.1 Consumption-Based Asset Pricing Models

There is vast literature modeling the connection between consumption and asset prices. Specifically, they study how the covariance between marginal utility growth and risky payoff streams affects the prices of these payoff streams (Guvenen and Lustig 2007). Our thesis connects to the concept of displacement risk, which is an augmentation of these types of models.

The consumption-based capital asset pricing model (CCAPM) is a model that connects macroeconomic risk to asset pricing, and was derived in the late 1970s. Some early contributors were Rubinstein (1976), Breeden and Litzenberger (1978), and Breeden (1979). These authors showed that there is more systematic risk in securities that have greater sensitivity of returns to movements in real consumption spending. This, they argue, should lead to higher excess returns, since, if an asset pays off more when marginal utility is low (and consumption is high), then they have higher returns in equilibrium and lower prices. Lucas (1978) also contributed early to this literature through his work on the Euler equation (which, shortly described, connects marginal utility of consumption today and tomorrow with asset returns), even though he was not deriving the CCAPM formula itself. Notably, the CCAPM builds on the market-based CAPM (Sharpe 1964; Lintner 1965) and intertemporal CAPM (ICAPM; Merton 1973), which we describe further down in the literature review. Intuition on how the CCAPM connects consumption growth and asset prices can be glanced from the basic Euler equation/fundamental asset pricing equation as exemplified by Cochrane (2005):

$$p_t = \mathbb{E}_t \left[\beta \frac{u'(c_{t+1})}{u'(c_t)} x_{t+1} \right] \tag{1}$$

Where x_{t+1} is the (expected) payoff of a risky asset at time $t+1$, p_t is the price at time t for the risky asset, β is an impatience parameter (typically <1; impatient), and $u'(c)$ is the marginal utility of consumption in the specified time period. Expressed in this equation is the "stochastic discount factor", usually denoted by "m" $\left(\text{in this case, } m_{t+1} = \beta \frac{u'(c_{t+1})}{u'(c_t)}\right)$, which prices all assets based on their expected future payoffs. Equation (1) illustrates one of the key intuitions of the CCAPM; the price of the asset is the expected discounted value of the payoff. Payoffs that occur in a state where marginal utility of consumption is high ("bad state") are less discounted than payoffs that occur when marginal utility of consumption is low ("good state"). This is indicated by the fact that the stochastic discount factor is higher in states where the marginal utility of consumption is high.

However, the CCAPM famously failed. Hansen and Singleton (1983) rejected the model when testing it on US consumption data. Mehra and Prescott (1985) showed that when calibrating the model to data, it is unable to explain the equity premium (excess return of the market after subtracting the risk-free rate) under reasonable parameters of, for example, risk-aversion. This is usually referred to as the "equity premium puzzle" (EPP). An alternative view of the EPP is provided by Hansen and Jagannathan (1991). They show that the stochastic discount factor/pricing kernel has an empirical lower bound, given by the Sharpe Ratio (the ratio of required excess return per unit of risk that investors bear). When taking this to the data, the volatility of the stochastic discount factor is too low – confirming that the low consumption growth volatility cannot explain the high expected returns in the data. The EPP garnered great attention, and many have since tried to solve the "puzzle", improving both the theory and empirics.

Our thesis is primarily related to the strand of models working on improving the *theory* of the CCAPM, and there are many such models. Alternative constructions include rare disaster events (through modifying probability distributions), survival bias, incomplete markets, market imperfections, and alternative assumptions regarding preferences (Mehra 2012). One famous example is Campbell and Cochrane (1999), integrating a consumption habit into the utility function, which alters the stochastic discount factor and thus has an effect on asset prices. The model reconciles asset market and consumption data by effectively increasing the sensitivity of investors to changes in consumption. However, it is unclear what exactly the habit level represents.

Our thesis is most closely related to Gârleanu, Kogan, and Panageas ("GKP", 2012), who present another expansion on the standard aggregate-consumption-based asset pricing model, based on innovation activity. GKP argue that the CCAPM ought to be augmented with a "displacement risk factor", since there is a wedge in consumption between existing and future cohorts, due to innovation shocks (i.e. this risk is distinct from aggregate consumption risk), that cannot be perfectly insured against, since existing agents cannot trade with unborn agents. On the one hand, innovation shocks (which in their model create a "stochastically expanding variety of intermediate goods") can be beneficial for the economy, by raising productivity which improves aggregate consumption, wages and output. On the other hand, these intermediate goods are partial substitutes, so when there is an increased variety (due to innovation shocks), competition is intensified and existing firms are replaced by new entrants – i.e. there is risk of displacement. The model helps solve the EPP due to this extra risk for existing firms; investors require a higher return for holding existing stocks than what is implied from a standard CCAPM model. Further, existing firms have different exposures to this displacement risk. "Growth firms", which GKP define as having high price/earnings (P/E) ratios, are more innovative. Thus, they earn higher valuation ratios, since they derive a larger part of their value from future innovations, and are more shielded against innovation shocks. Less innovative ("value", low P/E) firms however, are not as innovative and are thus more exposed to displacement risk. Innovation shocks thus create variable effects within these two types of existing firms, giving rise to the value-growth factor (as seen in Fama and French (1993)). A recent, related model by Gârleanu and Panageas (2025) expands on the notion of displacement risk by constructing a similar model including private equity firms. Here, existing agents *can* share risk between generations by investing in private equity firms' stakes in new companies. However, risk-sharing is imperfect: only a subset of agents invest in some of the new firms and, because the success of any subset of new firms is unknown, investing in them carries undiversifiable, idiosyncratic risk. This model thus expands the share of asset pricing phenomena attributable to displacement risk effects. High private equity returns are explained by their exposure to idiosyncratic risk, reconciling these with the hedging effect associated with holding high-tech, new firms, while still allowing for the existence of a displacement-hedging value premium among public equities.

2.2 Factor Models in Empirical Asset Pricing

Our thesis is also related to factor pricing models, a concept which lies at the core of empirical asset pricing, and helps create a connection in the data between expected returns and covariances. Factor pricing models are connected to the consumption-based models in that they "replace the consumption-based expression for marginal utility growth with a linear model of the form":

$$m_{t+1} = \beta \frac{u'(c_{t+1})}{u'(c_t)} \approx a + b' f_{t+1} \tag{2}$$

where f_{t+1} is the factors, a and b are free parameters (Cochrane 2005). This is equivalent to a multi-beta model:

$$\mathbb{E}(R_{t+1}) = \gamma + \beta' \lambda \tag{3}$$

Where β are multiple regression coefficients of factor returns and γ and λ are free parameters. These factor models "look for variables that are good proxies for aggregate marginal utility growth" and the "factors are variables that indicate that these 'bad states' have occurred" (Cochrane 2005). In our thesis, we argue that displacement risk affects marginal utility growth, following the insights of GKP. We further argue that the Magnificent Seven act as a proxy for AI displacement risk, which we subsequently can use within this factor framework. The literature regarding factor pricing models is vast, but we summarize some key developments within this literature connected to our analysis.

The"birth of asset pricing theory" is noted by Fama and French (2004) as being the arrival of the Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965), developed from a model of portfolio choice by Markowitz (1952) and Markowitz (1959). This model predicts that: (1) the market portfolio (in theory, all the assets in the economy) is mean-variance efficient; (2) its market efficiency entails market betas are enough to describe the cross-section of expected returns; and (3) securities' expected returns are a positive linear function of their market betas. The model further posits that for an asset to give a risk reward, it should be correlated with the market return (captured in their slope; "beta") — otherwise it just earns the risk-free rate (the intercept). In other words, the only risk rewarded should be systematic risk – not unsystematic (idiosyncratic) risk that can be diversified away. Below is an illustration of the CAPM, where i is the risky asset, f is the risk-free rate, and M is the market:

$$\mathbb{E}[r_i] = r_f + \frac{Cov(r_i, r_M)}{\sigma_M^2}(\mathbb{E}[r_M] - r_f) = r_f + \beta_i \mathbb{E}([r_M] - r_f) \tag{4}$$

Early tests of the CAPM showed market betas can explain expected returns and that their risk premium is positive, but that the intercept is not equal to the risk-free rate. One way to validate the model empirically is seen in Fama and MacBeth (1973), who use asset panel data to perform two-step regressions. We will perform such regressions in this thesis, and explain them in more detail in the section outlining our methodology.

The CAPM has however long since been disproved, and evidence shows that much of the variation in the expected return is not related to market beta. There have arguably been two main stories as to the failure of the CAPM – behavioral factors, or the need for a more complex model (Fama and French 2004).[3] Roll's (1977) critique additionally postulates the CAPM is inherently untestable, since any test of the factor only uses a proxy of the market and not the true portfolio. Fama and French (2004), however, argue for a more pragmatic approach. By finding a market proxy on the minimum variance frontier, this can be used to describe differences in expected returns, since CAPM is the minimum variance condition that holds in any efficient portfolio, but which is applied to the market portfolio.

Despite its failure, the CAPM spurred extensive research on what factors *can* explain the cross-section of returns. Merton (1973) extends the CAPM into the ICAPM (Intertemporal CAPM). In the ICAPM, investors still care about the optimal risk-return tradeoff, but they also care about how their portfolio returns co-vary with state variables. This makes the optimal portfolios multifactor efficient, opening up for multiple factors explaining the cross-section of expected returns. Ross (1976) proposes another theory opening up for multiple factors, namely the Arbitrage Pricing Theory (APT). APT starts in statistical characterization when trying to identify common movements in stocks beyond the big common market factor (this could be for example utilities, small stocks, and value stocks). The intuition from the APT is that idiosyncratic movements should not be priced, since holding portfolios can diversify this risk. Only covariance with common factors should carry risk prices.

The multi-factor approach eventually led to the seminal Fama and French (1993)[4] three-factor model, constructing additional factors using stock characteristics, alongside the market factor. Fama and French posit that the two additional factors size (SMB) and book-to-market equity (HML) reflect unidentified state variables which cannot be diversified away, thus proxying

[3] We primarily focus on rational explanations, due to the scope of the thesis.

[4] Expanding on their work from Fama and French (1992) and revisited in Fama and French (1996)

common risk factors. Fama and French show that returns on high book-to-market (value) stocks co-vary more with one another than returns on low book-to-market (growth) stocks, and similarly for the stocks of small firms versus large firms. The empirical study was made using 25 portfolios' excess returns sorted on book-to-market equity and size and using NYSE, NASDAQ and Amex stocks between 1963-1990. Below is an illustration of the FF3, where the new factors are: SMB, the size factor portfolio (buy small and sell big stocks), and HML, the value factor portfolio (buy value and sell growth stocks):

$$\mathbb{E}[r_i] = r_f + \beta_{i,M}\mathbb{E}([r_M] - r_f) + \beta_{i,s}\mathbb{E}(SMB) + \beta_{i,h}\mathbb{E}(HML) \tag{5}$$

Fama and French (1993) shows that there is a negative relationship between average excess returns and size (thus, smaller stocks gain a higher risk premium) and a positive relationship between average excess returns and book-to-market equity ("value stocks" earn a higher risk premium than "growth stocks"). The Fama and French model explains approximately 90% of the variation in the data – notably higher than the 70% of the CAPM.

However, despite its initial empirical success, the Fama-French model also has issues. According to Fama and French (2004), its most serious problem is that it fails to explain Jegadeesh and Titman's (1993) momentum effect. This effect is related to the behavioral strand of the literature and posits that securities that have performed relatively well on average continue their out-performance, and vice versa (Asness et al. 2014). Carhart (1997) added a momentum factor (using the difference between the short-term winners' and losers' diversified portfolios) to the three-factor model. An extensive quest to explain the cross-section of stock returns has since produced many new factors (named the "Factor Zoo"). For example, Fama and French (2015) add differences in returns of portfolios sorted on profitability and investment as new factors (constructed similarly to prior HML and SMB factors). Feng, Giglio, and Xiu (2020) evaluate many of the newly proposed factors via the LASSO machine learning method, and conclude that many factors are, in fact, redundant, but find support for e.g. profitability and investment. Finally, Harvey, Liu, and Zhu (2016) propose that any newly researched risk factors ought to cross a higher probability threshold to be considered legitimate, suggesting a modified t-statistic threshold of 3. We follow this guideline, evaluating our factor accordingly.

2.2.1 Note on Granularity

Granularity refers to the theory put forth by Gabaix (2011), showing that idiosyncratic movements of large firms can drive economic aggregates. Traditionally, idiosyncratic movements have been thought to diversify away in the aggregate, with N number of firms having independent shocks diversifying away in $1/\sqrt{N}$ as N increases (reasonable, since there are many firms in modern economies). However, if the firm-size distribution is fat-tailed (where very large firms occur more frequently), through Zipf's (1949) law, these stocks do not diversify; we get a diversification that decays according to $1/\ln N$. The central limit theorem thus breaks down. Gabaix constructs a "granular residual" – the idiosyncratic shock to a firm – for the top 100 US firms and shows it can explain around one third of GDP fluctuations. Gao (2023) studies granularity and asset pricing, and shows that granularity provides a channel for idiosyncratic risks in the largest firms to affect the cross-section of asset prices. In addition to the factor risk premiums, granularity creates a idiosyncratic risk premium in expected returns. We connect the Magnificent Seven to granularity theory, since they are of considerable size and could thus be considered to be large "granules" in the economy. Their idiosyncratic fluctuations could subsequently have an effect on aggregate returns.

2.3 AI and Displacement

There are two distinct but related dimensions of displacement risk, labor and companies. They are distinct, since labor may be displaced with the introduction of new technologies while the underlying companies, and their common equity, remain intact or even benefit from productivity gains or cost savings (Acemoglu and Restrepo 2019a). At the same time, all incumbent companies are exposed to the risk that innovation will result in added competitive pressure on their existing business models, through e.g. the entry of startup competitors (Gârleanu, Kogan, and Panageas 2012; Gârleanu and Panageas 2025). Additionally, they show that value firms are more exposed to displacement risk than growth firms, where value firms are defined as having low price/earnings ratios and growth firms, high ones. This stronger exposure results in value firms having higher expected returns than growth firms. We focus on the latter type of displacement risk which describes innovation's effects on incumbent, and particularly, value firms.

Many studies have been dedicated towards understanding the ways in which new technologies impact the labor market, with Acemoglu and Restrepo (2019a) providing a summary of research on the topic. Less work, however, has been dedicated to studying the equity-specific firm displacement effect resulting from the asymmetric development and distribution of new innovations. Studies on this topic that most inspired this paper include Gârleanu, Kogan, and Panageas (2012), Kogan, Papanikolaou, and Stoffman (2020), and Gârleanu and Panageas (2025). All of these papers evaluate the effect of innovation on asset returns, with the 2012 and 2025 papers particularly highlighting the value effect that arises due to displacement risk.[5]

We seek to evaluate the displacement risk equity effect within the context of AI, suggesting that subsequent rapid development of AI-related technologies constitutes an increase in displacement risk. We reason that the rise of large, AI-focused companies (in our case, the Magnificent Seven) and displacement risk are connected as follows: the AI firms provide the infrastructure (e.g. data centers, cloud computing capacity) enabling innovative growth (e.g. better margins through the implementation of AI-enabled automation) in other companies. This innovation, in turn, could lead to increased displacement risk, both in terms of severity and probability, as more innovative firms find ways to incorporate these technologies into their business models, seeking to gain a competitive advantage.[6] These companies go on to proliferate throughout various business sectors, increasing the risk that incumbent, slower-moving firms will be displaced throughout the economy. As such, we propose that the returns on the equity of these large AI companies are good proxies for displacement risk; their returns ought to reflect the degree of

[5] Chen (2025) goes so far as to suggest that the possibility of "AI singularity" constitutes a disaster risk for the representative investor.

[6] Existing, nascent examples are manifold, including firms providing AI-enabled solutions for the parsing of legal documents, web design, software development, employee training, among many others.

potential displacement risk associated with AI-related innovation.

There are a few recent papers supporting the idea that AI specifically may result in negative outcomes for some firms, while advantaging others. Acemoglu and Restrepo (2019b) describe developments in AI as seeking to solely automate human labor, rather than adding new tasks for workers. They argue that advances in purely automotive technologies can result in worse labor outcomes, such as stagnant labor demand, declining share of labor income and slowing productivity growth. A recent empirical paper suggests that employment declines are more likely in occupations where AI automates tasks, instead of raising human productivity (Brynjolfsson, Chandar, and Chen 2025). Tying this to aggregate company-level effects, Knesl (2023) suggests that firms with a large share of displaceable labor have a "negative exposure to technology shocks", earning a 4% annual premium because of this. In equilibrium, labor displacement brings down profits and firm value. At the same time, an empirical study by Babina et al. (2024) find that firms that invest in AI see higher growth, primarily through increased product innovation. They also find that AI contributes to the rise of "superstar firms" and increases in industry concentration. AI models also tend to become better with added data, a greater number of parameters and extra computational resources (Samborska 2025). This suggests that a small number of firms already controlling a large number of these resources and know-how, e.g. Magnificent Seven, could be able to disproportionately benefit from supplying the infrastructure needed for further AI development.

In essence, AI can have positive effects among firms that actively adopt it. At the same time, incumbent firms are likely to be either out-competed in this race by AI-first startups or, at the very least, face the risk of increased competition stemming from existing competitors' adoption of new technologies. At the same time, a small number of "hyperscalers" stand to benefit from their already dominant positions within cloud computing and microprocessor manufacturing. As such, we find that there is sufficient evidence suggesting that AI contributes to displacement risk, and that the Magnificent Seven may well act as proxies for an increase in this risk, since they stand and are anticipated to benefit significantly from it.

2.4 Motivation and Research Question

Our contribution to the above strands of economic literature is in evaluating an empirical asset pricing factor proxy for AI-related displacement risk, borne out of the observed link between AI, the Magnificent Seven and technological displacement. Technological displacement is an undiversifiable source of risk, and thus ought to be priced by the market. Such sources of risk can be proxied for using factors constructed out of asset returns distinctly exposed to them. The Magnificent Seven are strong contenders for harboring this risk within their returns, due to their positive exposure to AI-related innovation.

We aim to isolate this portion of their returns, by residualizing them against common asset pricing factors. We then evaluate whether this proxy fulfills all of the theoretically-implied conditions of displacement risk, testing it on 11 P/E sorted portfolios, so that we can evaluate whether it is a compelling value-growth factor. Namely, our proxy has to be priced in the cross-section of returns, explain the value premium, and correlate with other factors that explain the value premium. Further, it should be a priced factor when evaluated using alternative portfolio sorts and additional risk factors. In summary, our primary research question is:

Is the residual variation in the Magnificent Seven a proxy for displacement risk?

To answer this question, we empirically test the following hypotheses:

H1. The displacement risk proxy is a priced part of the risk premium in the cross-section of P/E sorted stocks' returns.

H2. The displacement risk proxy is negatively associated with lower P/E values.

H3. The displacement risk proxy correlates with the Fama-French High-Minus-Low factor and "AI" term searches.

We also conduct additional tests (found in the Appendix) that evaluate three supplementary hypotheses:

H_A. The displacement risk proxy correlates concurrently with P/E sorted stocks' returns.

H_B. The displacement risk proxy's factor premium is robust to alternative portfolio sorting specifications.

H_C. The displacement risk proxy's factor premium is robust to the inclusion of additional risk factors within the two-stage regression model specifications.

3 Methodology

In order to evaluate the AI displacement risk associated with the Magnificent Seven ("M7"), we construct 11 P/E sorted portfolios using Compustat data and use value-weighted M7 portfolio returns' regression residuals to create a displacement factor proxy. Then, we conduct and report the results of three different analyses, alongside various additional pricing tests. First, we run Fama and MacBeth (1973) style cross-sectional, two-pass regressions, looking at whether our factor is priced by the market ex ante in the value premium. Second, we report the sums of squared errors obtained when comparing predicted and actual value premia across the 10 positive P/E sorted portfolios, to see whether our factor reduces these. Third, we plot the relationship between our M7 and High-Minus-Low factors, looking for an inverse co-movement between the two. Additionally, we report its correlation with recent search trends for the term "AI", to evaluate whether increased interest in the term correlates with our factor's returns. Finally, we conduct further checks to see if the factor is priced when using alternative portfolio sorts and controlling for additional factors. More detail on each of the tests is given in dedicated subsections.

Factor	Mean	Std	Sharpe	Cumulative Return
Mkt_{vw}	18.50	20.48	0.911	153.48
Mkt_{ew}	19.87	24.54	0.826	169.93
SMB	-0.80	13.31	-0.064	-4.31
HML	3.61	18.95	0.204	21.46
M7_{vw}	28.70	32.13	0.905	298.55

Table 1: Summary Statistics.

Description: All values are calculated using daily log returns and are in percent terms except for the Sharpe ratios. Reported are mean annualized returns and standard deviations, their Sharpe ratios and cumulative returns between Apr. 2020 and Sep. 2025. Note that the Sharpe ratios are calculated using the daily log return values and are therefore slightly different from the values obtained by dividing the reported mean annualized returns and mean annualized standard deviations.

3.1 Data

Our raw data consists of (1) daily US stock close prices and EPS for stocks with "exchg" codes of 11 and 14, delimiting listing on the NYSE and NASDAQ-NMS exchanges, respectively, taken from Compustat (accessed through WRDS); and, (2) the Fama-French ("FF") 5 factors, accessed through Kenneth French's data library (Fama and French 2025). Note that the FF3 factors are used in the main body of our paper while the additional two factors of the FF5 specification are used in the latter robustness checks. All raw data spans between Apr. 1, 2020 and Sep. 30, 2025. We choose this period in order to isolate the most recent bull market, where sentiment has been generally consistent regarding different asset's near-term prospects, and to study the effects of the M7 at their most influential, overlapping with the rapid roll-out of AI-related technologies. This also justifies the use of daily data: the short study horizon necessitates the use of higher-frequency observations than is standard in most factor-based research, where monthly observations are most common.

We aggregate and transform the data as follows. We use the daily close prices in order to evaluate (1) M7 value-weighted portfolio returns (hereafter "M7_{vw}"), which are rebalanced annually on Mar. 31, except for in the first year, where the weights are set on April 1, (2) all other stocks' daily returns, (3) equal-weighted P/E (Price/Earnings) decile sorted portfolio returns, and (4) an equal-weighted portfolio of all stocks with good data ("Mkt_{ew}"). All returns are converted into log returns, in order to alleviate the problem of daily returns' non-normal distributions, and taken in excess of the risk-free rate used by Fama and French.

The M7 portfolio is constructed on a value-weighted basis in order to emphasize the returns of the largest stocks within the grouping, particularly in the first half of the period when Nvidia is small relative to the other firms. This also allows us to proxy for the relative rise in AI's importance to M7's returns and investor sentiment. We also filter out stocks that either have missing values or have a single-day return in excess of 100%, in order to reduce single-day volatility in our portfolios. These two steps reduce the total population of individual stocks

	Mkt_{ew}	SMB	HML	M7_{vw}
Mkt_{vw}	0.871	0.236	-0.200	0.871
Mkt_{ew}		0.643	0.131	0.595
SMB			0.333	-0.037
HML				-0.487

Table 2: Correlation Matrix.

from 3,779 to 2,150 not counting the M7. There are a total of 11 P/E sorted portfolios, where a rank of 1 indicates the lowest positive P/E on the formation date and 10, the highest. We also construct a portfolio with rank 0 for stocks with a negative EPS on the portfolio formation date (denoted "EPS<0" in tables). The portfolios are formed annually, based on firms' P/E ratios on Apr. 2, or the first trading day thereafter, if markets are closed on Apr. 2.

As an aside, since we use daily prices in order to estimate stock returns, dividends are conspicuously left out, which may bias results somewhat. Additionally, this introduces the problem of correcting for stock splits, especially among the M7, where 95% overnight "drops" in price can very negatively affect the group's mean return for the entire period. We identify all such splits in the M7, as far as we know, but make no effort to adjust for this in the remaining more than 2,000 stocks. We believe that any such splits ought not be an issue, since the sector portfolios we construct out of the remaining stocks are equal-weighted and contain hundreds of stocks each, meaning that any one-time virtual stock price drop should be evened out enough not to affect the aggregate significantly.

Tables 1 and **2** neatly summarize the characteristics of the main studied factors. The market has performed well over a relatively short period of time, both in risk-adjusted and cumulative terms, M7 stocks have performed similarly to the market in risk-adjusted terms, and small stocks have lagged large stocks overall, while value stocks' returns in excess of growth have been positive, albeit small.

3.2 Factor Construction: M7 Residuals

Since our aim is to evaluate the displacement risk assignable strictly to the M7 stocks, we wish to isolate this risk as completely as possible. We elect to do this by residualizing these stocks' returns by regressing our M7_{vw} portfolio against the FF3 factors, using the specification:

$$r_{M7,t} - r_{f,t} = \alpha_{M7} + \beta_{M7}\mathbf{\Phi}_t + \epsilon_{M7,t}, \tag{6}$$

Where $r_{M7} - r_f$ is the excess return of the M7_{vw} portfolio, α_{M7} is its time-unvarying return in excess of systematic risk factors, β_{M7} is the vector of beta coefficients measuring their exposure to these factors, $\mathbf{\Phi}$ is the matrix of FF3 factor returns, and ϵ_{M7} are their residual returns. We are particularly interested in the ϵ_{M7} terms (hereafter "M7_{res}"), which are orthogonal to the FF3 factors, i.e. their Pearson correlation coefficient with any of the FF3 factors is exactly zero, capturing the variation in M7 returns entirely unique to them, while also being distinct from their alpha, which is invariable within the estimation horizon. Note that since our primary test involves a modified Fama-MacBeth (1973) approach, $M7_{res}$, and its betas, is evaluated during the same time horizons as the remaining factors' betas during the first regression pass and uses the same regression approach (more on this in the subsequent section).

Given the properties of regression residuals, the $M7_{res}$ factor is by definition "unpriced", in that its cumulative return for any estimation horizon is zero. As such, its "market return" can only stem from correlation with assets or portfolios that do have an excess return. Additionally, since this residual does not correlate with the factors used to construct it, any correlation between the $M7_{res}$ factor itself and other assets must stem from a different source of undiversifiable risk (assuming that the regression factors themselves are good proxies of the systematic risks they measure). We use this statistical property of residuals to identify risk shared between the M7 stocks and the 11 P/E sorted portfolios that is statistically distinct from the FF3 factors, providing evidence for displacement risk inherent to the M7 stocks.

3.3 Cross-Sectional, Two-Pass Regressions

Since time-series tests suffer from a number of drawbacks, such as look-ahead bias, time-unvarying betas, and overestimation of factor returns (Hollstein and Prokopczuk 2022), and because our factor is by definition not priced by the market, we opt to test it using an augmented Fama-MacBeth (1973) approach. We conduct the test using the 11 P/E sorted portfolios and four separate matrix specifications of factor returns, F_j. These are: (1) the market-return factor (CAPM), (2) FF3 factors, (3) CAPM+$M7_{res}$, and (4) FF3+$M7_{res}$. This approach requires two distinct empirical steps. First, estimating conditional factor betas, and second, estimating cross-sectional factor premia, using those beta estimates.

Since our study period is quite short, we elect to estimate our factor betas over rolling 12 month windows and estimate factor premia (hereafter "lambdas") one month ahead, using said beta estimates. A 12 month beta estimate using daily returns should provide a good mix of beta conditionality and accuracy, while giving us enough time windows to also accurately estimate factor lambdas. In line with recommendations from Hollstein and Prokopczuk (2022), we use the Generalized Least Squares (GLS) estimation method, since daily returns tend to be more volatile and GLS specifically under-weighs more volatile securities. In the same vein, we use Newey-West standard errors. Lastly, following the recommendation of Harvey, Liu, and Zhu (2016) we use a modified t-statistic threshold of 3, as opposed to the traditional threshold of around 2, as the signifier of statistical significance.

With reference to Hollstein and Prokopczuk, the two estimation steps can be represented mathematically as:

$$r_{i,\tau} - r_{f,\tau} = \alpha_{i,\tau} + \beta_{i,\tau} F_{j,\tau} + \epsilon_{i,\tau}, \tag{7}$$

$$r_{i,t} - r_{f,t} = a_i + \lambda_t \hat{\beta}_{i,\tau} + \nu_{i,t}, \tag{8}$$

Where the first step estimates factor betas for all periods τ, using a subset of the data of length $\tau - k$, where in our case $k = 252$, i.e. the approximate number of trading days in a calendar year. Using this method, we obtain a matrix containing 54 sets of time-conditional beta estimates, which are then used in the second stage. Every cross-section of daily portfolio returns in the period $\tau+\gamma-1$, i.e. between τ and the day before the start of the next estimation period $\tau+\gamma$, roughly equal to 20 days depending on the exact estimation date, is regressed on the vector of betas, $\hat{\beta}_{i,\tau}$. This allows us to, at every point in time τ, directly test whether the previous year's betas predict the coming month's returns.

The cross-sectional approach satisfactorily addresses all of the mentioned set-backs of the time-series approach. It allows us to estimate betas as they would have appeared to an investor the moment they considered trading an asset, let betas vary over time, and infer factor returns from historic betas and portfolio returns. Additionally, since $\mathrm{M7_{res}}$ inherently has a zero expected return during a given evaluation period, the cross-sectional test allows us to assign it an implied return based on other stocks' correlation with it. Nevertheless, the cross-sectional approach suffers from its own set-backs, such as model mis-specification and errors in variable estimates. To evaluate the different model specifications and see whether the $\mathrm{M7_{res}}$ factor is priced ex ante, we compare the mean lambda estimates, $\bar{\lambda}_j$, mean adjusted R^2 values, $\bar{R}^2$, and calculate the lambda t-statistic:

$$t(\lambda_j) = \frac{\bar{\lambda}_j}{Std(\lambda_j)/\sqrt{N}}. \tag{9}$$

3.4 Estimating the Value Premium

As part of our assessment of the usefulness of M7 returns as a proxy for displacement risk, we wish to evaluate whether the $\mathrm{M7_{res}}$ factor improves our ability to model the value premium, to check if our results are consistent with the Gârleanu, Kogan, and Panageas (2012) and Gârleanu and Panageas (2025) models of displacement risk. We do this using the cross-sectional model. First, we define the value premium to be the difference between the returns in the 9 lower, positive P/E deciles (ranks 1 through 9) and the highest P/E decile, consistent with Gârleanu and Panageas's definition of the "value premium". These value premia vary from greatest, between ranks 1 and 10, and smallest, between ranks 9 and 10. We then use the estimated lambdas to calculate the expected value premium, by multiplying our lambda and beta estimates across all portfolios, and then subtract this expected premium from the observed premium, squaring the errors across all time periods and reporting these sums of squared errors (SSEs). A lower reported SSE is indicative of a better value premium estimate.

3.5 Plotting the Factor

We propose that if the $\mathrm{M7_{res}}$ factor is a sufficiently good proxy for displacement risk, it ought to generally move inversely to the HML factor. This is because of how displacement risk is seen to influence the value premium: value stocks are generally poor hedges against displacement risk. They therefore command higher expected future returns in times when displacement risk is increasing, realizing smaller gains concurrently with high-tech stocks realizing large gains (Gârleanu, Kogan, and Panageas 2012). By design, this relationship between $\mathrm{M7_{res}}$ and HML will not be captured using the Pearson correlation coefficient in-sample, since the sum of GLS residuals is zero, but could appear in their estimated lambda time-series (found using equation 8) and their plots.

As such, we calculate the Pearson correlation coefficient and conduct visual evaluations of the time-varying relationship between $M7_{res}$ and HML by plotting their 90-day running average lambda returns and cumulative returns for the period. We expect the 90-day moving averages to move in broadly opposite directions at any given point in time, while the cumulative returns will reflect the paths taken by these factors' returns during the observation period.

In addition to this, to better pin-point the source of the $M7_{res}$ factor's influence on other stocks' returns, we graph the cumulative return of the factor's Fama-MacBeth lambdas against the US online search trend for the term "AI", providing suggestive evidence for the connection between M7 residuals and innovative technology.

3.6 Robustness Tests

We conduct the following robustness tests to verify and evaluate our analysis and conclusions: (1) a time-series regression using the same model specifications as for the cross-sectional regressions, (2) cross-sectional test results with the Fama-French 25 size-value, size-investment, size-profitability and value-profitability sorted portfolios, (3) cross-sectional test with momentum added to all model specifications, (4) cross-sectional test using the FF5 factor model, and (5) cross-sectional test results for data only going back to the beginning of 2023. Most robustness test results are presented in the Appendix, while some directly supplement and are displayed in the discussion subsection 5.1. Note that when we estimate factor lambdas for the robustness tests, we use modified M7 residuals which are calculated using the FF3+momentum factors and the FF5 factors for tests (3) and (4), respectively.

4 Results

In summary, we find that our $M7_{res}$ factor is not priced in the cross-section (using a t-stat threshold of 3), despite moderately augmenting the performance of the FF3 factor model; improves both the CAPM and FF3 model value premium estimates (measured as the return difference between the each of the lower 9 and the highest decile P/E portfolios); and, correlates inversely with the HML factor and positively with the "AI" term search trend. Furthermore, $M7_{res}$ does not have a statistically significant lambda estimate using any alternative portfolio sorting method and is further weakened when momentum, or the Conservative-Minus-Aggressive and Robust-Minus-Weak factors are added to the two-pass regressions. The factor is statistically significant in the time-series, producing the expected betas across P/E deciles, and appears to have a higher magnitude when we evaluate factor lambdas from 2023, rather than 2020, following the rapid expansion of AI-related technologies than before it. Nevertheless, it does not cross our statistical significance threshold when specified this way.

	(1) $\bar{R}^2$: 0.220		(2) $\bar{R}^2$: 0.469		(3) $\bar{R}^2$: 0.560		(4) $\bar{R}^2$: 0.602	
	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$
Intercept	-6.86	-0.62	-12.98	-1.12	-22.53	-1.73	-37.31	-2.22
Mkt_{vw}	9.97	0.71	14.26	1.01	26.96	1.35	27.53	1.27
SMB	-	-	-	-	4.65	0.53	26.11	2.28
HML	-	-	-	-	2.60	0.30	19.38	1.72
M7_{res}	-	-	-13.78	-0.92	-	-	-41.05	-2.58

Table 3: Cross-Sectional Regression Results.

Description: (1) CAPM, (2) CAPM+M7_{res}, (3) FF3, (4) FF3+M7_{res}. CAPM estimates portfolio returns based on their correlation with the market factor, Mkt_{vw}, the Fama-French 3-factor (FF3) model estimates these based on correlations with Mkt_{vw}, the Small-Minus-Big (SMB) factor and High-Minus-Low (HML) factor. Our Magnificent Seven (M7) factor, M7_{res}, calculated as the regression residuals of the M7 value-weighted portfolio's returns against the FF3 model, see equation (6), is added to both to test its mean value premium, $\bar{\lambda}$. Reported are the $\bar{\lambda} = \frac{\Sigma\lambda}{N}$ values and their t-statistics, calculated from the daily lambdas obtained using augmented Fama and MacBeth (1973) two-pass GLS regressions, where the two passes estimate equation (7) and equation (8). The first equation estimates factor betas over rolling 1-year windows using daily log returns, while the second estimates the daily lambdas over rolling 1-month windows. $\bar{\lambda}$ values are reported in annualized percent terms. $t(\lambda)$ values are calculated using equation (9). $\bar{R}^2$ values are calculated as the equal-weighted mean of adjusted R^2 values found across all lambda evaluation periods. The beta estimation window is from Apr. 2020 through Aug. 2025, while the lambda window is Apr. 2021 through Sep. 2025.

4.1 Cross-Sectional Results

Aggregate cross-sectional results for the second-stage Fama-MacBeth regressions are presented in **Table 3**. We can see that the CAPM, FF3 and CAPM+M7_{res} regression specifications result in no significant factor premia across all of the included factors. This is broadly in line with the findings of Hollstein and Prokopczuk (2022), who fail to find any of the FF3 factors to be statistically significant when running similar regressions, though in their estimations, the HML factor does considerably better, potentially suggesting that our factor partly subsumes the HML factor. Adding our residual factor to the CAPM does substantially improve its $\bar{R}^2$, while also increasing the mean factor return associated with the market factor as well as the intercept.

The most interesting part of the results is the FF3+M7_{res} regression specification, which has lower-threshold significant SMB, M7_{res} and intercept lambdas, alongside an improved $\bar{R}^2$. But, none of the factors cross a t-stat threshold of 3. Our factor exhibits the expected sign lambda, indicating that P/E portfolios which are positively correlated with M7 residuals tend to have lower returns and vice versa for negatively correlated portfolios. At the same time, while HML remains completely statistically insignificant, both it and SMB were significantly boosted by the M7_{res}'s negative lambda, their performance being biased by the risk associated with M7_{res}. Recall that the annualized market risk premia associated with SMB and HML, reported in **Table 1**, were -0.80% and 3.61%, compared to the cross-sectional 26.11% and 19.38%.

P/E Decile:	EPS<0	1	2	3	4	5	6	7	8	9	10
$\bar{\beta}^{pre}{}_{\text{M7res}}$	-0.050	-0.111	-0.139	-0.116	-0.126	-0.180	-0.213	-0.227	-0.243	-0.213	-0.117
$\bar{\beta}^{post}{}_{\text{M7res}}$	-0.082	0.048	0.095	0.050	-0.056	-0.135	-0.207	-0.236	-0.281	-0.220	-0.157

Table 4: Cross-Sectional M7_{res} Mean Betas, Pre- and Post-2023.
Description: Shown values are the mean monthly betas calculated using equation (7) for the M7_{res} factor. $\bar{\beta}^{pre}{}_{\text{M7res}}$ is calculated using betas spanning Apr. 2020 to Dec. 2022, $\bar{\beta}^{post}{}_{\text{M7res}}$ is calculated using betas spanning Jan. 2023 to Sep. 2025. 1 = Lowest P/E.

We also report the conditional mean betas of our M7_{res} factor in **Table 4** for two distinct periods, pre- and post-2023, where the beginning of 2023 roughly coincides with the rapid advancement in public awareness of and exposure to AI-enabled technologies, marked by the release of ChatGPT in late 2022. Additionally, past this point, pledged and realized investment into AI-related R&D among the Magnificent Seven also quickly increases (Wiltermuth 2025), suggesting a change in anticipated displacement risk for incumbent firms. We find that M7_{res} mean betas undergo a significant change, becoming positive for value stocks and more negative for growth stocks. Recall that the sign of M7_{res} lambdas is negative, meaning that a positive beta with the factor risk reduces a portfolio's returns, and vice versa for negative betas. This is in line with our increasing displacement risk hypothesis: value stocks' prices are dampened in anticipation of displacement by new technologies, while growth stocks are seen as a hedge against this risk, enjoying relatively higher prices.

4.2 Value Premium Errors

Table 5 shows the sum of squared errors obtained when estimating the returns of various value premia, ranging from the largest (rank 1 minus rank 10) to the smallest (9-10) premium. These offer an insight into how well the cross-sectional model predicts return differentials across the P/E deciles. Here, a smaller value indicates better model performance. The CAPM performs the worst by far, having difficulty modeling the improved returns of lower P/E portfolios compared to higher ones. Our residual-based factor offers a marked improvement, particularly at the higher ranges of the value premium, while leaving the spreads closest to P/E parity broadly unchanged. The FF3 model performs better than the M7_{res}-augmented CAPM, but still retains errors in the higher and lower ranges of the value premium. The final, FF3+M7_{res} model performs the best of all, evenly reducing the estimation errors across the entire value premium range. This suggests that our factor supplements the performance of the HML factor, explaining a distinct subset of variation in the value premium.

4.3 Factor Plots

Our final evaluation of the M7_{res} factor revolves around three comparative plots: 90-day moving average lambdas with the HML factor (*Figure 3*), cumulative lambdas with the HML factor (*Figure 4*) and scaled cumulative lambdas and relative Google search trend for the term "AI" (*Figure 5*). Also reported are the Pearson correlation coefficients between the displayed plots.

	1-10	2-10	3-10	4-10	5-10	6-10	7-10	8-10	9-10
CAPM	0.0425	0.0350	0.0287	0.0198	0.0160	0.0126	0.0128	0.0115	0.0094
CAPM+$M7_{res}$	0.0184	0.0112	0.0135	0.0130	0.0127	0.0128	0.0119	0.0117	0.0089
FF3	0.0084	0.0053	0.0049	0.0050	0.0058	0.0083	0.0065	0.0072	0.0080
FF3+$M7_{res}$	0.0049	0.0039	0.0036	0.0038	0.0041	0.0043	0.0034	0.0041	0.0067

Table 5: Cross-Sectional Value Premium Estimates' SSEs.
Description: Shown values are the sum of squared errors calculated using the difference between observed and expected return spreads between stated P/E deciles. Expected returns calculated using Fama and MacBeth (1973) lambda and beta estimates, described in Table 3, while actual returns were calculated from the data. 1 = Lowest P/E.

We see considerable inverse correlation in the moving-average plot of the HML and $M7_{res}$, confirmed by the correlation coefficient, while still retaining distinct differences, facilitating our factor's improvement of the FF3 model. The cumulative returns plots in *Figure 4* help show how the value premium has continued to perform quite well during the observed period, while $M7_{res}$-driven returns have been decidedly and consistently negative since around mid-2022.

Finally, *Figure 5* aims at connecting the cross-sectional returns of the $M7_{res}$ factor to the continuing proliferation of and interest in artificial intelligence. The two plots' trends are closely related, with a correlation of 0.906, with certain spikes and troughs in each plot being distinctly similar, if separated somewhat in terms of timing. This plot helps us support the hypothesis that AI is related to the M7 residual.

5 Discussion and Limitations

5.1 Discussion

This subsection contains our thoughts about the factor's empirical results and how these connect to our overarching hypothesis of AI displacement risk being inherent to the M7 stocks' returns. We consider both the evidence for and against this hypothesis, offering a synthesis in Section 6.

5.1.1 Cross-Sectional Regressions and Correlation with Value Factors

Firstly, the large and negative return premium attributable to stocks correlating with the $M7_{res}$ factor is exactly what one expects to see from a factor correlated with displacement risk (recall that we need to think about this factor in the inverse, since it is "going long" displacement risk), since increased displacement risk raises the risk premium associated with less-innovative stocks, thus driving down their prices, i.e. lowering realized returns (Gârleanu, Kogan, and Panageas 2012). The inclusion of our displacement risk proxy also improves the performance of both the SMB and HML factor, which are otherwise too small to have a statistically significant return in the cross-section. This is consistent with the sign and nature of the displacement risk effect on less-innovative/incumbent firms. Since they perform broadly worse than they would have in the absence of heightened displacement activity, it is harder to identify classical risk factors such

	(1) $\bar{R}^2$: 0.375		(2) $\bar{R}^2$: 0.515		(3) $\bar{R}^2$: 0.593		(4) $\bar{R}^2$: 0.620	
	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$
Intercept	-12.34	-0.79	-25.65	-1.79	-34.35	-2.08	-35.32	-1.79
Mkt_{vw}	14.52	0.76	31.22	1.62	42.83	1.61	28.25	1.07
SMB	-	-	-	-	7.60	0.70	18.20	1.42
HML	-	-	-	-	16.87	1.64	22.65	1.82
Mom	-13.71	-0.85	-5.74	-0.36	-2.96	-0.12	-8.45	-0.35
$\text{M7}_{\text{res,mom}}$	-	-	-10.76	-0.68	-	-	-29.65	-1.62

Table 6: Cross-Sectional Regression Results with Momentum.

Description: (1) CAPM, (2) CAPM+$\text{M7}_{\text{res,mom}}$, (3) FF3, (4) FF3+$\text{M7}_{\text{res,mom}}$, with Momentum factor added to all models. Here, $\text{M7}_{\text{res,mom}}$ is evaluated as the GLS residual of the M7_{vw} portfolio regressed on the FF3+Mom model. See Table 3 for a full description of variables.

as HML, which predicts higher returns for firms that stand to struggle most during periods of high disruption, value firms.

However, the lambda estimate in the augmented FF3 cross-sectional test is not statistically significant to a t-stat threshold of 3, and fares even worse with the addition of other Fama-French-style factors: momentum, CMA and RMW (**Tables 6** and **7**). Including momentum significantly decreases the annualized return of the M7_{res} factor (**Table 6**), makes the intercept lambda more insignificant, and further makes the SMB factor lambda estimate more insignificant, as well. This suggests that at least a part of M7 residual pricing is captured by momentum, but not all, since it retains a relatively large lambda coefficient. At the same time, the momentum lambda is not statistically significant itself, making exact result interpretation complex. It is also possible that adding momentum when residualizing the M7 portfolio return simply reduces the share of variation in it sufficiently to make its lambda coefficient estimate less significant.

The results of the FF5+M7_{res} test offer more interesting insight into the nature of our residual factor (**Table 7**). Note, that the M7 residual factor (denoted "$\text{M7}_{\text{res,FF5}}$") is calculated as the residual of the FF5 model factors, and as such has different lambdas to the FF3 model residual. Here, the model's overall ability to capture return variation is broadly unaffected by the addition of the $\text{M7}_{\text{res,FF5}}$ factor, indicated by virtually no change in the adjusted $\bar{R}^2$, but the lambda coefficients and their significance are affected strongly. The intercept lambda becomes less significant, the HML lambda variance is increased (indicated by a lower t-statistic but an unchanged mean estimate), CMA's lambda return is reduced and RMW's is much higher in magnitude. All of these changes suggest that the residual factor determines an important component of stock's returns, such that its presence better reconciles the FF5 model with the conditions of the APT (requiring that assets have no returns in excess of their systematic risk factors, captured by the intercept $\bar{\lambda}$). Seeing these results, we were also immediately interested in the correlations between the different factors, wondering whether any of them co-move together with the M7 residual lambda return. We found that the SMB and CMA factors were broadly

	(1) $\bar{R}^2$: 0.633		(2) $\bar{R}^2$: 0.634	
	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$
Intercept	-39.98	-2.56	-37.55	-1.86
Mkt_{vw}	56.11	2.05	41.41	1.47
SMB	3.91	0.29	6.77	0.47
HML	27.43	2.10	28.34	1.48
CMA	64.14	3.53	49.20	2.77
RMW	-2.93	-0.31	-12.19	-1.02
$\text{M7}_{\text{res,FF5}}$	-	-	-14.56	-0.62

Table 7: Cross-Sectional Regression Results with the FF5 Factor Model.

Description: (1) FF5, (2) FF5+$\text{M7}_{\text{res,FF5}}$. Here, $\text{M7}_{\text{res,FF5}}$ is evaluated as the GLS residual of the M7_{vw} portfolio regressed on the FF5 factors. See Table 3 for a full description of variables.

uncorrelated with the $\text{M7}_{\text{res,FF5}}$ factor (Pearson $r = -0.055$ and $r = -0.185$, respectively), the market factor was weakly and negatively correlated ($r = -0.277$), the HML factor was moderately and negatively correlated ($r = -0.685$), and the RMW factor was moderately, positively correlated ($r = 0.611$). Knowing these values, we attempted to create an illustrative replicating portfolio of the $\text{M7}_{\text{res,FF5}}$ out of the RMW and HML factors, by taking the difference in lambda returns between them, creating the "RMW-Minus-HML" factor. See *Figure 6* for a plot of the resulting factor against the $\text{M7}_{\text{res,FF5}}$ factor.

It is notable that the RMW and HML factor lambdas are the ones most strongly correlated with the residual lambdas, suggesting that while neither RMW nor HML correlates with the residuals concurrently, all of these factors explain similar types of variation among the P/E sorted portfolios in the cross-section. Both HML and RMW aim to explain the value premium, the former by looking at portfolios' valuation, predicting that stocks with higher book-to-market ratios ought to have higher returns, the latter by looking at profitability, where stocks with higher profitability will command a premium as well (Fama and French 2015). We suggest that this correlation is indicative of the $\text{M7}_{\text{res,FF5}}$ (and the simpler M7_{res}) factor tracking the value premium, while enhancing the explanatory power of the broader model by subduing the magnitude of the intercept lambda. The reason our residual factor does not broadly affect the adjusted $\bar{R}^2$ is that in the presence of other factors that explain the value premium, like HML and RMW, the three factors simply cannibalize each other's share of the overall value premium, all explaining it through different causal channels. Notably, aggregating these various determinants of the value premium into a single factor may alleviate the problem of their individual statistical insignificance in the cross-section.

5.1.2 Other Explanations for Residual Correlation with the Cross-Section of Returns

Variation attributable to the M7 residual can have many origins outside of co-variation with displacement risk. But, these sources have to be those of systematic risk, otherwise the residual would not produce identifiable lambdas, nor would it correlate with the cross-section of returns. So, what possible confounders could produce similar results to displacement risk, that is, a mean (although not robustly significant) factor premium in the cross-section, improved value premium estimation and correlation with HML and RMW factors?

The most straightforward answer is other factors aimed at explaining the value premium. These include, but are not limited to: return horizon (Lettau and Wachter 2007), asset risk and leverage (Choi 2013), intangible value (Eisfeldt, Kim, and Papanikolaou 2022), and value-price divergence (Cong, George, and Wang 2023). Lettau and Wachter's explanation of the value premium suggests that growth firms attract higher valuations due to their cash flows being more heavily weighted towards the future, while value firms' cash flows are heavily weighted to the present. This results in lower expected returns in the former and higher in the latter, assuming that shocks to dividends are priced while shocks to the discount factors are not. The M7 do fit the description of stocks with potentially much higher future cash flows than today. Nevertheless, this dynamic should be sufficiently captured by the HML and RMW factors, since they consider the book-to-market and profitability differences between the M7 and other firms. As such, this explanation of the value premium does not clash strongly with ours.

Choi's rationalization of the value premium suggests that the difference in returns between high and low book-to-market ratio stocks is partly the product of value firms taking on more leverage than growth firms, and therefore being inherently more risky during certain phases of the business cycle. Namely, value firms' debt-to-market equity ratio increases during economic downturns, sharply increasing their equity risk and time-conditional market betas, resulting in more volatile and risky returns than growth stocks, earning them a conditional risk premium. This explanation of the value premium is relevant in our case in the sense that if $\mathrm{M7}_{\mathrm{res}}$ is a proxy for displacement risk, it is then also inherently a proxy for one bad state of the world for value firms, in which case they would likely have to take on relatively more leverage and have their market betas increase. However, this explanation merely gives one pathway through which the value premium would materialize in the case that mass displacement of old firms by new does occur, rather than conflicting with our argument.

Intangible value, proposed as an extension of the Fama-French HML factor by Eisfeldt, Kim, and Papanikolaou, expands on the traditional factor by including intangible assets in the book value component of the book-to-market ratios used to form the BM portfolios. This inclusion can result in traditionally asset-light firms being sorted into portfolios that were populated exclusively by tangible asset-heavy firms in the Fama-French construction. This construction generally results in a higher observed value premium. This line of reasoning could be a true confounder in our case, since the M7 firms are generally tangible asset-light, but can accrue high amounts of selling, administrative and general expenses (used by Eisfeldt et al. as the proxy for intangible asset investment). As such, if this share of the "true" value premium is baked into the residual and remains there, we would expect the M7 to predict higher returns for other, similar growth firms, explaining their negative factor lambda and negative betas (resulting in a positive premium) with high growth firms (see, for example, the results in **Table 4** or **9**). Our best assumption limiting the effect of this confounder is that it is sufficiently captured by the RMW factor, but this is not a given, and thus remains a valid limitation of this study.

Finally, we consider whether Cong, George, and Wang's value-price divergence is a valid confounder potentially affecting our results. Here, value-to-price ratios are first calculated, where a firm's value proxy is calculated using forward-looking analyst forecasts and the residual income model. These ratios are used to calculate long-short portfolios (called "VP" portfolios) going long high value-to-price ratio stocks and shorting low value-to-price ratio stocks, while sorting firms by size. Value-price divergence ("VPD") is then calculated as the equal-weighted average of these VPs. A model containing the market factor, SMB, VPD and a momentum factor was found to significantly outperform a number of traditional models. The main benefit of VPD is that it uses forward-looking cash flows to estimate stocks' fair value, potentially improving an investor's ability to rank stocks as under-, fairly- and over-valued. Similarly to the intangible value-augmented HML measure, this improved measure of value could be present in the residual if our $M7_{vw}$ portfolio is not properly priced using the traditional factors of HML and RMW, resulting in omitted variable bias.

While both the intangible value-augmented HML and VPD factors could result in an omitted variable bias passing through our residual, it is also possible that they too have dimensions which are concurrently uncorrelated with the residual, like the HML and RMW factors, but correlate in the estimated cross-sectional lambdas. Alternatively, these factors may also help explain the value premium, but by doing so they detract from the share of the total value premium left to be explained by the residual. Using simple residual regressions, it is not possible to determine whether these factors truly confound displacement risk as a value factor or whether they generally improve the HML factor's value premium pricing. Due to the construction complexity of these factors and them not being readily available, we are unable to test these hypotheses. As such, we leave them as possible confounders that may well explain part of the observed value-pricing effect of our $M7_{res}$ factor and detract from displacement risk as a source of the value premium.

5.2 Limitations

Some of our study's limitations include: displacement risk being inherently difficult to isolate, high daily return volatility, and decreasing share of residual variation making it difficult to attain statistical significance. First, displacement risk is opaque and requires us to lean heavily on positive, circumstantial, indirect evidence to argue for it. Given our factor construction, the only plausible ways to make a case for displacement risk in M7 residuals is to look at how their lambdas affect the data: do they result in the expected premium sign, do they decrease the estimated value premium, and do they correlate negatively with the HML factor? The answer to all of these questions is "yes", but we cannot definitively reject the possibility that non-value factor related confounders are responsible for these observations. That is because we cannot reasonably construct a test that would isolate all confounders using a regular regression approach across a significant period of time.

Second, daily returns are highly volatile compared to monthly returns, even when transformed into logs. This requires borderline unreasonable thresholds of statistical significance for factor lambdas, many of which need to be 2-4 times as large as their observed returns to be considered statistically significant. Of course, our short study time-frame necessitated daily returns to accurately estimate factor betas, so this drawback is inevitable.

Third, it is difficult to strike a good balance when designing a residual factor, particularly in answering the question, what and how many confounders should be included in the initial regression? What is a "reasonable" share of "unexplained" or "idiosyncratic" variation? These questions come up and are important for the purpose of making a model construction robust outside of its test sample: explaining 95% of variation in-sample is good until you find that the out-sample result is closer to 50%. While we did not deal directly with this issue, a similar variant of it can come up: M7 variation may be explained very well by the Fama-French 5-factor model within the past year, but what if adding CMA to the residualizing regression worsens the overall power of the residual-augmented model for the coming month? Even more broadly, although the FF5 factors may explain variation, and may even be ex ante priced factors in the cross-section, how useful are they in their own right? What does it mean for a high book-to-market ratio firm to perform better, on average, than a low B/M firm? Is AI displacement risk behind the entire value premium, is it only behind the share that is not statistically attributable to the HML, CMA and RMW factors, or is it behind the shares that are? While there are no easy ways to answer these questions, we have worked towards expanding the academic understanding of the world's largest and some of the most innovative firms by providing comparative quantitative evidence for their proxying AI displacement risk, a risk distinct from, but at the same time intertwined with the value premium.

Given the above limitations, we suggest that future researchers should consider either alternative factor construction or an alternative estimation method to the Fama-MacBeth (1973) cross-sectional regressions altogether. Such methods could for example use instrumental variables to directly isolate displacement risk from the M7 or other highly influential, innovative stocks (see e.g. Jegadeesh et al. 2019); conduct a regression discontinuity analysis on a date when information suggestive of future displacement is revealed, such as the launch of a major technology, and its effect on the value premium or directly affected stocks (see e.g. Chemmanur and Tian 2018; Chang, Hong, and Liskovich 2015); use an overnight return sentiment proxy to evaluate the effect of M7 sentiment on industries or firms prone to technological disruption (Aboody et al. 2018); or, following Knesl's (2023) approach, create a long-short portfolio which goes long the displacement hedging benefit of the M7 while shorting the losses of negatively exposed stocks. Notably, we initially attempted something similar to the last approach, but found no sufficiently robust proxy for the short arm of the portfolio that could be readily constructed (see Appendix: *Alternative Factor Construction: M7-Minus-Growth*).

6 Conclusion

In this thesis, we evaluate the relationship between technological displacement, the risk associated with the replacement of old/incumbent firms and technologies by new ones, and the Magnificent Seven firms' returns. We consider the plausible hypothesis that Magnificent Seven stocks' residual returns are a proxy for AI-related displacement risk, while critically evaluating our proposed empirical method. We find that, when residualized against the Fama-French 3-factor model, Magnificent Seven returns do exhibit some features suggestive of displacement risk: they correlate with a broad set of portfolio returns, despite not earning a statistically significant factor premium, improve value premium estimates (measured as the differences in P/E sorted portfolios' returns), and their factor premium correlates with standard value factors such as High-Minus-Low and Robust-Minus-Weak, and sentiment regarding AI adoption (evaluated using the trend for "AI" term online searches).

However, the factor is weak against standard robustness checks we test, such as introducing additional factors or testing on different portfolio sorts. Using our empirical approach, we are also not able to completely isolate AI displacement risk from other factors that explain the value premium. This leads us to the conclusion that our factor is either subsumed by other factors, not priced in the cross-section of returns, or is not a sufficiently robust proxy isolating AI-related displacement risk. None of these propositions necessarily imply the absence of displacement risk per se, but may suggest that it is priced by other factors or potentially that AI-related innovation within the Magnificent Seven is not a systematic risk in the cross-section of returns. At the same time, we cannot be sure in these propositions either, due to the looming possibility that the factor construction itself attenuates the total magnitude of AI-related displacement risk.

As such, while our findings provide suggestive, early evidence for displacement risk driving some part of Magnificent Seven's and other equities' returns, the above limitations remain. These need to be addressed in future research on technological displacement risk, in order to better evaluate the relationship between the largest and most innovative public firms' returns and the broader economy.

Figures

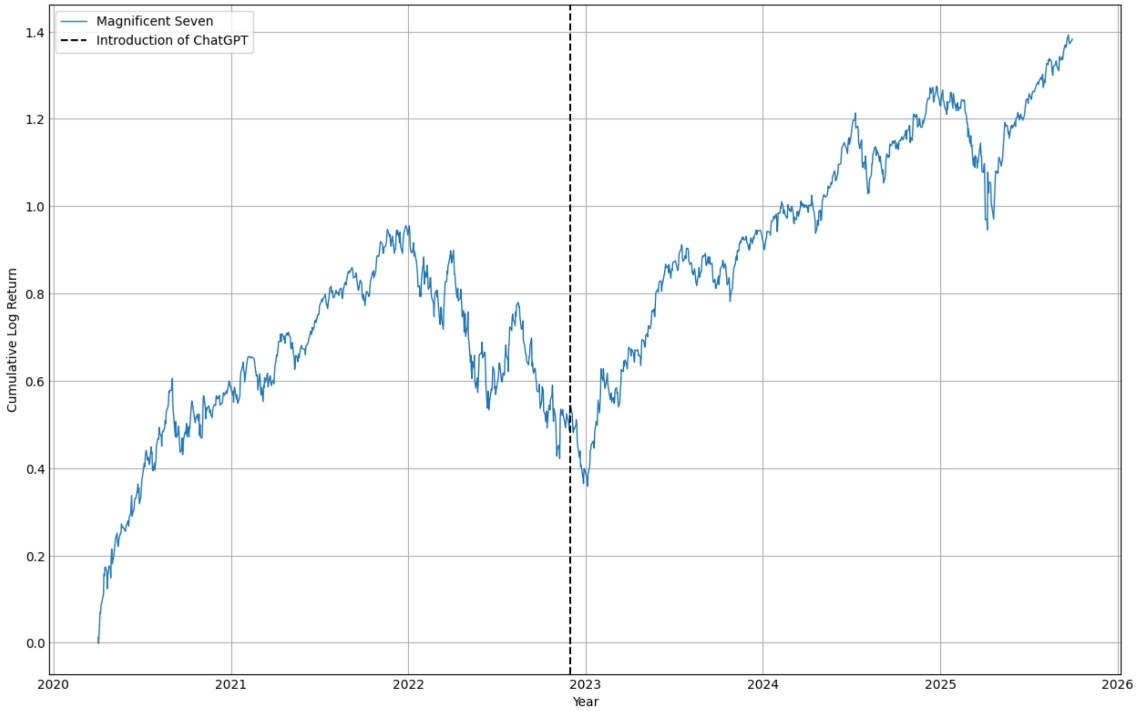

Figure 1: Cumulative Return of Magnificent Seven Stocks.

Description: Calculated as the sum of log returns over the stated period. Exact portfolio construction is documented in Section 3. ChatGPT launch date set as Nov. 30, 2022.

Figure 2: 180-Day Moving Average Log Return of the Value-Growth Premium.

Description: Calculated as the difference in returns between the lowest and highest decile P/E portfolios. Evaluated using Compustat data, see Section 3 for a full description of P/E sorted portfolio construction.

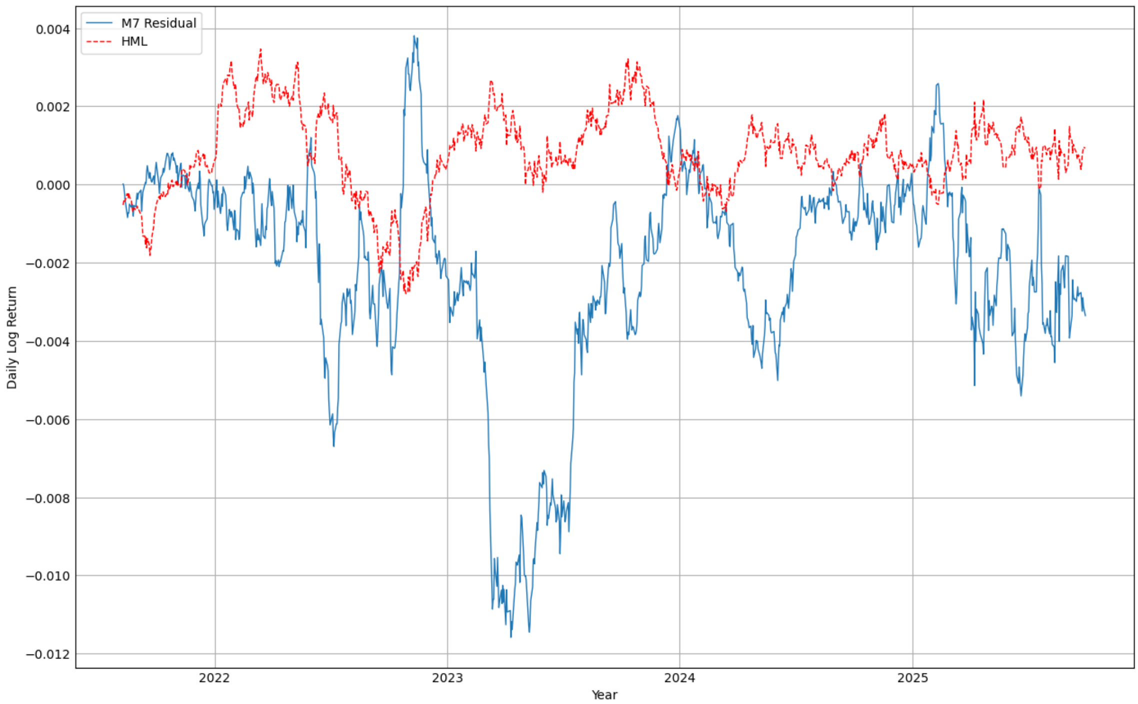

Figure 3: 90-Day Moving Average Log Lambdas for $M7_{res}$ and HML Factors.

Description: Calculated using the Fama and MacBeth (1973) two-pass GLS regressions, see Table 3 or Section 3 for details. Pearson $r = -0.568$.

Figure 4: Cumulative Log Lambdas for $M7_{res}$ and HML Factors.

Description: Calculated using the Fama and MacBeth (1973) two-pass GLS regressions, see Table 3 or Section 3 for details. Pearson $r = -0.951$.

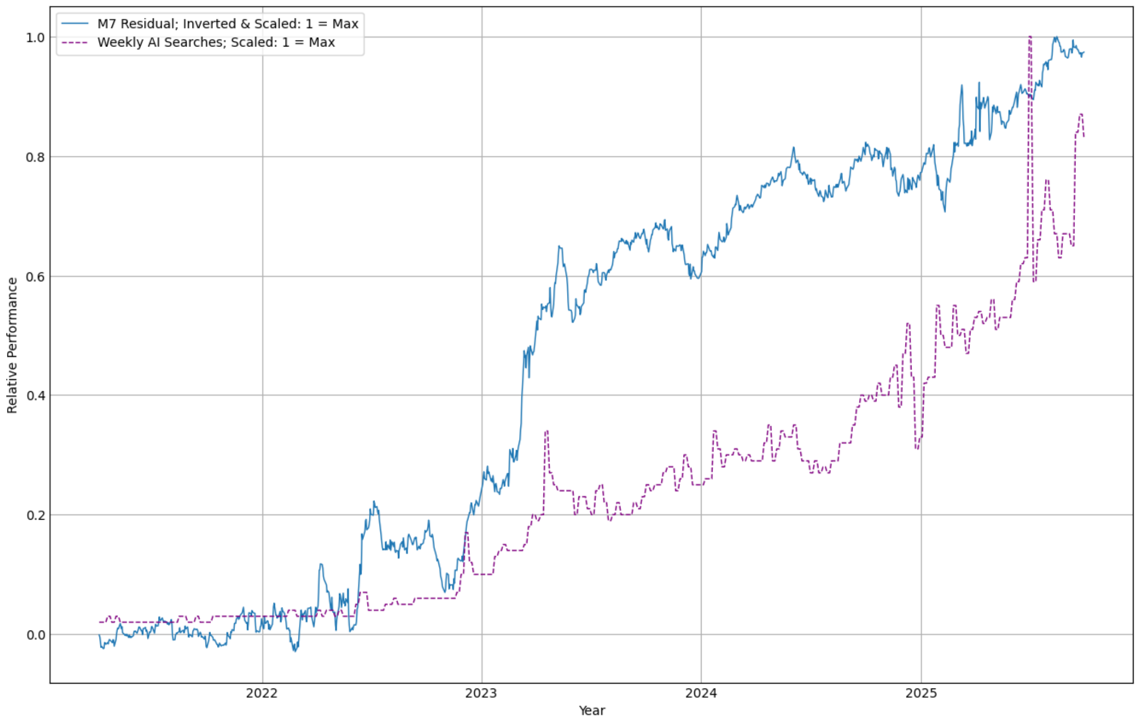

Figure 5: Cumulative Log Lambdas for $M7_{res}$ and Google Searches for Term "AI".

Description: $M7_{res}$ calculated using the Fama and MacBeth (1973) two-pass GLS regressions, see Table 3 or Section 3 for details. "AI" term searches are relative and span Nov. 2020 to 2025, where the highest observation was 100, rescaled to 1. $M7_{res}$ cumulative log lambdas are inverted along the x-axis and scaled so that the maximum value is 1. Pearson $r = 0.906$.

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Appendix

Time-Series Regression Results

Model	$\bar{\alpha}$	$t(\alpha)$	$\bar{\beta}_{\text{M7res}}$	$t(\beta_{\text{M7res}})$	adj. R^2
CAPM	4.41	0.95	-	-	0.692
CAPM+M7$_{\text{res}}$	4.41	0.97	0.119	4.80	0.697
FF3	4.56	1.78	-	-	0.936
FF3+M7$_{\text{res}}$	4.56	1.87	0.119	9.34	0.942

Table 8: Aggregate Time-Series Regression Results.

Description: Reported are aggregated mean measures of each model's performance across the 11 P/E sorted portfolios. Each P/E portfolio's excess returns are OLS regressed on each model's factors, satisfying the equation: $r_{i,t} - r_{f,t} = \alpha_i + \beta_i F_{j,t} + \epsilon_{i,t}$, where F_j is the matrix of factor returns for a given model specification. $\bar{\alpha}$, $t(\alpha)$, $\bar{\beta}_{\text{M7res}}$ and $t(\beta_{\text{M7res}})$ are all calculated as $\bar{x} = \frac{\Sigma abs(x_i)}{11}$, where x_i is each portfolio's individual regression result of α_i, β_{M7res} and their respective t-statistics. $\bar{\alpha}$ is reported in annualized percent terms. Adjusted R^2 is calculated as the simple mean of all portfolios' adjusted R^2 values for the stated model.

	CAPM+M7$_{\text{res}}$		FF3+M7$_{\text{res}}$	
P/E Decile	β_{M7res}	$t(\beta_{\text{M7res}})$	β_{M7res}	$t(\beta_{\text{M7res}})$
EPS<0	-0.056	-1.38	-0.056	-2.72
1	0.006	0.11	0.006	0.25
2	-0.002	-0.05	-0.002	-0.14
3	-0.009	-0.20	-0.009	-0.58
4	-0.064	-1.69	-0.064	-4.94
5	-0.146	-4.33	-0.146	-11.51
6	-0.191	-7.04	-0.191	-15.30
7	-0.218	-8.73	-0.218	-17.32
8	-0.267	-12.53	-0.267	-21.66
9	-0.213	-10.66	-0.213	-18.00
10	-0.138	-6.12	-0.138	-10.27

Table 9: P/E Portfolio-wise, Time-Series Regression Results.

Description: See Table 8 for the beta evaluation method. 1 = Lowest P/E.

Cross-Sectional Regression Results for the 25 Fama-French Size-Value Sorted Portfolios

	(1) $\bar{R}^2$: 0.185		(2) $\bar{R}^2$: 0.225		(3) $\bar{R}^2$: 0.458		(4) $\bar{R}^2$: 0.480	
	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$
Intercept	26.74	1.85	30.27	1.98	7.76	0.86	3.10	0.32
Mkt_{vw}	-14.50	-1.07	-16.10	-1.17	2.07	0.19	8.72	0.74
SMB	-	-	-	-	-6.86	-1.30	-7.84	-1.51
HML	-	-	-	-	6.16	0.87	4.59	0.66
M7_{res}	-	-	5.24	0.72	-	-	9.23	1.44

Table 10: Cross-Sectional Regression Results, Fama-French 25 Size-Value Sorted Portfolios.

Description: (1) CAPM, (2) CAPM+M7_{res}, (3) FF3, (4) FF3+M7_{res}. See Table 3 for a complete description of variables.

Cross-Sectional Regression Results for the 25 Fama-French Size-Investment Sorted Portfolios

	(1) $\bar{R}^2$: 0.137		(2) $\bar{R}^2$: 0.145		(3) $\bar{R}^2$: 0.396		(4) $\bar{R}^2$: 0.416	
	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$
Intercept	15.20	1.39	20.66	1.87	-3.13	-0.30	-3.90	-0.37
Mkt_{vw}	-6.51	-0.54	-9.68	-0.80	14.16	1.09	16.39	1.20
SMB	-	-	-	-	-6.37	-1.21	-6.78	-1.30
HML	-	-	-	-	4.53	0.58	6.77	0.84
M7_{res}	-	-	12.07	1.67	-	-	15.56	2.13

Table 11: Cross-Sectional Regression Results, FF 25 Size-Investment Sorted Portfolios.

Description: (1) CAPM, (2) CAPM+M7_{res}, (3) FF3, (4) FF3+M7_{res}. See Table 3 for a complete description of variables.

Cross-Sectional Regression Results for the 25 FF Size-Profitability Sorted Portfolios

	(1) $\bar{R}^2$: 0.155		(2) $\bar{R}^2$: 0.207		(3) $\bar{R}^2$: 0.451		(4) $\bar{R}^2$: 0.474	
	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$
Intercept	12.95	0.98	20.99	1.45	-4.36	-0.38	-10.60	-0.98
$\mathrm{Mkt}_{\mathrm{vw}}$	-5.28	-0.40	-10.84	-0.77	15.55	1.11	25.18	1.73
SMB	-	-	-	-	-7.21	-1.40	-7.69	-1.50
HML	-	-	-	-	6.49	0.76	6.45	0.75
$\mathrm{M7}_{\mathrm{res}}$	-	-	4.34	0.56	-	-	14.68	1.98

Table 12: Cross-Sectional Regression Results, FF 25 Size-Profitability Sorted Portfolios.

Description: (1) CAPM, (2) CAPM+$\mathrm{M7}_{\mathrm{res}}$, (3) FF3, (4) FF3+$\mathrm{M7}_{\mathrm{res}}$. See Table 3 for a complete description of variables.

Cross-Sectional Regression Results for the 25 Fama-French Value-Profitability Sorted Portfolios

	(1) $\bar{R}^2$: 0.122		(2) $\bar{R}^2$: 0.151		(3) $\bar{R}^2$: 0.309		(4) $\bar{R}^2$: 0.323	
	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$
Intercept	10.20	0.91	16.18	1.31	1.44	0.15	12.63	1.01
$\mathrm{Mkt}_{\mathrm{vw}}$	-0.44	-0.04	-4.20	-0.34	8.92	0.79	-0.01	-0.00
SMB	-	-	-	-	-5.65	-0.83	-5.21	-0.70
HML	-	-	-	-	4.14	0.57	4.33	0.60
$\mathrm{M7}_{\mathrm{res}}$	-	-	13.00	1.69	-	-	20.31	2.44

Table 13: Cross-Sectional Regression Results, FF 25 Value-Profitability Sorted Portfolios.

Description: (1) CAPM, (2) CAPM+$\mathrm{M7}_{\mathrm{res}}$, (3) FF3, (4) FF3+$\mathrm{M7}_{\mathrm{res}}$. See Table 3 for a complete description of variables.

M7 Residual and HML-Minus-RMW Plot

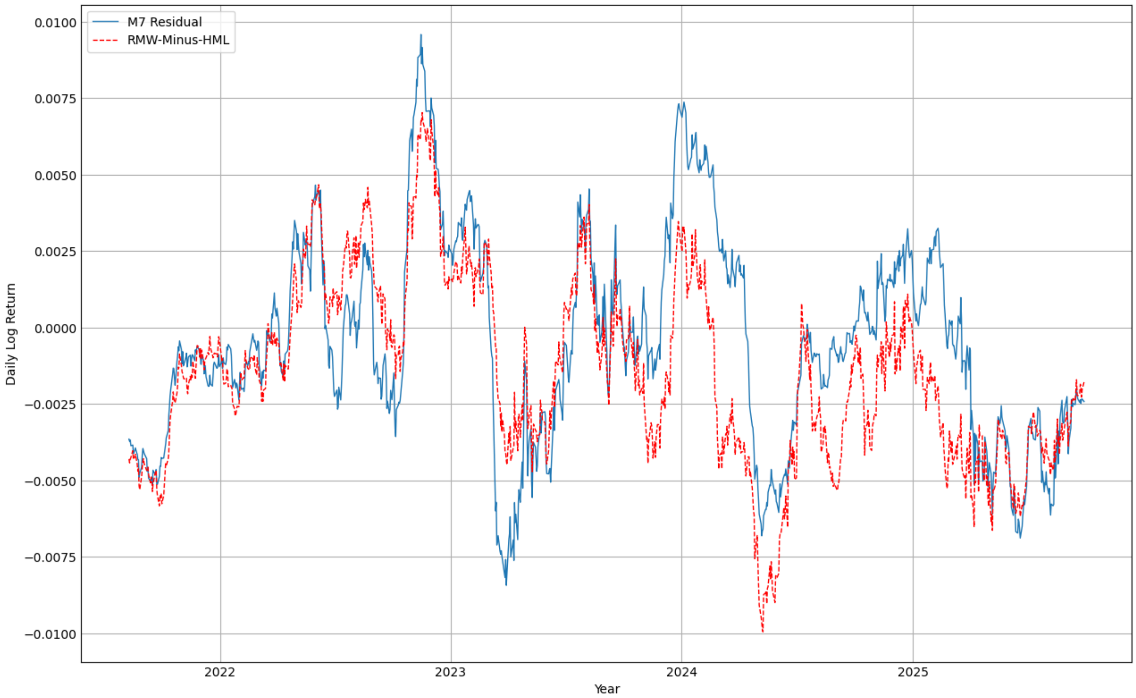

Figure 6: 90-Day Moving Average Log Lambdas for $M7_{res,FF5}$, RMW-Minus-HML Factors. **Description:** Calculated using the Fama and MacBeth (1973) two-pass GLS regressions, see Table 3 or Section3 for details. Pearson $r = 0.742$.

Cross-Sectional Regression Results Starting in 2023

	(1) $\bar{R}^2$: 0.170		(2) $\bar{R}^2$: 0.508		(3) $\bar{R}^2$: 0.552		(4) $\bar{R}^2$: 0.616	
	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$	$\bar{\lambda}$	$t(\lambda)$
Intercept	-20.23	-1.54	-19.34	-1.29	-27.26	-1.98	-50.50	-2.40
Mkt_{vw}	35.75	1.86	34.55	1.76	38.54	1.69	62.27	2.09
SMB	-	-	-	-	10.67	0.96	33.27	2.30
HML	-	-	-	-	-0.92	-0.10	23.89	1.62
$M7_{res}$	-	-	2.95	0.15	-	-	-48.36	-2.38

Table 14: Cross-Sectional Regression Results Using 2023-2025 Data.

Description: (1) CAPM, (2) CAPM+$M7_{res}$, (3) FF3, (4) FF3+$M7_{res}$. See Table 3 for a complete description of variables.

Alternative Factor Construction: M7-Minus-Growth

We summarize an alternative M7 factor construction method that we initially considered as a displacement risk proxy. Gârleanu and Panageas (2025) mention that the return of a buyout private equity firm can be thought of as the weighted average return of a portfolio consisting of a value firm and the idiosyncratic return of a portfolio of new blueprints (innovations), where a value firm is one with a low P/E ratio. We extend this line of reasoning and suggest that the M7 portfolio can be thought of as the weighted average of the return on a growth stock portfolio and that of new blueprints, considering the high-growth, innovative nature of the M7. As such, one should be able to isolate one from the other. We attempt this by constructing a long-short portfolio factor which we call M7-Minus-Growth (M7MG), calculating its return as the difference in the $M7_{vw}$ return and the return of the highest-decile P/E sorted portfolio. This is identical to going long M7 stocks while shorting the highest-priced growth stocks.

Upon further reflection, we figured that this construction may not sufficiently isolate the desired AI displacement risk, which we also wished to capture in excess of traditional risk factors. Ultimately, such a construction could be useful, but would ideally pin the M7 against stocks that are directly and negatively exposed to AI-related displacement risk, such as a certain subset of value firms (see Knesl (2023) for one such portfolio and factor construction method). This is why we choose to go with M7 residuals, which are fully orthogonalized relative to the FF3 factors and better isolate the "excess" variation in the M7.

Disclosure on Use of Generative Artificial Intelligence Tools

We have nothing to disclose.