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GUILHERME DA CRUZ SOUZA

# Essays in empirical finance

Orientador: Prof. Ruy Monteiro Ribeiro

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Tese de doutorado apresentada ao Programa de Doutorado em Economia dos Negócios como requisito parcial para a obtenção do título de Doutor em Economia.

Orientador: Prof. Ruy Monteiro Ribeiro
Área de concentração: Economia dos negócios
Linhas de Pesquisa: Finanças

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# RESUMO

Essa tese é composta por três artigos, todos explorando a relevância de fatores financeiros no comportamento dos retornos de ativos e na precificação de risco. Em todos os capítulos, a estrutura de fatores e suas implicações na volatilidade e nos retornos desempenham um papel central.

O primeiro capítulo investiga a relação entre fatores de risco financeiro e a renda do trabalho, com foco no fator Value. A análise documenta como o crescimento dos rendimentos laborais se expõe aos fatores de risco de ações, revelando heterogeneidade substancial nas exposições a risco financeiro entre diferentes segmentos da força de trabalho. O estudo identifica que a assimetria nos rendimentos laborais está correlacionada positivamente com o fator Value, sugerindo que aspectos relacionados a empregos ou setores de valor podem contribuir para a probabilidade de flutuações expressivas nos rendimentos.

O segundo capítulo examina a volatilidade dos fatores de risco e sua influência sobre a variação transversal nas expectativas de retornos das ações. O estudo propõe um modelo no qual a volatilidade dos fatores é considerada um elemento de risco e analisa como as inovações na volatilidade dos fatores impactam os retornos dos portfólios. A pesquisa identifica um fator comum de volatilidade, construído a partir da análise de componentes principais, que ajuda a explicar parte da variação nos retornos esperados das ações, destacando a necessidade de incorporar tais fatores de volatilidade na análise de precificação de ativos.

O terceiro capítulo explora a relação entre política e retornos acionários, focando em um fator baseado no alinhamento partidário das empresas. A pesquisa documenta a existência de um prêmio associado a ações alinhadas ao Partido Republicano nos Estados Unidos, independente do partido no poder. A análise sugere que esse fator político não é explicado por fatores tradicionais de risco, ciclo econômico ou viés setorial, indicando a presença de uma anomalia de precificação de ativos associada à ideologia política corporativa.

Palavras-chave: Fatores de risco. Volatilidade. Precificação de ativos. Política e mercados financeiros.

# ABSTRACT

This thesis consists of three chapters, all examining the role of financial risk factors in asset returns and risk pricing. In each chapter, factor structures and their implications for volatility and returns play a central role.

The first chapter investigates the relationship between financial risk factors and labor income, focusing on the Value factor. The analysis documents how labor earnings growth is exposed to the equity risk factors, revealing substantial heterogeneity in financial risk exposures across different worker profiles. The study identifies a positive correlation between earnings skewness and the Value factor, suggesting that value-related jobs or industries may contribute to the likelihood of pronounced earnings fluctuations.

The second chapter examines factor volatility and its impact on the cross-section of expected stock returns. The study proposes a model in which factor volatility is considered a fundamental source of risk and analyzes how innovations in factor volatilities affect portfolio returns. The research identifies a common volatility factor, constructed through principal component analysis, that helps explain stock return variation, emphasizing the importance of incorporating factor volatility considerations into asset pricing models.

The third chapter explores the intersection of politics and asset returns by constructing a factor based on firms' political alignment. The research documents the existence of a premium associated with stocks linked to the Republican Party in the United States, independent of the party in power. The analysis suggests that this political factor is not explained by traditional risk factors, business cycles, or sector biases, indicating the presence of a pricing anomaly associated with corporate political ideology.

**Keywords:** Risk factors. Volatility. Asset pricing. Politics and financial markets.

# LISTA DE ILUSTRAÇÕES

# LISTA DE TABELAS

# SUMÁRIO

# INTRODUCTION

This thesis is composed of three self-contained chapters in financial econometrics, each exploring the role of financial risk factors in asset returns, risk pricing, and volatility modeling. A central theme across all chapters is the role of factor structures in shaping market dynamics and risk exposure.

The first chapter, "The Value Factor and Labor Income Risk,"investigates the relationship between financial risk factors and labor income, with a particular focus on the Value factor. The study examines how individual earnings growth responds to financial market fluctuations, documenting significant heterogeneity in risk exposures across worker profiles. The analysis finds a strong link between earnings skewness and the Value factor, suggesting that value-oriented industries or jobs are more prone to pronounced income fluctuations. By integrating labor economics with asset pricing, this chapter provides new insights into the systematic risk embedded in labor income.

The second chapter, "A Factor of Factor Volatilities,"explores the role of factor volatility in explaining the cross-section of stock returns. While traditional asset pricing models account for factor betas, this chapter emphasizes the importance of innovations in factor volatilities. By employing a principal component analysis on a broad set of volatility factors, the study identifies a common volatility component that significantly influences stock returns. The findings highlight the necessity of incorporating factor volatility considerations into financial models, offering a novel perspective on systematic risk.

The third chapter, "The Republican Factor Puzzle,"examines the relationship between political alignment and asset returns. The study constructs a "Republican Factor,"a long-short portfolio based on firms' stock market reactions to U.S. elections or their political donation patterns. The results indicate that stocks linked to the Republican Party consistently outperform those associated with the Democratic Party, even during Democratic administrations. The findings remain robust after controlling for business cycles, sectoral biases, and risk factors, suggesting the existence of a political anomaly in asset pricing. This chapter contributes to the growing literature on the intersection of politics and financial markets.

Overall, this thesis advances the understanding of financial risk factors by analyzing their impact on labor income, volatility structures, and political risk in asset pricing. The findings offer new insights into financial econometrics, with potential applications in portfolio management, risk assessment, and economic policy analysis.

# 1 VALUE FACTOR AND IDIOSYNCRATIC LABOR INCOME RISK

**Resumo**

We present evidence of a robust relationship between idiosyncratic labor income risk and equity risk factors in the US market. Notably, the value factor stands out as more significant than other factors in explaining well-known patterns in idiosyncratic labor income risk. Idiosyncratic labor earnings dispersion tends to increase with greater dispersion in factor exposure or volatility, reflecting significant heterogeneity in exposure to equity risk factors across different income quintiles and sectors. Furthermore, we identify a positive correlation between idiosyncratic earnings skewness and the value factor, suggesting that labor earnings tail risk is driven by value-related risks in the job market. Extending our analysis to firm-level data, we find that firms' net income and revenue dispersion also correlate with risk factor volatility, mirroring the patterns observed in labor earnings

## 1.1 Introduction

Understanding the dynamics of labor income risk is relevant for individuals' financial planning, as individuals may search for ways to hedge against potential labor income volatility, and for governments, as insights into income risk can provide inputs for economic policy. Traditional analyses often focus on the relationship between labor income and macroeconomic variables, but less attention has been given to the intersection of individual earnings risks and financial market risks. Recent work by Guvenen et al. (2014) and Guvenen et al.(2017) expands the understanding of income dynamics by showing that labor income risk varies significantly across demographic dimensions such as age, sex, and income level and that these variations become skewed and more volatile during downturns. In particular, workers may have heterogeneous exposure to market risks. In the other direction, research in the finance literature has highlighted the importance of labor income risk in asset pricing. For instance, Constantinides and Duffie (1996) argue that consumer heterogeneity, due to idiosyncratic labor income risks, plays a crucial role in explaining the equity risk premium. Similarly, Meeuwis (2022) emphasizes the role of idiosyncratic labor income risk as a key priced risk. Additionally, Ai and Bhandari (2018) and Storesletten, Telmer, and Yaron (2007) explore how labor income risk and incomplete insurance mechanisms influence the equity premium.

Building on these insights, our research explores the possibility that individuals' labor earnings may have heterogeneous exposure to equity risk factors, particularly the Fama-French five factors. We hypothesize that workers face heterogeneous exposures not only to macroeconomic and market-wide forces but also to more specific equity market risks. If so, these equity risks may also explain the dispersion and skewness of both individual income and firm-level outcomes. For instance, consider a person working at a small tech startup versus another employed at a multinational oil and gas company. The first worker would likely have a higher exposure to the size factor, as smaller firms tend to have distinct risk characteristics compared to larger corporations. Similarly, a person employed by a consumer non-cyclical firm, like a supermarket, may face different risk exposures than someone working at a bank, where factors such as operating profitability — often associated with quality—may be more prominent. These examples illustrate how individual characteristics, such as the sector of employment, can link individuals to specific equity risk factors.

One of our notable findings is that the value factor (HML) appears especially relevant in explaining labor earnings dispersion and skewness. Why might value be important? Value firms—often mature companies with high book-to-market ratios—can be more sensitive to adverse economic conditions or sector-specific downturns. This vulnerability can lead to more pronounced fluctuations in both firm revenue and wages, implying a greater pass-through of firm-specific risk to the workforce. Put differently, value companies may "share" more risk with their workers because of tighter margins, lower growth opportunities, or fewer financial buffers compared to high-growth firms. Consequently, workers employed in these value-oriented settings experience higher income volatility (both on average and in the form of tail risks), which is reflected in the strong role of the HML factor in our regressions. Our core premise is that part of a firm's risk exposure is passed on to its employees. The empirical analysis suggests that in certain sectors or for certain groups of workers, these equity risk factors provide helpful explanations for the variability and skewness of their labor earnings. Hence, if a firm is strongly exposed to the value factor, labor income in that firm will tend to be more volatile whenever the underlying value factor experiences higher volatility.

Our analysis finds significant heterogeneity in worker betas with respect to equity risk factors, indicating that exposure to equity risks varies widely among different income quintiles and sectors. Lower earners have higher susceptibilities to fluctuations in key market factors like market (MKT), size (SMB), and value (HML), while middle-income groups demonstrate greater stability.

This differential exposure is relevant for understanding how labor income risk interacts with financial market risk. We find a statistically significant relationship between the cross-sectional variance in labor income and the Fama-French five factors, especially strong in the case of the value factor (HML). Moreover, dispersion in idiosyncratic earnings is higher whenever we observe a higher dispersion in factor betas or higher time-series volatility in factor returns.

Additionally, findings suggest that the value factor not only correlate with the variability of earnings but also links with the skewness in earnings distributions, indicating its potential utility as a hedge factor in portfolio strategies. When we look at intra-sector workers earnings we also find that higher value and size beta dispersion correlates to higher intra-sector earnings variance. When it comes to firms fundamentals, we find a positive relation between HML return variance and dispersion in revenue growth and net income growth.

As our first and main contribution we show that adding equity risk factors, such as the Fama-French 5 factors, help us explain patterns in labor income risk. Building on Guvenen (2007), who highlights the importance of individual-specific income growth rates in understanding consumption inequality, our analysis connects labor income variability directly to financial markets dynamics. Expanding on Guvenen et al. (2014), who document countercyclical left-skewness in earnings shocks, and Busch et al. (2022), who show procyclical income growth skewness, this research also introduces equity risk factors into the analysis of earnings skewness. We consider state-dependent and cyclical risks in labor income distribution, aligning with Schmidt (2022), who constructs a measure of cyclical idiosyncratic tail risk in asset prices, and Meeuwis (2022), who models idiosyncratic income risk within a New Keynesian framework. By including equity factors, our findings highlight how financial market dynamics amplify income distribution asymmetries, which is particularly relevant for understanding labor income risks during economic downturns.

Our analysis also examines firm-level fundamentals, adding a new dimension to how equity risk factors impact income distributions for both individuals and firms. Storesletten, Telmer, and Yaron (2007), who analyze capital's influence on the equity premium under idiosyncratic risk. Constantinides and Duffie (1996) emphasize the role of income heterogeneity and incomplete markets in shaping asset prices, highlighting that both individual and firm-level income dynamics are closely tied to systemic financial risks. Our results suggest that firm fundamentals, like individual earnings, are exposed to heterogeneous financial risk factor sensitivities.

Across all dimensions of our analysis, the value factor emerges as particularly influential, displaying a significant relationship with labor income variance, skewness, and firm-level fundamentals. Related to these results, research by Liew and Vassalou (2000) demonstrates that the Fama-French factors, including the value factor (HML), are predictive of future economic growth, suggesting their relevance as proxies for broader economic risks. Vassalou (2003) further supports this by showing that HML and SMB incorporate information about future GDP growth, connecting their performance to fundamental economic news. Choi (2013) identifies the value factor's link to conditional asset risk and leverage, emphasizing its role during economic downturns when equity betas for value firms rise sharply.

While this is not the purpose of this paper, our results suggest that the existence of the value premium may be linked to its connection to labor income risk. The literature have not so far related labor income idiosyncratic risk to cross-sectional asset pricing patterns. Nevertheless, other papers in the finance literature have suggested that labor income idiosyncratic risk may help explain market-wide risk premium. For example, Constantinides and Duffie (1996) emphasize that heterogeneous exposures to uninsurable idiosyncratic income shocks can significantly influence asset prices, arguing that such heterogeneity leads to higher equity premiums in incomplete market models. Storesletten, Telmer, and Yaron (2007) extend this perspective by demonstrating how countercyclical variations in idiosyncratic labor income risk interact with capital accumulation to affect the equity premium. Their findings show that during economic downturns, increased income volatility exacerbates risk premiums, providing a macroeconomic mechanism that ties labor income risk to broader asset pricing outcomes.

Our analysis proceeds in three stages, utilizing US data from the Survey of Income and Program Participation (SIPP) and Kenneth French's factors database[1]. In the first stage, we run a Mincerian equation to identify idiosyncratic labor income. Subsequently, we conduct a regression of changes in idiosyncratic labor income on the equity risk factors to document heterogeneity in factor exposures across different worker profiles, including earnings quintiles and sectors. This stage establishes how individual earnings are related to financial market

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

risks. In the second stage, we estimate the dispersion in betas among grouped individuals, building a time series for beta dispersion. Concurrently, we estimate the time series variance of equity risk factor series. We then regress the cross-sectional variance of earnings changes on these created measures, which illustrates that heterogeneity in individual risk factor exposure might explain why we observe that financial market risk correlates to labor income risk as well. In the third stage, we estimate the cross-sectional earnings skewness, creating a time series for skewness at each period. We then regress this measure on the equity risk factor returns, particularly focusing on the value factor (HML). This analysis explores how the value factor helps in explaining the tail risks of labor income.

We further explore the sectorial dimension of our analysis by looking at intra-sector beta dispersion and the correlation between the value factor and sectorial firms fundamentals. Additionally, we check if value factor variance also correlates to intra-sector earnings and revenue growth dispersion by looking at S&P 500 firms using the NAICS sector classification from 2010 to 2024.

Recent studies have advanced our understanding of labor income risk and its cyclical behavior. For example, Busch et al. (2022) document procyclical fluctuations in income growth skewness across various countries, while Meeuwis et al. (2023) demonstrate how time-varying risk premia affect fluctuations in idiosyncratic income risk, particularly impacting low-wage workers. Additionally, Gomes, Iachan, and Santos (2020) identify disparities in earnings fluctuations between formal and informal sectors in Brazil, with informality linked to more volatile earnings and asymmetric shocks during sector transitions. Building on these findings, our research contributes by indicating that labor income may possess a factor structure, which implies that equity risk translates into labor income risk. Furthermore, we show that the value factor, alongside GDP growth, might be useful in explaining tail risk in labor income, enhancing the understanding of how macroeconomic conditions and financial market dynamics interact with labor income.

The rest of the paper is organized as follows. Section 2 discusses data and methods, section 3 presents results using SIPP data for the US and section 4 concludes.

## 1.2 Data and Methods

### *1.2.1 Data Description*

This study primarily uses data from the Survey of Income and Program Participation (SIPP) for the United States. The SIPP dataset, spanning 2013 to 2021, provides detailed information on American households' income and program participation, including labor earnings, demographic characteristics, and job sector information. This rich dataset allows for an in-depth exploration of labor income dynamics across different segments of the U.S. workforce. To assess the impact of financial risk factors on earnings, we incorporate the Fama-French five factors (US) dataset obtained from Kenneth French's website. These factors represent different dimensions of risk in the U.S. stock market and serve as proxies for financial market conditions. By merging the SIPP data with the Fama-French five factors, we can analyze the relationship between financial market dynamics and individual earnings in the U.S. context. Additional financial data comes from Eikon, both for fundamental and price data. The sample spans the period between 2010 and 2024. All data is analyzed at a quarterly frequency.

### 1.2.2 Methods

Our methodological approach uses workers microdata and cross-sectional regressions to examine the heterogeneity in earnings growth exposure regarding financial risk factors. We specify a model where changes in residual net earnings are regressed against a set of independent variables representing heterogeneous factor risks, macroeconomic risks, and idiosyncratic risks. This allows us to isolate the effect of financial risk factors on labor income risk. We employ pooled OLS regressions to test the hypothesis that financial risk factors help explain the variance in earnings growth among individuals with different characteristics.

**Analytical Framework**

We begin with the construction of an earnings model that bases on the Mincer equation, a standard approach in labor economics for analyzing determinants of earnings. This model incorporates a range of variables to control for individual, temporal, and sectoral influences on earnings:

$$\begin{aligned} \text{Earnings Model:} \quad \ln y_{i,t} &= AGE_j + YEAR_t + QUARTER_t \\ &+ INDUSTRY_k + REGION_p + e_{i,t} \end{aligned} \tag{1}$$

Here, $\ln y_{i,t}$ represents the natural logarithm of earnings for individual $i$ at time $t$, capturing the log-linear relationship between earnings and the included covariates. $AGE_j$, $YEAR_t$, and $QUARTER_t$ control for age effects, year-to-year changes, and seasonal variations, respectively, while $INDUSTRY_k$ and $REGION_p$ account for industry-specific (NAICS Industry code) and regional (monthly state of residence) influences on earnings. $e_{i,t}$ denotes the idiosyncratic earnings component, which we aim to isolate and examine.

**Residual Earnings Change**

To capture the dynamics of earnings over time, we calculate the change in residual earnings as follows:

$$\text{Residual Earnings Change:} \quad \Delta \hat{e}_{i,t} = \hat{e}_{i,t} - \hat{e}_{i,t-4} \tag{2}$$

This measure, $\Delta \hat{e}_{i,t}$, represents the year-over-year change in idiosyncratic earnings, eliminating regular patterns and focusing on the fluctuations attributable to external factors, including risk exposures.

**Risk Exposure Model**

To measure the relation of equity risk factors and earnings changes, we employ a risk exposure model that links residual earnings changes to a set of financial risk factors:

$$\text{Risk Exposure Model:} \quad \Delta \hat{e}_{i,t} = \alpha_G + \sum_{j=1}^{J} \beta_{G,j} F_{j,t} + \epsilon_{i,t} \tag{3}$$

In this model, $\Delta \hat{e}_{i,t}$ is regressed against financial risk factors $F_{j,t}$, where $\beta_{G,j}$ measures the sensitivity of group G earnings to each risk factor. $\alpha_G$ captures group-specific fixed effects, and $\epsilon_{i,t}$ is the error term, representing unexplained variations in earnings changes.

This framework, based in the Mincer equation and extended to incorporate financial risk exposures, enables an examination of how equity risk factors correlate to labor income volatility. By focusing on the changes in idiosyncratic earnings and their relation to risk factors.

### *1.2.3 Heterogeneity Analysis*

We employ pooled OLS regressions, stratifying the sample by income levels and sectors, to identify systematic variations in factor betas and assess their implications for earnings dynamics. This allows us to understand how exposure to financial risk factors differs across various worker profiles. For example, we can compare the factor betas of high-income earners to those of low-income earners, or the betas of workers in different industries, to see if certain groups are more or less sensitive to specific risk factors. This analysis helps to better capture how financial market risks might affect different segments of the workforce.

### *1.2.4 Variance Analysis*

Building on the observed heterogeneity in individual exposures to financial risk factors, we hypothesize that both the time-series variance of the risk factors ($\text{Var}(F_t)$) and the cross-sectional variance in individual betas ($\text{Var}(\beta_i)$) are key drivers of the variance in idiosyncratic earnings ($\text{Var}(\Delta \hat{e}_{i,t})$). Specifically, $\text{Var}(F_t)$ reflects the fluctuations in the underlying market conditions over time, while $\text{Var}(\beta_i)$ captures differences across individuals in their sensitivity to these conditions. Together, these variances represent complementary dimensions of risk, where the former highlights systemic shocks and the latter emphasizes individual heterogeneity. We use the following baseline model to decompose the variance in idiosyncratic earnings into components attributable to factor and beta variance:

$$Var(\Delta \hat{e}_{i,t}) = Var(\beta_i)Var(F_t) + E[\beta_i]^2 Var(F_t) + E[F_t]^2 Var(\beta_i) + Var(\epsilon_{i,t}) \quad (4)$$

This analytical framework sets the stage for our regression models by highlighting the importance of both factor and beta variances in explaining earnings variance. In other words, we investigate whether workers with more exposure to financial risk factors or who are exposed to more volatile risk factors themselves experience greater fluctuations in their earnings.

To further explore the stability of risk exposures over time and their influence on earnings variance, we proceed with the cross-sectional and time-series analyses. Initially, we estimate group betas through the previous regression. We identify heterogeneity in betas across income groups using pooled OLS for each group. Subsequently, we conduct a cross-sectional analysis for each period, computing idiosyncratic earnings variance (Var($\Delta \hat{e}_{i,t}$)), estimating factor variance (Var($F_t$)) for each risk factor quarterly, and calculating beta variance (Var($\beta_i$)) across groups each quarter. This approach provides insights into the temporal dynamics of financial risk factors and labor income, affirming the hypothesis that higher Var($F_t$) or Var($\beta_i$) is associated with greater Var($\Delta \hat{e}_{i,t}$). Additionally, we also build the betas for intra-sector income groups, such that each income group in each sector has a beta, and we build a time series with the dispersion of the betas in inside each sector.

We build a toy model to elucidate the intuition. Lets suppose we have a factor with returns that follows an i.i.d. standard normal distribution and that we have five individuals with beta coefficients -2, -1, 0, 1 and 2, with an earnings equation that follows the structure $\Delta Y_i = \beta \times X_i$. So, in a period where the factor has a return of 0.5, individual 1 has a change in earnings of -1, individual 2 has a change of -0.5, individual 3 a change of 0, individual 4 a change of 0.5 and individual 5 a change of 1. Now, we perform a simple test where we double the beta coefficients of each individual (-4, -2, 0, 2, 4), a second test where we double the variance of the factor returns, and a last test where we double the coefficients and double the variance of the factor returns. We simulate 100 periods on this toy model and plot the time series and the density plots for the earnings changes in figure 1.1. As expected, increasing beta dispersion or factor variance, increases earnings changes dispersion as well.

### 1.2.5 Skewness Analysis

We examine the skewness of earnings to understand the asymmetry of its distribution around the mean. Skewness provides insights into the likelihood of extreme earnings fluctua-

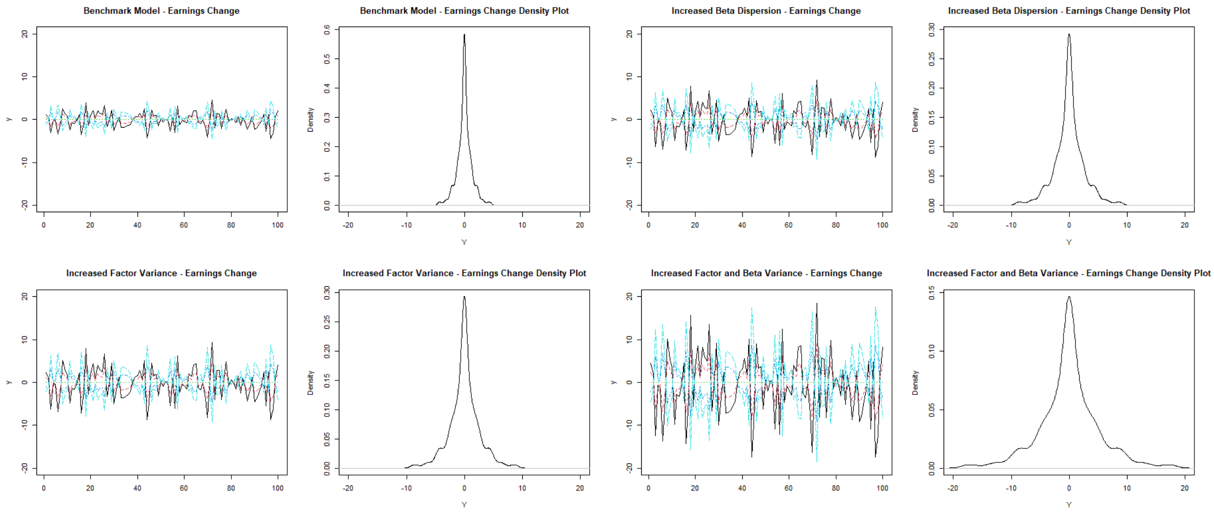


Figura 1.1 – Toy Model - Beta dispersion, factor variance and earnings variance

tions, which can have significant implications for financial planning and risk management. For this analysis, we utilize Kelly's measure of skewness:

$$S_k = \frac{(P90 - P50) - (P50 - P10)}{(P90 - P10)} \tag{5}$$

This formula uses percentiles to gauge earnings dispersion. A positive skewness value indicates that the distribution has a longer tail on the right side, meaning there is a greater likelihood of experiencing large positive earnings deviations from the mean compared to large negative deviations. Conversely, a negative skewness value indicates a longer tail on the left side, suggesting a higher probability of large negative deviations. Our analysis focuses on the relationship between earnings skewness and both macroeconomic factors and equity risk factors. We investigate whether GDP growth, a key macroeconomic indicator, has a significant impact on earnings skewness. Additionally, we examine the relationship between earnings skewness and the Fama-French five factors, particularly the value factor (HML). This allows us to explore how these factors contribute to earnings risk asymmetry and the potential for extreme earnings fluctuations.

$$\text{Skew}(\Delta\hat{e}_{i,t}) = \alpha_i + \beta_{i,j} F_{j,t} + \epsilon_{i,t} \tag{6}$$

We employ linear regressions to quantify these relationships, regressing earnings skewness on the equity factors. This analysis allows us to test the hypothesis that the value factor, along with other financial and macroeconomic factors, significantly relate to the asymmetry of earnings distributions.

### *1.2.6 Firms Fundamentals*

To investigate the relationship between sectorial fundamentals and the value factor (HML), we collected revenue and net income growth data for S&P 500 firms, classified under the NAICS sector classification, such that the sectors are the same from the ones used in the SIPP. We use data from Eikon for the period 2010 to 2024. Revenue and Net Income growth are calculated for each firm and extreme values from the top and bottom 0.5% of observations are dropped. We then computed the dispersion (standard deviation of earnings growth) for each variable growth in each sector.

## 1.3 Results

### *1.3.1 Heterogeneous Factor Exposure*

Our analysis reveals significant heterogeneity in worker betas with respect to equity risk factors. This heterogeneity indicates that exposure to market risks varies widely among workers across different income quintiles and sectors. Regression models demonstrate that these differences in factor exposures help explain the variance in earnings growth, supporting our hypothesis that financial market conditions are connected to labor income dispersion. Figure 1.2 illustrates the heterogeneity in worker betas across earnings quintiles for various risk factors. Notably, the betas for MKT, SMB, and HML are highest among the lowest earners, suggesting their income is most vulnerable to fluctuations in these factors. For middle income levels, betas for these factors tend to be closer to zero, indicating that these groups might enjoy greater stability. For higher income groups, coefficients tend to be higher, in absolute terms. This variability in risk exposure is helps the understanding of how the financial market fluctuations link with labor income risk. Workers in certain sectors or income brackets may be more vulnerable to market downturns, potentially exacerbating income inequality and economic instability.

One reason for the observed pattern could be that lower-income earners are more likely to work in smaller or value-oriented firms with fewer buffers against adverse shocks. As a result, the “pass-through” of firm-level risk to wages is greater in these firms. Studies by Friedrich, Laun, Meghir, and Pistaferri (2024) and Guvenen et al. (2021) show that lower-income or lower-skilled employees face a concentrated pass-through of financial and macro volatility. In these environments, wage cuts and earnings drops are more frequent and have more persistent effects, amplifying the link between market fluctuations and individual pay. Middle earners may have somewhat more stable labor contracts or work at firms that better shield employees from day-to-day market volatility. In effect, these groups experience less of that “pass-through” of firm-level shocks. Meanwhile, higher earners frequently occupy

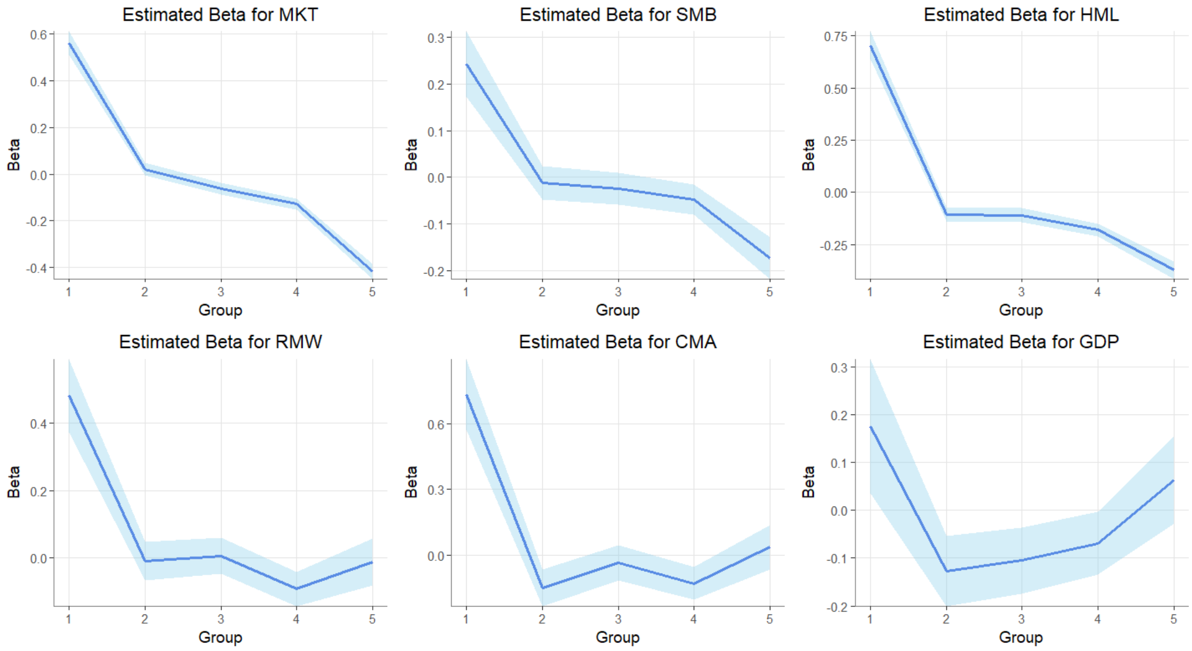


Figura 1.2 – Worker Betas - Pooled OLS coefficients of change in idiosyncratic earnings on risk factors, by earnings quintile.

positions at more profitable or large-cap firms, which typically maintain stronger financial buffers. Moreover, higher earners often hold roles that offer stronger insulation from adverse shocks compared to those of middle or low-income workers.

Table 1.1 further explores the relationship between earnings variance and the Fama-French five factors: Market, SMB (Small Minus Big), HML (High Minus Low), RMW (Robust Minus Weak), and CMA (Conservative Minus Aggressive). The analysis reveals that the coefficients for the Market, SMB, HML, and RMW factors are positively correlated with earnings variance, indicating a statistically significant relationship between these factors and earnings volatility. This suggests that fluctuations in these financial risk factors are associated with greater variability in individual earnings. The positive correlation with the value factor (HML) is particularly noteworthy. This finding suggests that workers in industries or job roles associated with high book-to-market ratios may experience more pronounced fluctuations in their earnings. This aligns with the notion that value stocks tend to be more sensitive to economic conditions and exhibit higher volatility compared to growth stocks.

Moving beyond the direct impact of factor variances, we look at the relationship between earnings variance and the interaction between individual beta variances and the Fama-French five factors. This analysis investigates how dispersion in workers' sensitivity to these factors (beta variances) interact with the factors themselves to influence earnings variability. The results indicate that the interaction terms between beta variances and factor variances are meaningful in explaining variations in earnings. This suggests that workers' earnings risks are not only affected by market conditions but also by how their earnings are

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Earnings Variance | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| MKT | 0.390$^{**}$ | | | | |
| | (0.181) | | | | |
| SMB | | 0.484$^{***}$ | | | |
| | | (0.172) | | | |
| HML | | | 0.453$^{**}$ | | |
| | | | (0.175) | | |
| RMW | | | | 0.351$^{*}$ | |
| | | | | (0.184) | |
| CMA | | | | | 0.247 |
| | | | | | (0.190) |
| Constant | 15.704$^{***}$ | 15.367$^{***}$ | 15.575$^{***}$ | 15.506$^{***}$ | 15.594$^{***}$ |
| | (0.207) | (0.262) | (0.220) | (0.287) | (0.320) |
| Observations | 28 | 28 | 28 | 28 | 28 |
| $R^2$ | 0.152 | 0.234 | 0.206 | 0.124 | 0.061 |
| Adjusted $R^2$ | 0.119 | 0.204 | 0.175 | 0.090 | 0.025 |

$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

This table reports the regression coefficients of a regression of idiosyncratic earnings cross sectional variance on risk factors quarterly time series variance.

Tabela 1.1 – Idiosyncratic Earnings Variance and Factor Variance

exposed to these conditions. For example, two workers in the same industry may experience different levels of earnings volatility depending on their individual sensitivities to the value factor. This individual sensitivity can be influenced by factors such as their earnings quintile or specific job role within the sector. It suggests that both the macroeconomic environment and individual-level responses to this environment contribute to earnings volatility. This shows the importance of considering not only aggregate market risks but also individual-level risk exposures when assessing and managing labor income risk.

### *1.3.2 Earnings Skewness*

Next we explore the skewness of earnings distributions to understand the asymmetry in earnings growth across different workers and its relationship to financial risk factors and macroeconomic conditions. This analysis utilizes Kelly's measure of skewness, which captures the degree to which the distribution of earnings deviates from symmetry around its mean. A positive skewness indicates a higher likelihood of experiencing large positive earnings deviations, while a negative skewness suggests a greater probability of large negative deviations. Linear regression are employed to assess the relationship between earnings skewness and the Fama-French five factors, as well as GDP growth. The results reveal significant coefficients for

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Idiosyncratic Earnings Variance | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| MKT Beta Var x MKT Var | 0.461 | | | | |
| | (0.412) | | | | |
| SMB Beta Var x SMB Var | | $0.179^{**}$ | | | |
| | | (0.070) | | | |
| HML Beta Var x HML Var | | | $0.121^{*}$ | | |
| | | | (0.063) | | |
| RMW Beta Var x RMW Var | | | | $0.262^{**}$ | |
| | | | | (0.118) | |
| CMA Beta Var x CMA Var | | | | | 0.041 |
| | | | | | (0.073) |
| Constant | $15.700^{***}$ | $15.360^{***}$ | $15.514^{***}$ | $15.376^{***}$ | $15.709^{***}$ |
| | (0.235) | (0.258) | (0.255) | (0.277) | (0.276) |
| Observations | 21 | 21 | 21 | 21 | 21 |
| $R^2$ | 0.062 | 0.258 | 0.160 | 0.206 | 0.016 |
| Adjusted $R^2$ | 0.012 | 0.219 | 0.115 | 0.164 | −0.035 |

$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

This table presents the coefficients from a cross-sectional regression where the dependent variable is the variance of idiosyncratic earnings growth across individuals within earnings quintiles. The key independent variable is the interaction between the quarterly time-series variance of risk factors and the cross-sectional variance of individual betas.

Tabela 1.2 – Earnings Variance, Factor Variance and Beta Variance - Interaction

HML (value factor) and CMA (Conservative Minus Aggressive factor), along with GDP growth, indicating a relationship between these factors and earnings skewness. The strong statistical significance of the HML factor suggests that value-related aspects of jobs or industries may influence the likelihood of seeing more pronounced earnings increases or decreases. The significant coefficient for GDP growth reaffirms the macroeconomic influence on earnings skewness. This suggests that periods of economic expansion or recessions may be associated with greater earnings skewness, potentially leading to wider disparities in earnings outcomes across different workers. For example, the identified relationships suggest that individuals in certain sectors or with specific risk exposures might experience more significant fluctuations in their earnings, potentially leading to increased economic inequality and instability.

One potential explanation for the value factor (HML) as a significant predictor of idiosyncratic earnings skewness is the inherent characteristics of value-driven economic activities. Value firms, often characterized by high book-to-market ratios, tend to operate in more mature industries with stable cash flows but limited growth opportunities. This stability may translate into lower earnings volatility for workers in these sectors. However, value firms can also be more susceptible to economic downturns or industry-specific shocks, potentially leading to pronounced negative earnings deviations and increased skewness in

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | *Idiosyncratic Earnings Skewness* | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| MKT | 0.077 | | | | | |
| | (0.196) | | | | | |
| SMB | | 0.144 | | | | |
| | | (0.194) | | | | |
| HML | | | $0.497^{***}$ | | | |
| | | | (0.170) | | | |
| RMW | | | | 0.292 | | |
| | | | | (0.188) | | |
| CMA | | | | | $0.397^{**}$ | |
| | | | | | (0.180) | |
| GDP | | | | | | $0.486^{***}$ |
| | | | | | | (0.171) |
| Constant | $1.009^{***}$ | $1.046^{***}$ | $1.095^{***}$ | $0.970^{***}$ | $1.054^{***}$ | $0.664^{***}$ |
| | (0.208) | (0.191) | (0.168) | (0.189) | (0.177) | (0.214) |
| Observations | 28 | 28 | 28 | 28 | 28 | 28 |
| $R^2$ | 0.006 | 0.021 | 0.247 | 0.085 | 0.158 | 0.236 |
| Adjusted $R^2$ | −0.032 | −0.017 | 0.218 | 0.050 | 0.126 | 0.207 |

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the regression coefficients of a cross sectional regression of idiosyncratic earnings changes cross sectional skewness on risk factors quarterly time series returns.

Tabela 1.3 – Earnings Skewness and Equity Risk Factors

earnings distributions. Another possible explanation relates to the compensation structures and employment contracts prevalent in value-driven industries. For example, workers in these sectors may have a higher proportion of their compensation tied to performance-based bonuses or stock options. While this can lead to higher earnings during periods of economic expansion, it can also result in significant earnings declines during downturns, contributing to earnings skewness. Furthermore, the positive correlation between the value factor and earnings skewness aligns with the notion of tail risk. Value stocks are often considered to have higher tail risk compared to growth stocks, meaning they are more susceptible to extreme negative returns. Our findings suggest that this tail risk may also be present in labor income, particularly for workers exposed to value-driven economic activities. This connection between the value factor and labor income tail risk offers a potential explanation for the premia associated with this factor in asset pricing models, as investors may be willing to accept lower average returns on value factor assets in exchange for the diversification benefits and risk reduction they provide against labor income risk.

| | *Dependent variable:* | | |
|---|---|---|---|
| | *Idiosyncratic Earnings Skewness* | | |
| | (1) | (2) | (3) |
| GDP | 0.486*** | | 0.439*** |
| | (0.171) | | (0.151) |
| HML | | 0.497*** | 0.451*** |
| | | (0.170) | (0.151) |
| Constant | 0.664*** | 1.095*** | 0.751*** |
| | (0.214) | (0.168) | (0.190) |
| Observations | 28 | 28 | 28 |
| $R^2$ | 0.236 | 0.247 | 0.437 |
| Adjusted $R^2$ | 0.207 | 0.218 | 0.392 |

*p<0.1; **p<0.05; ***p<0.01

This table reports the regression coefficients of a cross sectional regression of idiosyncratic earnings changes cross sectional skewness on risk factors quarterly time series returns.

Tabela 1.4 – Earnings Skewness and HML Factor

### 1.3.3 Intra-Sector Analysis

The results from the Intra-Sector Beta Variance and Earnings Variance table reveal that the positive and statistically significant coefficients for SMB and HML beta variances indicate that greater exposure to these risk factors is associated with higher earnings variance within sectors. This suggests that firms with higher sensitivity to size (SMB) and value (HML) factors experience more pronounced earnings variability, likely due to their inherent exposure to market conditions that disproportionately affect smaller and value-oriented firms. These findings highlight the importance of understanding sector-specific dynamics and their link to factor sensitivities, as different equity risk factors can drive substantial heterogeneity in earnings variance within industries.

The results in the Firms Fundamentals section highlight the significant role that HML variance plays in explaining intra-sector earnings dispersion for firms, similarly to individuals. The findings suggest that sectors with greater HML variance experience higher dispersion in revenue growth and net income growth among firms. This indicates that value-driven economic activities, as represented by HML, are linked to increased heterogeneity in firm performance within sectors. Such increased dispersion can be attributed to the varying impacts of macroeconomic factors on firms with different financial profiles within a sector. The variability in firm fundamentals driven by HML also suggests that workers in sectors with high HML variance might face greater earnings risk due to the heterogeneous nature of firms' responses to economic shocks, as we have analyzed previously. This result brings light to a possible channel for the results found throughout this paper. Risk Factors correlate to firms

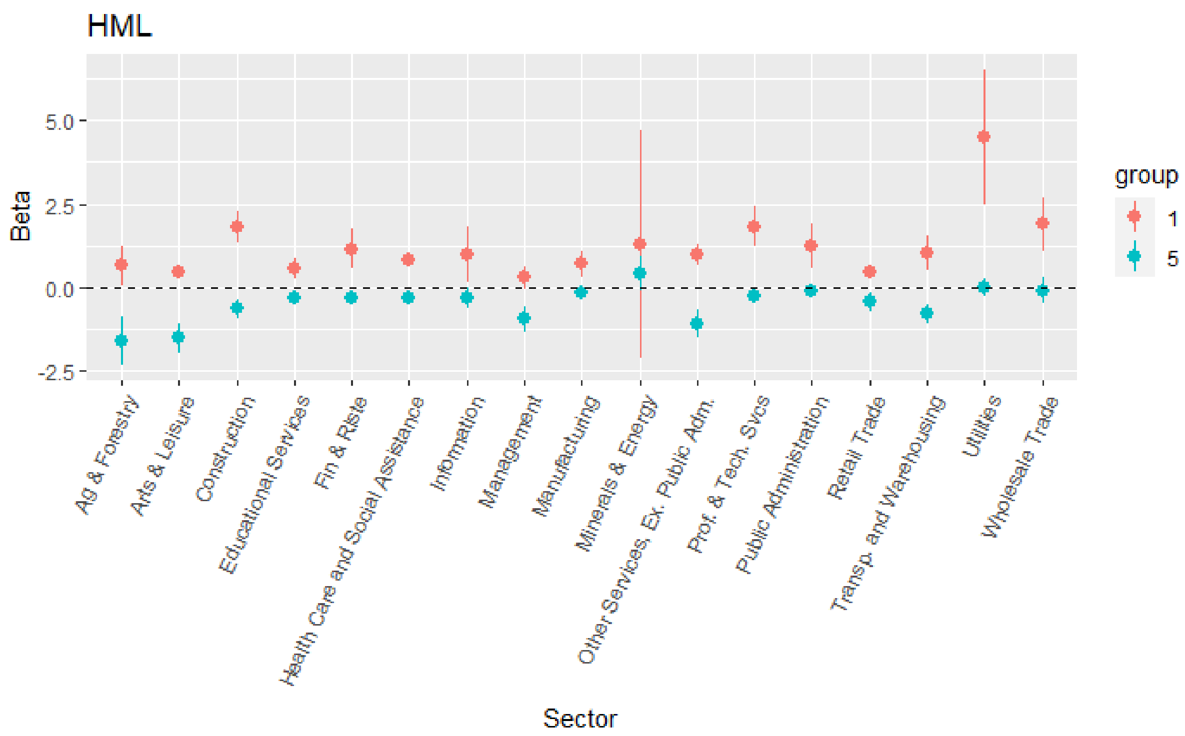


Figura 1.3 – Worker Betas - Risk Factors - Intra-sector and by earnings quintiles

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Intrasector Earnings Variance | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| MKT beta var | −0.067 | | | | | |
| | (0.051) | | | | | |
| SMB beta var | | 0.218*** | | | | 0.152*** |
| | | (0.050) | | | | (0.058) |
| HML beta var | | | 0.207*** | | | 0.131** |
| | | | (0.050) | | | (0.058) |
| RMW beta var | | | | −0.022 | | |
| | | | | (0.052) | | |
| CMA beta var | | | | | 0.029 | |
| | | | | | (0.052) | |
| Constant | −0.000 | −0.000 | −0.000 | −0.000 | −0.000 | −0.000 |
| | (0.051) | (0.050) | (0.050) | (0.051) | (0.051) | (0.050) |
| Observations | 378 | 378 | 378 | 378 | 378 | 378 |
| $R^2$ | 0.005 | 0.047 | 0.043 | 0.0005 | 0.001 | 0.060 |
| Adjusted $R^2$ | 0.002 | 0.045 | 0.040 | −0.002 | −0.002 | 0.055 |

*p<0.1; **p<0.05; ***p<0.01

This table reports the regression coefficients of a cross sectional regression of idiosyncratic earnings cross sectional variance on cross-sectional variance in betas across earnings quintiles and sectors.

Tabela 1.5 – Intra-Sector Beta Variance and Idiosyncratic Earnings Variance

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Idiosyncratic Earnings Variance | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| MKT Beta x MKT Var | 0.461 | | | | |
| | (0.412) | | | | |
| SMB Beta x SMB Var | | $0.179^{**}$ | | | |
| | | (0.070) | | | |
| HML Beta x HML Var | | | $0.121^{*}$ | | |
| | | | (0.063) | | |
| RMW Beta x RMW Var | | | | $0.262^{**}$ | |
| | | | | (0.118) | |
| CMA Beta x CMA Var | | | | | 0.041 |
| | | | | | (0.073) |
| Constant | $15.700^{***}$ | $15.360^{***}$ | $15.514^{***}$ | $15.376^{***}$ | $15.709^{***}$ |
| | (0.235) | (0.258) | (0.255) | (0.277) | (0.276) |
| Observations | 21 | 21 | 21 | 21 | 21 |
| $R^2$ | 0.062 | 0.258 | 0.160 | 0.206 | 0.016 |
| Adjusted $R^2$ | 0.012 | 0.219 | 0.115 | 0.164 | −0.035 |

$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

This table reports the regression coefficients of a cross sectional regression of idiosyncratic earnings cross sectional variance on the interaction between risk factors quarterly time series variance and cross-sectional variance in betas across earnings quintiles and sectors.

Tabela 1.6 – Earnings Variance, Factor Variance and Intra-Sector Beta Variance - Interaction

earnings and to individuals working in the firms as well.

| | *Dependent variable:* | |
|---|---|---|
| | *Disp. Rev. Growth* | *Disp. Net Inc Growth* |
| | (1) | (2) |
| HML Variance | $0.234^{***}$ | $0.164^{***}$ |
| | (0.035) | (0.036) |
| Constant | −0.000 | 0.000 |
| | (0.035) | (0.036) |
| Observations | 770 | 770 |
| $R^2$ | 0.055 | 0.027 |

$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

This table reports the regression coefficients of a cross sectional regression of firms revenues and net income growth cross sectional dispersion on HML factors quarterly time series variance.

Tabela 1.7 – Intra-Sector Fundamentals Growth and HML Variance

### *1.3.4 Results Summary*

Our analysis of SIPP data provides evidence of the significant relation of equity risk factors with labor income. We find substantial heterogeneity in worker betas, highlighting the varied relation of market risks across different segments of the workforce. Regression analysis reveal a relationship between the variance of equity risk factors and idiosyncratic earnings variance, suggesting that fluctuations in financial markets correlate with individual earnings stability. Furthermore, both higher beta variance and the interaction between beta variance and factor variance display a significant connection to idiosyncratic risk. Most notably, the value factor (HML) emerges as a significant link to idiosyncratic earnings skewness, together with the more standard GDP growth metric. This finding corroborates existing literature on the procyclicality of earnings skewness relative to GDP growth and extends our understanding by linking the value factor to earnings skewness. The positive correlation suggests that aspects of the premia associated with the value factor might be explained by its connection to labor income risk, particularly its ability to capture tail risk and serve as a potential hedge factor in portfolios. Overall, our research shows the importance of considering financial market dynamics when analyzing labor income risk, as it significantly relates to earnings variability and skewness, with implications for both individuals and policymakers.

## 1.4 Conclusion

This study has investigated the relationship between equity risk factors and labor income, with a particular focus on the value factor (HML) and its relation to workers earnings. By using US data from the Survey of Income and Program Participation (SIPP), we have explored the connection between financial market dynamics and individual earnings.

Our analysis reveals significant heterogeneity in worker betas, indicating that individuals exhibit diverse exposures to financial market risks. This heterogeneity is significant across different income quintiles and sectors, which we show that may be relevant when assessing labor income risks. We find a significant relationship between the variance of equity risk factors and idiosyncratic earnings variance, demonstrating that fluctuations in financial markets have an association with individual earnings stability. Moreover, both the variance in individual betas and the interaction between beta variance and factor variance also display significant coefficients on the idiosyncratic risk regression.

Most notably, our research identifies the value factor as a significant variable to explain idiosyncratic earnings skewness in the U.S. context. This finding suggests that value-related aspects of jobs or industries may contribute to the likelihood of pronounced earnings fluctuations for workers in those sectors. This connection between the value factor and labor income tail risk offers a potential explanation for the premia associated with this factor in asset pricing models, as it may serve as a valuable hedge against labor income risk in investment portfolios. Specifically, the positive correlation between the value factor and earnings skewness implies that growth firms, with their typically lower book-to-market ratios, may offer a hedge against tail risk in labor income. This is because growth firms tend to exhibit lower earnings volatility and skewness compared to value firms. By including assets with high exposure to growth factors in their portfolios, investors can potentially offset the risk of extreme fluctuations in their labor income. This increased demand for growth factor exposure due to its hedging properties could contribute to lower average returns on growth assets. Consequently, the value factor, which goes long on value firms and short growth firms, would command a positive premia due to the relatively higher returns offered by value firms compared to growth firms.

Intra-sector analysis for worker earnings further demonstrates that equity risk factors significantly relate to individual earnings variability within sectors. Workers in industries characterized by greater sensitivity to size (SMB) and value (HML) risk factors tend to experience higher earnings volatility, which suggests that labor income in these sectors is more exposed to fluctuations in market conditions. This means that workers in smaller firms or those associated with high book-to-market ratios face greater uncertainty in their earnings, which might be due to the firms' inherent risk exposures. Conversely, sectors where MKT, RMW, and CMA beta variances are not significant may offer more stable earnings prospects for workers, as these risk factors do not lead to substantial intra-sector variability. Understanding these dynamics is relevant for assessing the risks faced by workers and developing strategies to mitigate income instability across different sectors.

Additionaly, the intra-sector analysis through the lens of the firms reveals that different equity risk factors drive substantial heterogeneity in earnings variance within industries. Specifically, the significant coefficients of HML volatility indicates that firms are more prone to higher intra-sector earnings variability when factor volatility increases as well. This suggests that those with higher book-to-market ratios are particularly sensitive to market conditions that amplify earnings dispersion. These findings suggest the importance of sector-specific dynamics and their relationship with equity risk factor sensitivities.

Furthermore, our results indicate how "value firms" – often constrained by tighter profit margins or more volatile revenues – tend to share more of their risk with employees. This pass-through of shocks is particularly evident among lower-wage workers, who experience larger earnings swings when their firm's value exposure intensifies. By contrast, middle-income segments appear somewhat less vulnerable to these same disruptions. In effect, value firms' limited ability to buffer financial downturns translates into higher wage variability for workers, highlighting a form of "risk sharing" where employees bear a notable portion of the company's market-driven uncertainties.

In conclusion, this study makes several important contributions. First, it broadens our understanding of the economic forces influencing labor income by demonstrating the significant relation of equity risk factors, particularly the value factor, with earnings variability, for individuals and firms, and workers earnings growth skewness. Second, it bridges the gap between financial economics and labor market analysis by suggesting that factors traditionally associated with asset pricing can also be informative in understanding labor income risk. Finally, the findings offer implications for developing hedging strategies based on financial risk exposures, as well as for policy-making aimed at mitigating the adverse effects of financial market fluctuations on workers.

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## 1.6 Appendix

$$\Delta \hat{e}_{i,t} = \alpha_i + \beta_j GDP_t + \epsilon_{i,t}$$

$$\Delta \hat{e}_{i,t} = \alpha_i + \beta_j MKT_{,t} + \epsilon_{i,t}$$

$$\Delta \hat{e}_{i,t} = \alpha_i + \beta_j SMB_{,t} + \epsilon_{i,t}$$

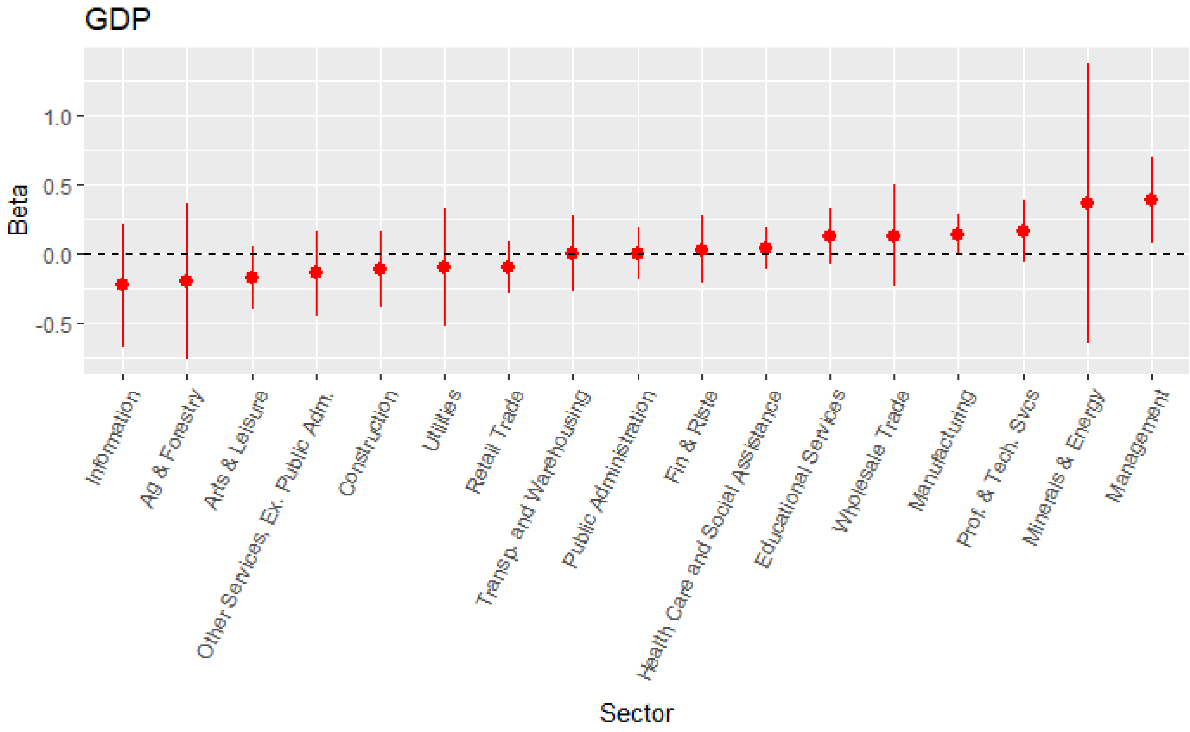



Figura 1.4 – Worker Betas - By Sector - GDP

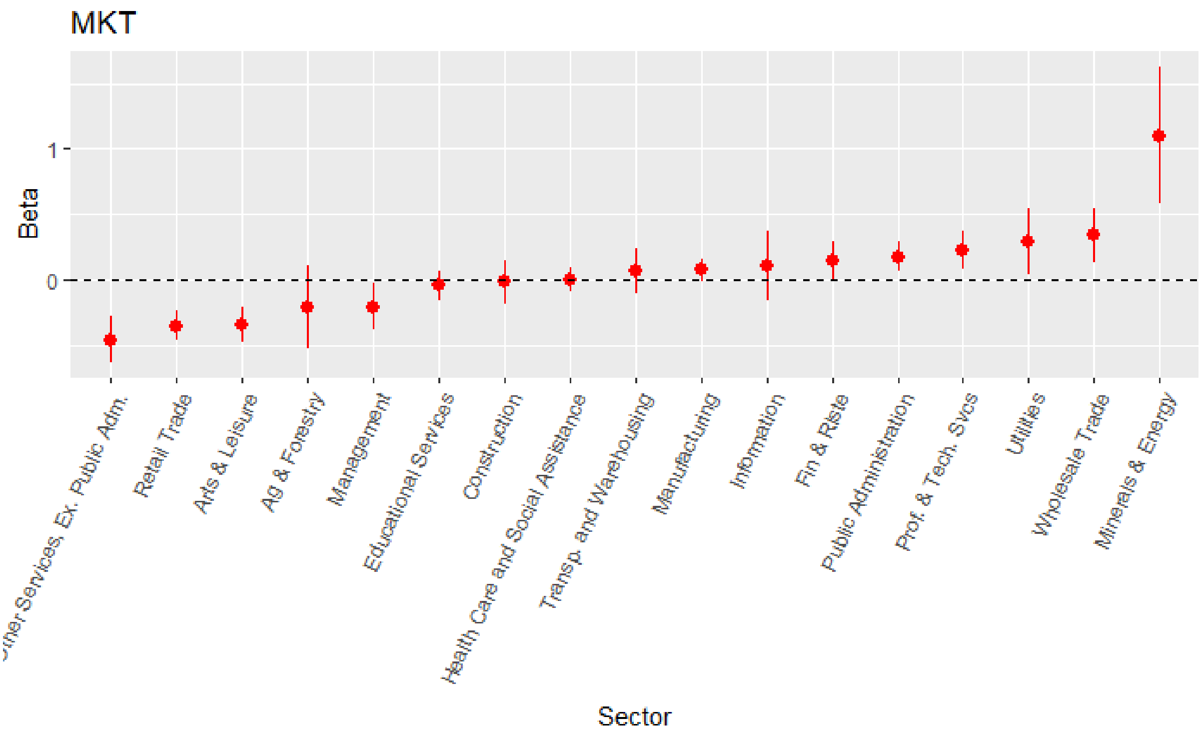



Figura 1.5 – Worker Betas - By Sector - MKT

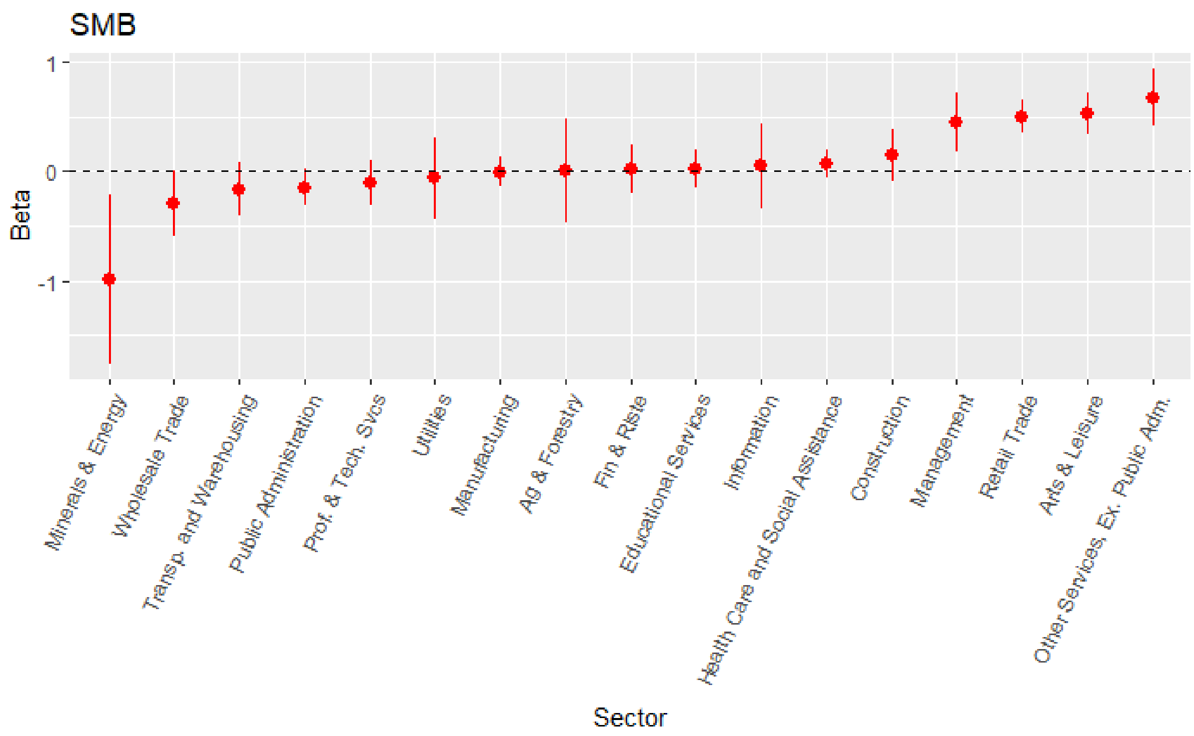



Figura 1.6 – Worker Betas - By Sector - SMB

$$\Delta \hat{e}_{i,t} = \alpha_i + \beta_j HML_{,t} + \epsilon_{i,t}$$

$$\Delta \hat{e}_{i,t} = \alpha_i + \beta_j RMW_{,t} + \epsilon_{i,t}$$

$$\Delta \hat{e}_{i,t} = \alpha_i + \beta_j CMA_{,t} + \epsilon_{i,t}$$

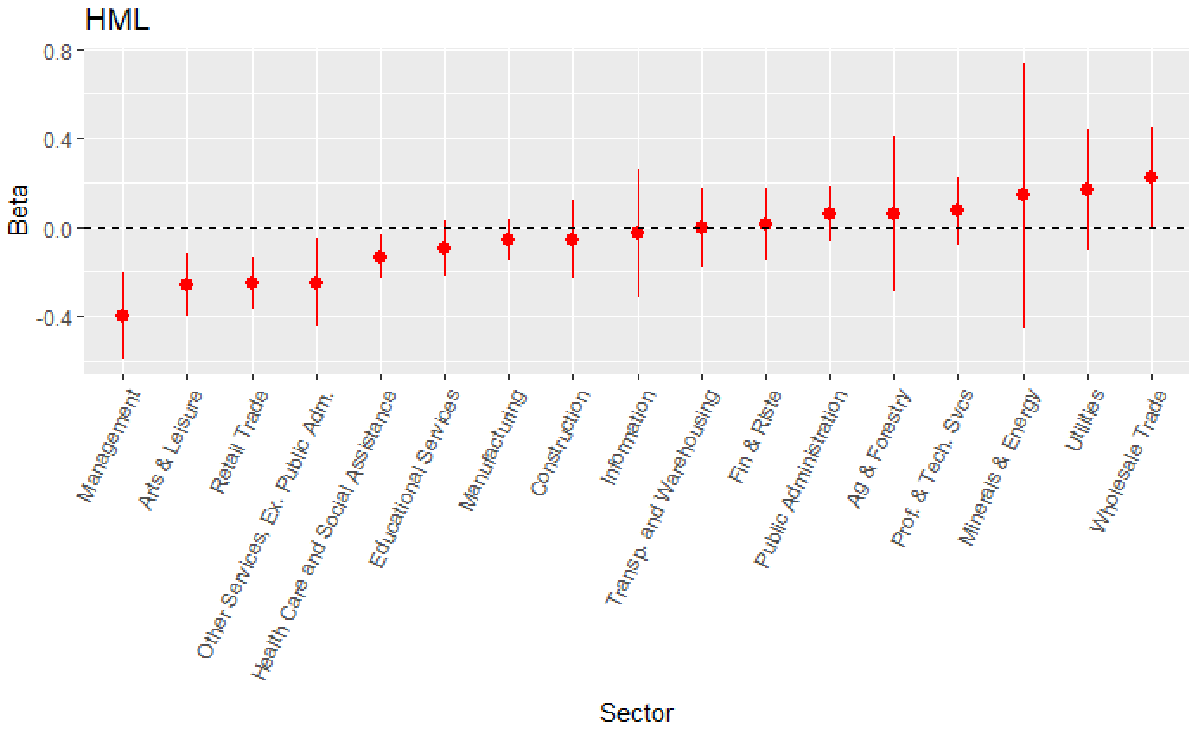



Figura 1.7 – Worker Betas - By Sector - HML

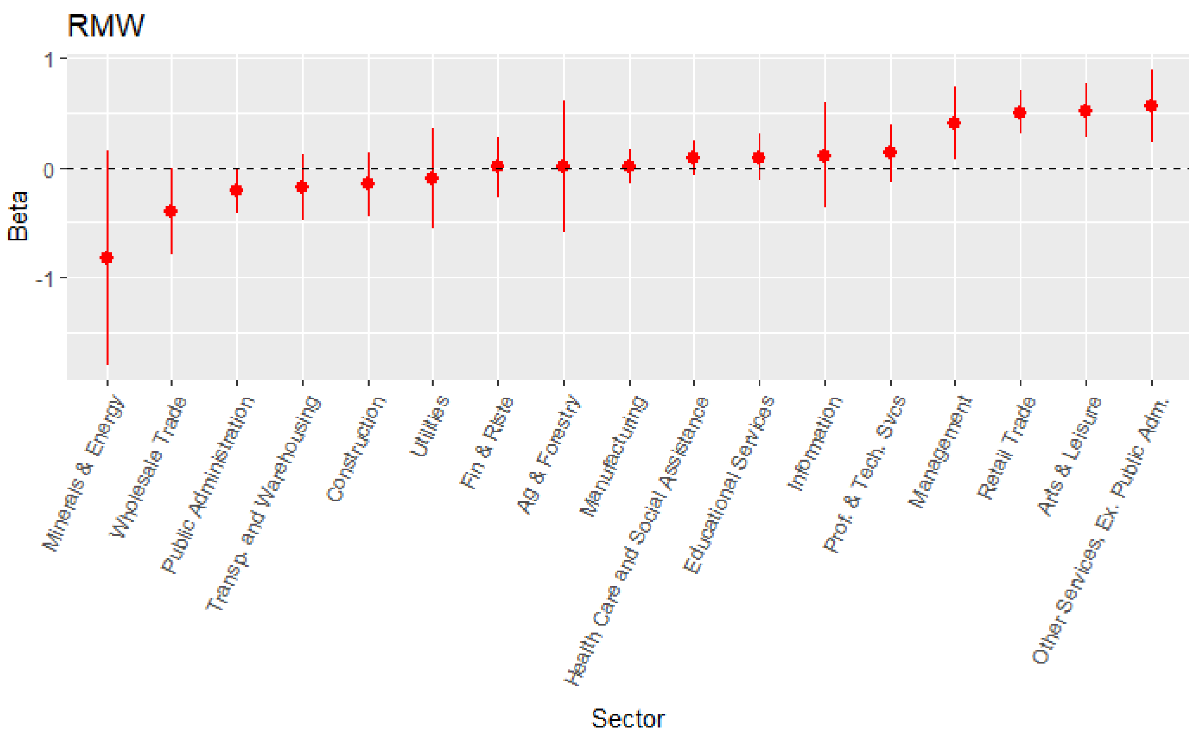



Figura 1.8 – Worker Betas - By Sector - RMW

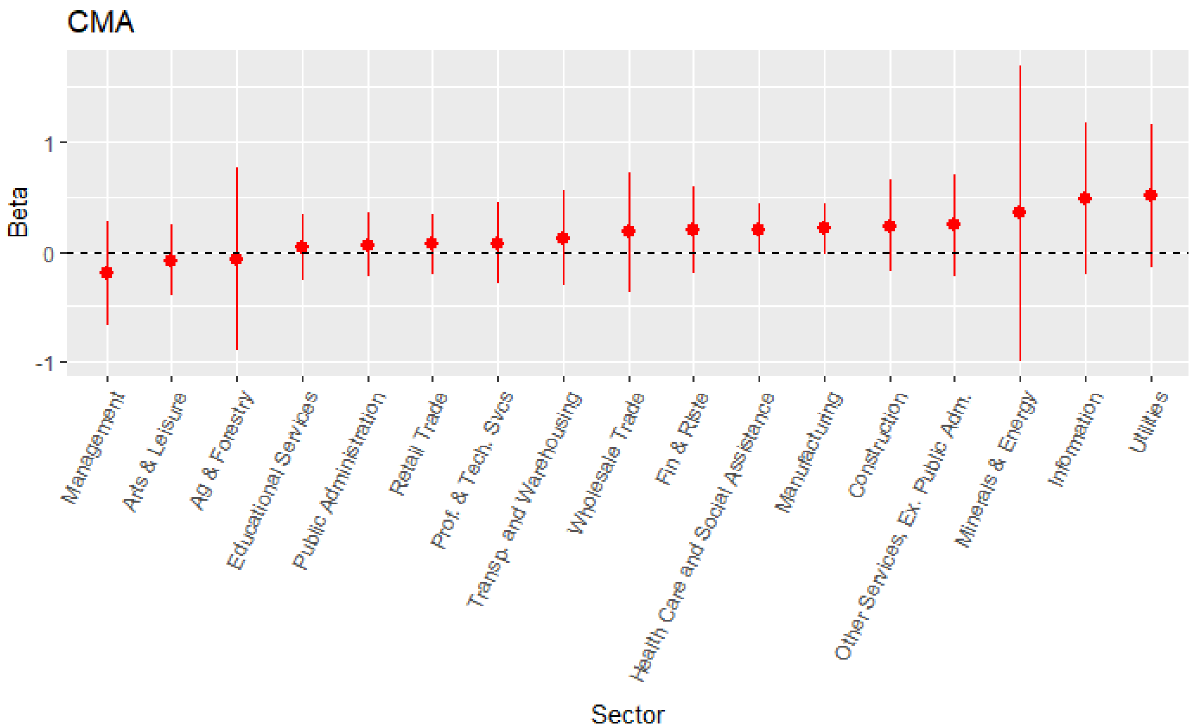
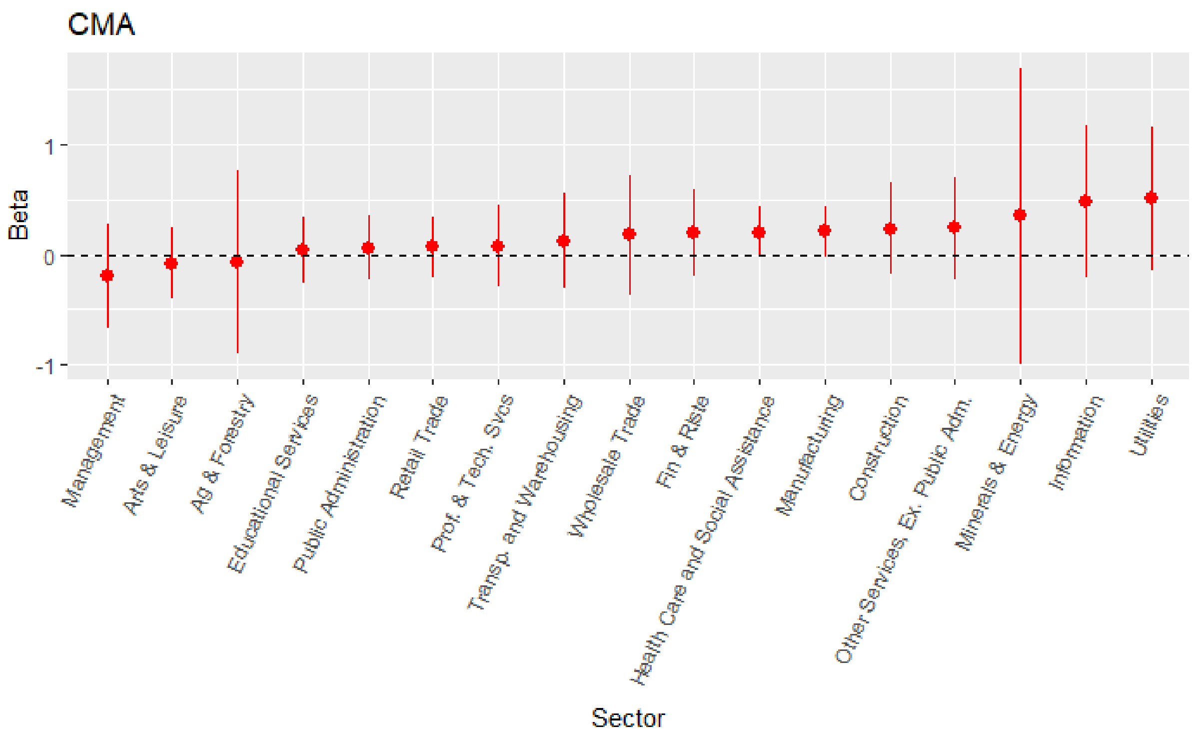



Figura 1.9 – Worker Betas - By Sector - CMA



| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Idiosyncratic Earnings Variance | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| MKT Beta | $-0.541^{**}$ | | | | |
| | (0.193) | | | | |
| SMB Beta | | $0.401^{*}$ | | | |
| | | (0.210) | | | |
| HML Beta | | | $0.483^{**}$ | | |
| | | | (0.201) | | |
| RMW Beta | | | | $0.468^{**}$ | |
| | | | | (0.203) | |
| CMA Beta | | | | | 0.192 |
| | | | | | (0.225) |
| Constant | $16.059^{***}$ | $15.049^{***}$ | $14.873^{***}$ | $15.292^{***}$ | $15.604^{***}$ |
| | (0.209) | (0.444) | (0.433) | (0.296) | (0.320) |
| Observations | 21 | 21 | 21 | 21 | 21 |
| $R^2$ | 0.293 | 0.161 | 0.234 | 0.219 | 0.037 |
| Adjusted $R^2$ | 0.256 | 0.117 | 0.193 | 0.178 | −0.014 |

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Tabela 1.8 – Earnings Variance and Beta Variance

# 2 A FACTOR OF FACTOR VOLATILITIES

**Resumo**

This study shows that the heterogeneous exposure to changes in factor volatility helps explain the cross-section of expected stock returns across a wide range of portfolios. Furthermore, we find that this explanatory power is subsumed by a common volatility factor, identified as the first principal component of all factor volatility factors. This factor remains relevant even after the inclusion of changes in market volatility as a factor and exhibits low correlation with the original risk factors used in its construction. Our findings suggest that investors consider changes in factor volatilities as a fundamental risk. This pattern can be justified by a model with "common factor risk news"in addition to market "risk news".

## 2.1 Introduction

Understanding the drivers behind differences in expected returns across different securities has long captivated finance researchers. Beyond traditional factor betas, risk metrics like total and idiosyncratic volatility have emerged as potential elements in explaining cross-sectional return differences. Studies focused on volatility — such as Blitz and van Vliet (2020), Chabi-Yo (2009), Adrian and Rosenberg (2008), Bollerslev, Tauchen, and Zhou (2009), and Ang et al. (2006) — have examined its role in the cross-section, while others, including Brockman et al. (2022), Bozhkov et al. (2020), and Liu et al. (2019), have explored the implications of idiosyncratic volatility. Despite the extensive scrutiny on various risk factors and deviations from the Sharpe-Lintner Capital Asset Pricing Model, a gap remains in understanding how factor volatility — distinct from total or idiosyncratic measures — drives variations in expected stock returns.

This study aims to address this gap by investigating the influence of factor volatility on stock returns across a wide range of portfolios, assessing whether heterogeneous betas to shifts in factor volatility contribute to explaining expected return differentials. Additionally, we explore the role of a common volatility factor, identified via principal component analysis, and its relevance as a fundamental risk factor influencing portfolio risk and performance. Our findings provide new insights into factor volatility's significance in asset pricing.

In this paper, we demonstrate that heterogeneous exposure to changes in factor volatility significantly influences the cross-section of stock returns. Unlike most previous studies, our findings align with a rational model in which the stochastic discount factor is a function of heteroskedastic state variables following a VAR process. Building on the framework established by Campbell et al. (2018) and the foundational model by Campbell and Vuolteenaho (2004), our research introduces an alternate version to their asset pricing approach. Campbell et al. (2018) expanded the traditional analysis of discount rate and cash flow news by incorporating an additional component, "risk news", suggesting that expected stock returns are proportional to news about market return variance.

Our approach extends this concept by constructing a generalized measure of "risk news"that relies on a broader basket of risk factor volatilities, rather than solely on market volatility. Empirically, we modify their model by integrating multiple risk factors and considering a common volatility component. Moreover, we construct a measure of "risk news"that is orthogonal to market volatility.

To build this measure, we extract the first principal component from the volatilities of 153 risk factors, capturing the common volatility shifts across all factors in our sample, termed the Factor Volatility Factor (FVF). Using this measure, we conduct pricing regressions and find that FVF significantly explains average returns on 550 anomaly portfolios from

Kozak, Nagel and Santosh (2020). Portfolios with high betas to FVF serve as hedge assets, yielding higher returns during periods of increasing volatility; conversely, these assets typically have lower returns on average due to their hedging nature. Importantly, our results are not driven by market volatility. Even when both FVF and market volatility are included in Fama-MacBeth regressions, both measures remain significant, indicating they contain orthogonal information.

We also run separate regressions for each of the 153 individual factor volatility changes and find that 122 yield significant coefficients, underscoring the relevance of individual factor volatilities in explaining cross-sectional differences in average returns. Additionally, we construct a tradable version of our FVF, which displays significant returns over our sample period. Testing the second principal component, however, did not yield promising results. As a robustness check, we also employ GLS regressions, confirming that our findings are robust to this alternative method. Finally, we show that FVF correlates with macroeconomic variables related to labor income risk, further linking our measure to real economic factors.

Our study examines volatility from multiple risk factors and shows that a large share of them is relevant in pricing the cross section of stock returns. Blitz and van Vliet (2020) demonstrate that portfolios with low historical volatility yield enhanced Sharpe ratios and positive alpha, while Chabi-Yo (2009) finds that the variance and correlation of Fama-French and momentum factors can significantly predict stock market returns. Our approach differs by focusing not on asset-level volatility but on factor volatilities across a broad set of risk factors, capturing a more diverse view of systematic risk. Similarly, Adrian and Rosenberg (2008) show that investors pay for protection against increases in volatility, even if it has limited persistence, highlighting the pricing of volatility risk in asset markets. Unlike Adrian and Rosenberg, our study examines a more diverse set of volatilities and find an overall hedging characteristic which we explore further.

We expand the analysis by exploring how the common component in risk factors volatilities, orthogonal to market volatility, improve pricing equations. Our work builds on Ang et al. (2006), who demonstrated that stocks with high sensitivities to aggregate volatility exhibit lower average returns. Their exploration of how aggregate volatility impacts expected stock returns provides a basis for our study, which introduces a broader basket of risk factors, going beyond the market volatility to include a variety of factor volatilities. Unlike previous studies that often focus on volatility as a characteristic of assets, our analysis treats these volatilities as systemic risk factors that are significantly priced in the market. Our findings diverge from Ang et al. (2006) by showing that our generalized measure of risk, derived from the first principal component of factor volatilities, captures orthogonal information not captured by market volatility. This principal component not only explains a significant portion of the variance in factor volatilities but also proves to be non-correlated with the individual risk factors, suggesting that it captures unique systematic information missed by single-factor models.

Other papers have also studied common factors in volatility but with different angles. Consistent with Bollerslev et al. (2018), who identified common components in multiple forms of financial market volatilities, our study extends this to show that commonalities are priced and are relevant in explaining expected stock returns. Herskovic et al. (2016)'s work, which also explores how sensitivity to volatility changes affects asset pricing, parallels our approach, but focus on the common component in idiosyncratic volatility, and does not examine the common components in equity risk factors volatility.

Our research advances the study of factor volatilities by introducing a tradable version of our common volatility factor, connecting the analysis between systemic risk measures and practical portfolio construction. Unlike prior studies, which largely focus on idiosyncratic volatility effects and market volatility exposures when building a set of portfolios robust to volatility, such as Herskovic et al. (2016) and Ang et al. (2006), our approach constructs our portfolios based on the common component discussed in previous paragraphs, offering an alternate view of volatility dynamics.

In summary, firms idiosyncratic risks increases during economic downturns, as well as households income risk. Such increases affect asset prices, be they through the demand for firms products, or by portfolio decisions, or some alternative channel not explored here. Those parallel events may lead to the the common volatility that we observe in financial markets and that we explore in more detail up next. We look at the pricing and portfolio formation potential of such behavior when used for asset pricing purposes.

The rest of the paper is organized as follows. Section 2 presents theoretical foundation, section 3 describes the data used in our analysis. In section 4 we present the results, and section 5 concludes.

## 2.2 Theory

### *2.2.1 Stochastic Volatility and Asset Pricing Models*

The role of factor volatility as a pricing factor is grounded in the theoretical framework of stochastic volatility within intertemporal asset pricing models. Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM) highlights the importance of considering the stochastic nature of investment opportunities for long-term investors. Building upon this, Campbell et al. (2018) extended the ICAPM by incorporating stochastic volatility, providing a framework to analyze how changes in volatility affect expected returns. Additionally, this study introduces a new model that further explores these ideas by defining the stochastic discount factor (SDF) as a function of common economic influences, including volatility. This model captures the impact of common volatility and other state variables on asset prices, allowing for a more comprehensive understanding of how changes in these factors influence expected returns. By considering the volatilities of individual risk factors as significant pricing factors, we can better account for the information conveyed by these volatilities about future risks and returns.

### *2.2.2 Modelling the SDF*

Let us model the log SDF as:

$$m_{t+1} = \alpha_M + \beta_M Z_{t+1} + \epsilon_{M,t+1} \tag{2.1}$$

The log of the SDF is modeled as a linear function of state variables Z, capturing the sensitivity of the SDF to economic factors.

Then, we assume that the state variables, including economic factors, follow a VAR process, allowing for time-varying volatility:

$$Z_{t+1} = \bar{Z} + \Gamma(Z_t - \bar{Z}) + \sigma_t u_{t+1} \tag{2.2}$$

where $Z_t$ is an $n \times 1$ vector of state variables that includes economic factors such as market returns and common volatility. The term $\bar{Z}$ is the long-run mean of these state variables, and $\Gamma$ is an $n \times n$ matrix of autoregressive coefficients. The vector $u_{t+1}$ represents shocks to the state variables and is normalized to have unit variance. The diagonal matrix $\sigma_t$ captures time-varying volatility in each of the state variables, with its elements representing different volatility components such as market volatility and common volatility. The key distinction in our model is that we use a diagonal matrix $\sigma_t$ to model the time-varying volatility of the state variables. This choice reflects the fact that different economic factors exhibit heteroskedasticity, with distinct volatility patterns across time. For instance, market volatility may evolve independently of other factors like common (non-market) factor volatility.

With those assumptions, the following equation connects expected returns to the SDF, its variance, and the covariance between returns and SDF innovations.

$$\mathbb{E}_t[R_{i,t+1} - R_{j,t+1}] = -\mathbb{E}_t\left[(r_{i,t+1} - r_{j,t+1})(\beta_M^\top \sigma_t u_{t+1} + \epsilon_{M,t+1})\right]$$

We transform to the following empirical format:

$$R_{i,t+1} - R_{j,t+1} = \lambda_0 + \lambda_u^\top u_{t+1} + \epsilon_{i,t+1} \tag{2.3}$$

This equation allows for empirical estimation, linking excess returns to shocks in state variables, capturing the impact of common volatility and other risk factors.

In essence, the model establishes that unexpected changes in the SDF, driven by shifts in risk factors and common volatility, lead to the emergence of risk premia in asset returns. Assets that are more sensitive to these shocks will demand higher expected returns as compensation for the additional risk they carry.

### 2.2.3 Factor Volatility as a Pricing Factor

This paper proposes that the volatilities of individual risk factors themselves can serve as significant pricing factors. By considering the stochastic nature of these volatilities, we acknowledge that shocks to factor volatilities carry important information about future risks and returns. The high correlations among factor volatility changes suggest a common underlying component, which we term the "Common Factor Volatility Factor."

### 2.2.4 Empirical Implications

The theoretical framework outlined above leads to specific empirical implications. If common factor volatility is a priced risk factor, we hypothesize that portfolios with higher betas with respect to changes in this factor should exhibit lower average returns. These portfolios can be interpreted as providing a hedge against increases in common volatility, justifying their lower expected returns.

## 2.3 Data and Methods

We utilize a set of stocks and risk factors to build our common volatility components. For the stocks, we use all components of the Dow Jones index since the start of the sample, with data coming from Eikon, and covering the period from 1984 to 2017. Risk factor data includes market excess returns (MKT), size (SMB), value (HML), Operating Profitability (RMW), Investment (CMA), and Momentum (MOM) and comes from Kenneth French's website[2], covering the period from 1926 to 2022. Industry and anomaly portfolios from French are also used as test assets on the appendix. The main test assets used are the anomaly portfolios from Kozak[3], which is used in Kozak, Nagel, Santosh (2020) and cover the period from 1963 to 2019. The benchmark data for CIV comes from Bernard Herskovic's website[4], and includes updated data on their created measure from 1926 to 2022. Additionally, we also collect 153 risk

[2]<https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html>
[3]<https://www.serhiykozak.com/data>
[4]<https://bernardherskovic.com/data/>

factors for the period from 1926 to 2021 from the Global Factor data website[5]. The common idiosyncratic volatility (CIV) data was obtained from Bernard Herskovic's website and covers the period from 1926 to 2022. Earnings growth data was obtained from Guvenen, Ozkan, and Song (2014) for the period from 1978 to 2011. The wages data was collected from the National Income and Product Accounts (NIPA) Regional Economic Information System and covers the period from 1969 to 2020. Employment data was obtained from the US Bureau of Labor Statistics, covering the same period as the wages data. House price data was collected from the Federal Housing Finance Agency, covering the period from 1947 to 2021. Country growth data was obtained from the International Monetary Fund (IMF) and covers the period from 1980 to 2022. Finally, the Betting Against Beta (BAB) data was collected from AQR and covers the period from 1930 to 2022.

### 2.3.1 Pricing Regressions: Cross-Section and GLS

### 2.3.2 Fama-Macbeth Regressions: Two-Phase Approach

The Fama-Macbeth regression methodology is a pivotal technique in empirical asset pricing for assessing the impact of risk factors on asset returns across a cross-section. This method allows for the estimation of risk premia while adjusting standard errors as it accounts for the potential cross-sectional correlation.

**Step 1: Time-Series Regressions**

The first phase of the Fama-Macbeth procedure involves conducting time-series regressions for each asset to estimate its exposure to various risk factors. For each asset we regress the excess returns against the risk factors:

$$R^e_{i,t} = \alpha_i + \beta_{i1} f_{1,t} + \beta_{i2} f_{2,t} + \cdots + \beta_{iK} f_{K,t} + \epsilon_{i,t} \tag{1}$$

Where $R^e_{i,t}$ is the excess return on asset $i$ at time $t$, $f_{k,t}$ represents the $k$th risk factor at time $t$, $\beta_{ik}$ is the sensitivity of asset $i$'s returns to the $k$th risk factor and $\epsilon_{i,t}$ is the idiosyncratic error term. From these regressions, we obtain the factor loadings ($\beta_{ik}$) for each asset.

**Step 2: Cross-Sectional Regressions**

In the second phase, unlike the traditional cross-sectional approach, Fama-Macbeth regressions involve running cross-sectional regressions in each time period t to estimate the risk premia for that period:

$$R^e_{i,t} = \gamma_t + \lambda_{1t} \hat{\beta}_{i1} + \lambda_{2t} \hat{\beta}_{i2} + \cdots + \lambda_{Kt} \hat{\beta}_{iK} + u_{i,t} \tag{2}$$

[5] <https://jkpfactors.com/>

Where $R^e_{i,t}$ is the excess return of asset i at time t, $\hat{\beta}_{ik}$ is the estimated factor loading of asset $i$ on the $k$th risk factor, $\lambda_{k,t}$ is the risk premium associated with the $k$th risk factor at time t. Each period's regression provides a set of risk premia $(\lambda_{kt})$, which are then averaged over all periods to obtain the overall risk premia estimates:

$$\bar{\lambda}_k = \frac{1}{T}\sum_{t=1}^{T}\lambda_{kt} \tag{2.4}$$

Where $T$ is the total number of time periods. The final step involves analyzing the average risk premia $(\bar{\lambda}_k)$ to determine which risk factors are significantly priced in the market. A statistically significant $\bar{\lambda}_k$ indicates that the corresponding risk factor is a priced risk across the assets within the sample period.

### 2.3.3 GLS Regressions

The two-step Generalized Least Squares (GLS) procedure is utilized to address potential issues with heteroskedasticity and correlation in the residuals of the cross-sectional regressions. This method offers more efficient estimators when such concerns are present.

**Step 1: Time-Series Regressions**

Similar to the OLS approach, the first step in the GLS procedure involves estimating factor loadings through time-series regressions for each asset:

$$R^e_{i,t} = \alpha_i + \beta_{i1}f_{1,t} + \beta_{i2}f_{2,t} + \cdots + \beta_{iK}f_{K,t} + \epsilon_{i,t} \tag{3}$$

From these regressions, we obtain the factor loadings $(\beta_{ik})$ and residuals $\epsilon_{i,t}$ for each asset.

**Step 2: GLS Cross-Sectional Regressions**

Given the correlated nature of the residuals $\epsilon_{i,t}$ across assets, a GLS adjustment becomes essential. By using the variance-covariance matrix of the residuals, denoted as $\Sigma$, from the time-series regressions, we weight the cross-sectional regressions to account for the heteroskedasticity and correlation:

$$\bar{R}^e_i = \gamma + \lambda_1\hat{\beta}_{i1} + \lambda_2\hat{\beta}_{i2} + \cdots + \lambda_K\hat{\beta}_{iK} + u_i \tag{4}$$

Where the GLS estimator for the risk premia $\lambda$ is given by:

$$\hat{\lambda} = \left(\beta^T\Sigma^{-1}\beta\right)^{-1}\beta^T\Sigma^{-1}\bar{R}^e \tag{5}$$

In this equation, $\Sigma^{-1}$ is the inverse of the variance-covariance matrix of the residuals from the first step, and $\bar{R}^e$ is the vector of average excess returns.

The coefficients $\lambda_k$ estimated via the GLS procedure provide insights into which factors are priced in the cross-section of returns. Significant $\lambda_k$ values indicate that the corresponding factor is a priced risk in the cross-section of asset returns, adjusting for potential heteroskedasticity and correlation.

### 2.3.4 Principal Component Analysis: Factor of Factors Volatilities

Principal Component Analysis (PCA) is a dimensionality reduction technique that transforms a set of possibly correlated variables into a smaller number of uncorrelated variables called principal components. The first principal component accounts for the largest proportion of the variance in the data, and each subsequent component accounts for the highest variance possible under the constraint that it is orthogonal to the preceding components. The principal components are then the eigenvectors of the covariance matrix, and the variance explained by each component corresponds to the eigenvalues.

In our study, applying PCA to factor volatilities allows us to determine if there is a common structure or movement among them. The first principal component essentially captures the dominant trend or pattern in the data, reflecting the combined movements of the factor volatilities. This leads to the derivation of the "Factor of Factor Volatilities."

By applying PCA, we aim to distill the essence of many factor volatilities into a smaller set of uncorrelated variables that capture the primary patterns in the data, providing a more concise yet informative representation. This is especially beneficial in finance, where multiple factors might exhibit collinearity, and a reduced set of independent factors can offer clearer insights.

### 2.3.5 Factor Model: Building a Tradable Factor

Constructing a tradable version of the "Factor of Factor Volatilities"involves several steps, leveraging historical data to form portfolios that capture the essence of this factor. Here is the detailed procedure:

**Step 1: Rolling Window Analysis**

We use the betas of 300 anomaly portfolios to measure their exposure to FVF over the last 42 days, where we have 100 portfolios double sorted on size and value, 100 portfolios double sorted on size and operating profitability and 100 portfolios double sorted on size and investment.

**Step 2: Factor Loadings Estimation**

Within each rolling window, linear regressions are employed to estimate factor loadings for every asset, representing the asset's sensitivity to the "Factor of Factor Volatilities."

**Step 3: Portfolio Formation**

Assets are ranked based on their estimated factor loadings. Using these rankings, quintile portfolios are constructed. The first quintile comprises assets with the highest sensitivity to the factor, while the fifth quintile contains those with the least sensitivity.

**Step 4: Out-of-Sample Portfolio Returns**

For the out-of-sample period, returns for each quintile portfolio are computed. This step involves averaging the returns of assets within each quintile to get a representative return for the portfolio.

**Step 5: Long-Short Strategy**

A long-short strategy is formulated using the quintile portfolios. Specifically, the strategy goes long on the fifth quintile (highest sensitivity) and short on the first quintile (lowest sensitivity). This portfolio captures the premium associated with the "Factor of Factor Volatilities"while neutralizing market-wide movements.

**Step 6: Aggregation**

The long-short portfolio returns are aggregated over time, resulting in a time series that embodies the tradable version of the factor.

Through this methodology, the theoretical "Factor of Factor Volatilities"is transformed into an actionable trading strategy, which aims to harness the associated risk premiums.

### 2.3.6 Income Risk Measures

We also explore in this paper the connection between our common volatility measure and a set of macroeconomic risk metrics. The income growth variables used in these analyses are built using the following method: first, we obtain annual growth rates for employment and wages from the US Bureau of Labor Statistics and the National Income and Product Accounts (NIPA) Regional Economic Information System, covering the period from 1969 to 2020. House price growth rates are sourced from the Federal Housing Finance Agency, spanning 1947 to 2021. Dispersion in these growth rates across US counties is measured as the standard deviation of growth rates. For earnings data, we utilize variance measures provided by Guvenen, Ozkan, and Song (2014) for the period 1978 to 2011. Sector-level growth is calculated from GDP growth rates across 66 sectors in the US economy, with data sourced from NIPA. Global growth rates are derived from GDP data for G20 countries, obtained from the International Monetary Fund (IMF) for the period 1980 to 2022.

## 2.4 Results

The volatility of risk factors is essential in pricing financial assets. In this study, we examine the volatilities of 153 risk factors and their impact on a broad pricing model. Our results show that 122 of these factors are significant in explaining the returns of 550 anomaly portfolios. Further, we apply principal component analysis to these volatilities and find that the first principal component alone explains more than 91% of the variance, signaling the presence of a dominant common volatility component.

We construct both tradable and non-tradable versions of this common volatility factor. These new measures are essentially uncorrelated with the original 153 risk factors. Moreover, the tradable factor exhibits significant predictive power over the period from December 1973 through June 2020. Incorporating different measures of common volatility into the pricing model improves its explanatory power and reduces estimation errors. As a robustness check, using GLS regressions confirms the consistency of our findings.

We also regress the tradable factor on various risk factors and control variables. Even after controlling for these additional variables, the tradable factor continues to deliver positive and statistically significant returns. Finally, we connect our common volatility measures to indicators of income risk—such as dispersion in wages and employment—providing further economic interpretation and relevance. Our findings provide insights on the importance of factor volatility in asset pricing and suggest that incorporating common volatility measures can enhance the accuracy and reliability of return predictions.

### 2.4.1 *Individual Factor Volatility Factors - Pricing*

In this section, we use a two-stage Fama-MacBeth procedure to determine whether changes in factor volatilities can explain abnormal returns in a broad set of equity portfolios. In the first stage we estimate betas from the time series regression of monthly excess returns from each portfolio on a constant, a set of risk factors and the changes in our common volatility measures, with changes being defined as $CommonVol_t - CommonVol_{t-1}$. The following results are the estimates from the second stage.

We begin with an analysis using 550 anomaly portfolios and 153 risk factor volatilities. Table 2.1 reports the regression coefficients and t-statistics for each factor. Notably, 122 of the 153 factors have significant coefficients. A significant negative coefficient implies that a given portfolio acts as a hedge against rising volatility: when volatility increases, such portfolios perform better, thereby commanding a lower risk premium.

Our regressions incorporate the Fama-French Five Factors, the risk factor itself, and changes in the factor's realized volatility. Figures 2 and 3 provide histograms of the t-statistics and coefficients, respectively, for all 153 regressions. The abundance of negative and significant results suggests that changes in factor volatility carry meaningful explanatory power for cross-sectional returns.

### 2.4.2 Individual Factor Volatility Factors - Correlations

In our correlation analysis, we examine how the factor volatilities relate to one another. As shown in Figure 2.4, changes in factor volatility measures exhibit high mutual correlations, suggesting the presence of a pervasive common component. The average correlation is 0.53 with a standard deviation of 0.15, indicating a consistently positive and substantial association among these volatilities.

This finding implies that a unified underlying force influences a range of factors. Such widespread commonality has important implications for portfolio diversification and risk management. If factor volatilities share a common driver, investors may need to adjust their strategies to hedge against this collective source of risk.

### 2.4.3 Individual Factor Volatility Factors - PCA

Given the strong correlations among factor volatility changes, we apply Principal Component Analysis (PCA) to uncover their shared structure. As shown in Table 2.2, the first principal component alone explains over 91% of the total variance, indicating that a single dominant common factor drives these volatilities.

This result highlights the importance of this common component in shaping risk factor behavior. Its dominance suggests that standard asset pricing models should account for this factor to better explain cross-sectional differences in equity returns. The fact that one factor can capture such a large portion of the variation in factor volatilities prompts a reconsideration of existing frameworks, paving the way for more nuanced models that incorporate this fundamental source of market-wide volatility.

### 2.4.4 Common Factor Volatility Factor - Pricing

Having identified a dominant common component in factor volatilities, we next assess its contribution to asset pricing models. Using the first principal component as our Common Volatility Factor, we examine its ability to explain anomaly portfolio returns. As shown in Table 2.3, portfolios more exposed to this factor act as hedges against rising volatility and thus tend to have lower average expected returns.

We also consider both tradable and non-tradable versions of the Common Volatility Factor. Table 2.5 shows that these factors have minimal correlation with the original 153 risk factors, distinguishing them as a unique source of risk. The tradable version, examined from December 1973 to June 2020, delivers an average annualized return of 2.76% and a Sharpe ratio of 0.37 (Table 2.4), confirming its economic viability.

The Common Volatility Factor's negative and significant price impact suggests that assets with higher factor loadings earn lower expected returns, confirming its relevance in explaining cross-sectional differences. Incorporating the factor into the pricing model improves accuracy and reveals significant negative coefficients, as illustrated in Figure 2.5. Figure 2.1 further emphasizes the factor's resilience and distinctiveness when controlling for a variety of risk factors.

In summary, our analysis confirms the Common Volatility Factor's crucial role in enhancing equity pricing. Its unique nature, persistent significance, and negative correlation with standard factors demonstrate its potential to deepen our understanding of how volatility influences asset returns.

### 2.4.5 *Common Factor Volatility Factor - Robustness*

We conduct several robustness checks to validate our findings:

- **GLS Regression:** Re-estimating our models using Generalized Least Squares methods confirms the OLS results, reinforcing the stability of our factor estimates.
- **Spanning Test:** Spanning tests show that traditional risk factors do not explain the returns of our new measure, supporting the unique informational content of the common volatility factor.
- **Alternative Measures:** Employing alternative volatility proxies yields consistent results, mirroring those of our primary measure.
- **Second Principal Component:** While the first principal component remains dominant, the second component does not generate significant results.

After establishing a common volatility measure, we introduce multiple versions of it, as shown in Table 2.3. The Factor Volatility Factor (FVF) displays the expected patterns, confirming its significance across different specifications. These results align with our earlier findings for individual factor volatilities, where the common volatility measures consistently generate negative and significant coefficients. This implies that stocks with higher exposure to common volatility serve as hedges during periods of increased market uncertainty.

In Table 2.6, we apply a GLS estimation approach, shifting from a purely cross-sectional to a generalized framework. The results remain consistent, displaying negative coefficients across all tested specifications. Further, the regression analysis in Table 2.9 underscores the robustness of our conclusions. While the first principal component is highly influential, the second principal component adds limited explanatory value.

Overall, incorporating risk factor volatilities enhances pricing efficiency by increasing explanatory power, reducing pricing errors, and consistently producing robust, negative coefficients across a wide range of models.

### 2.4.6 Income Growth Dispersion

Finally, we investigate the relationship between our common volatility measures and various forms of income dispersion. Since the Common Volatility Factor appears to function as a hedge during economic downturns, understanding its correlation with employment, wages, earnings, house prices, sectoral, and global growth dispersion provides additional economic context. Dispersion serves as a proxy for heightened idiosyncratic risk faced by individuals in the economy.

Table 2.8 presents these correlations. Three measures stand out—Common Risk Factor Volatility, Common Global Risk Factor Volatility, and Common Sector Volatility—due to their strong correlations with our income dispersion variables. We find that changes in these volatility measures are closely associated with increases in income dispersion at both domestic and global levels.

As firm-level risks and household income risk rise during economic downturns, these changes influence asset prices through shifts in product demand, portfolio rebalancing, or other channels beyond the scope of our current analysis. Our evidence of a strong positive correlation between common volatility measures and income risk underscores their economic relevance.

## 2.5 Conclusion

This paper investigated the influence of factor volatility on the cross-section of stock returns and examined how common factor volatility relates to measures of income risk. Our analysis of 153 risk factors reveals that changes in factor volatilities are significantly priced in 122 cases (when combined with the Fama-French Five factors and the factor itself), showing the importance of incorporating factor volatilities into asset pricing models. Additionally, utilizing various robustness checks, including GLS regressions, confirms that our core findings remain stable under different estimation methods.

Principal component analysis (PCA) indicates that the first principal component of these 153 factor volatilities explains 91% of the total variance and is uncorrelated with the underlying risk factors. This discovery highlights the presence of a distinct, common factor volatility component. Importantly, while the first principal component consistently proves significant, the second principal component does not yield meaningful results, reinforcing the dominance and unique relevance of the first factor in explaining cross-sectional return variation. Introducing both tradable and non-tradable versions of this common volatility factor further substantiates its economic value, as the tradable factor delivers robust returns and remains largely unspanned by conventional risk factors.

In addition to its influence on stock returns, the common factor volatility also shows strong connections to macroeconomic conditions. Our results link it positively to earnings, employment, house prices, wages, and GDP growth, suggesting that it serves as a meaningful bridge between financial markets and broader economic risks. Moreover, the factor's predictive ability is not limited to one particular volatility measure; employing alternative volatility proxies or controlling for market volatility does not diminish its explanatory power. Incorporating different measures of common volatility into pricing models improves their accuracy and reduces pricing errors, providing a more nuanced understanding of the risk structure in equity markets.

In summary, this study contributes to the existing literature by demonstrating that changes in factor volatilities are significant drivers of cross-sectional stock returns, even after controlling for standard factors and market volatility. We also identify a dominant common factor volatility component that is distinct from known risk factors and robust to various specifications, including GLS estimation and alternative volatility measures. Moreover we show that portfolios with higher exposure to common factor volatility serve as hedges against volatility spikes, resulting in lower expected returns and underscoring the factor's economic interpretation. The study also establishes a strong link between common factor volatility and macroeconomic risk proxies, strengthening its relevance for both asset pricing and risk management strategies.

These findings deepen our understanding of factor volatilities and their significance in financial markets, highlighting the need for asset pricing models to incorporate these elements for improved risk evaluation and more accurate return predictions.

## 2.6 Tables and Figures

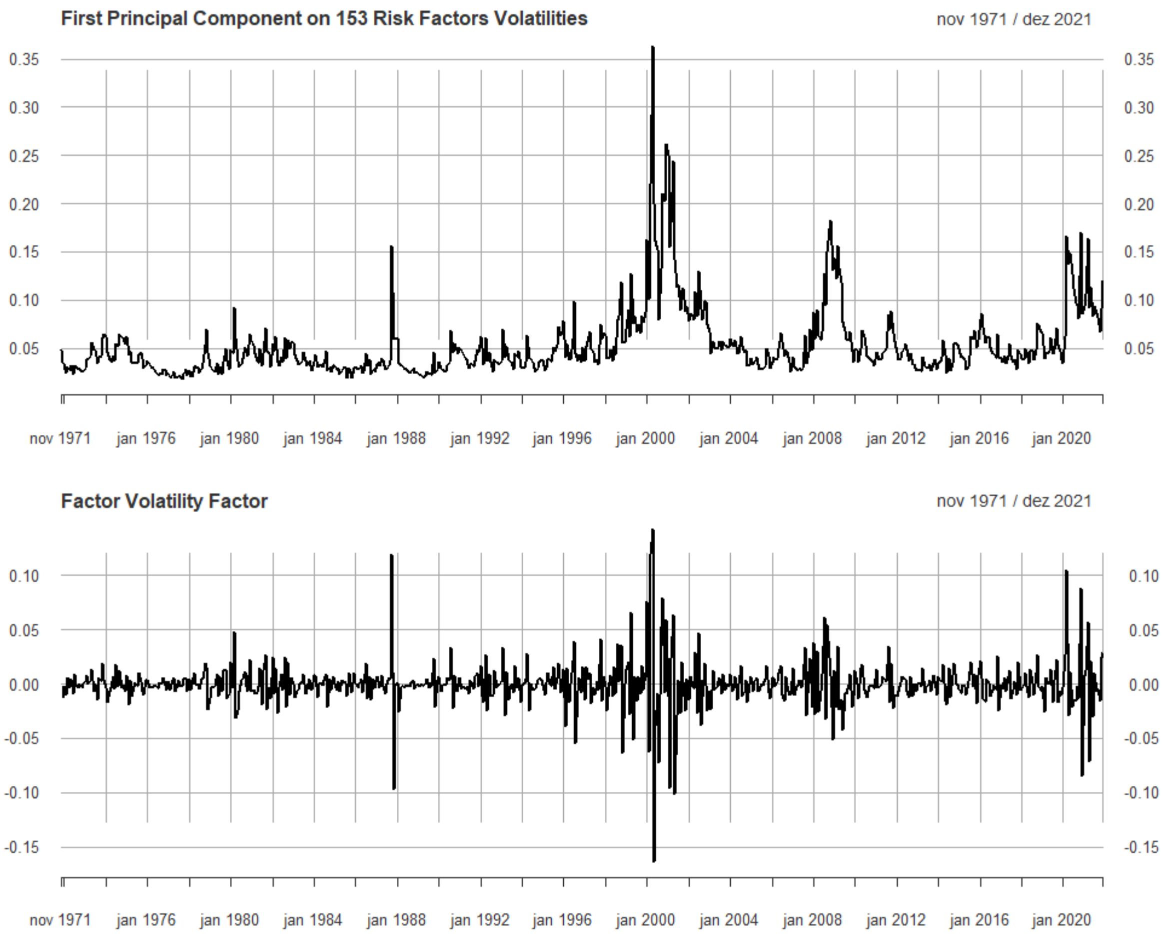



Figura 2.1 – Historical FVF

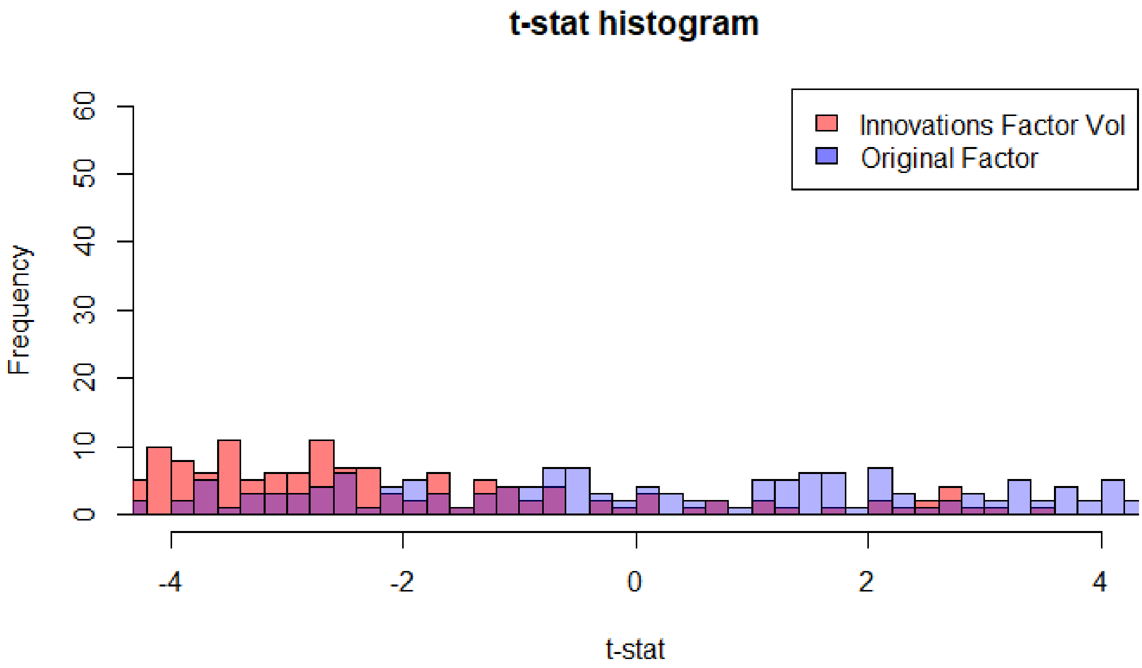



Figura 2.2 – Histogram of t-stats

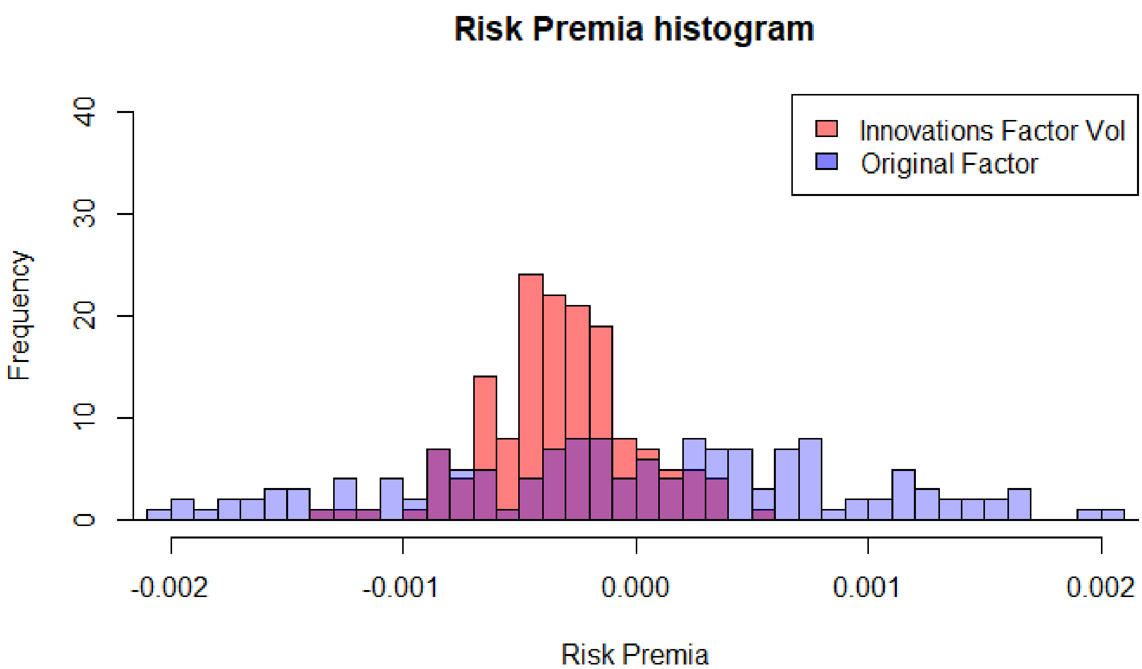



Figura 2.3 – Histogram of coefficients

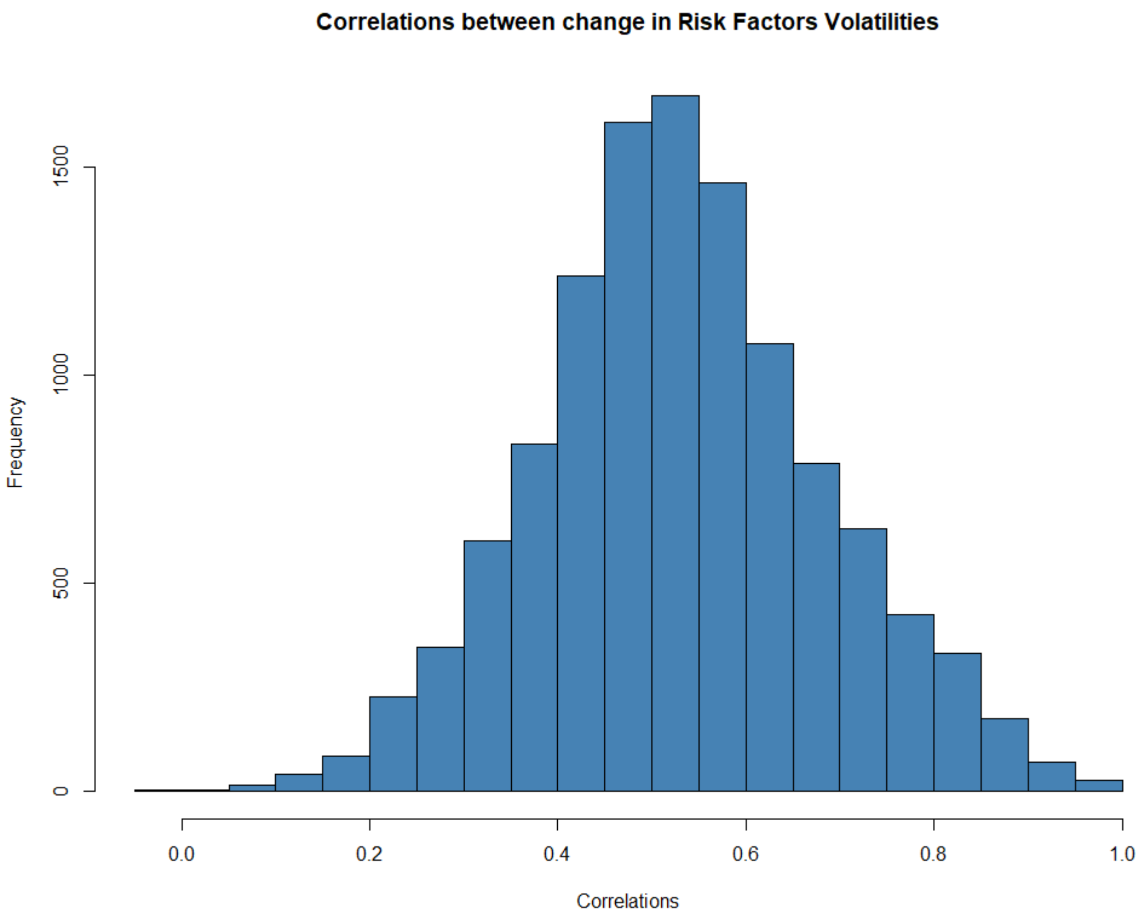



Figura 2.4 – Individual Factor Volatility Factors: Correlations and PCA

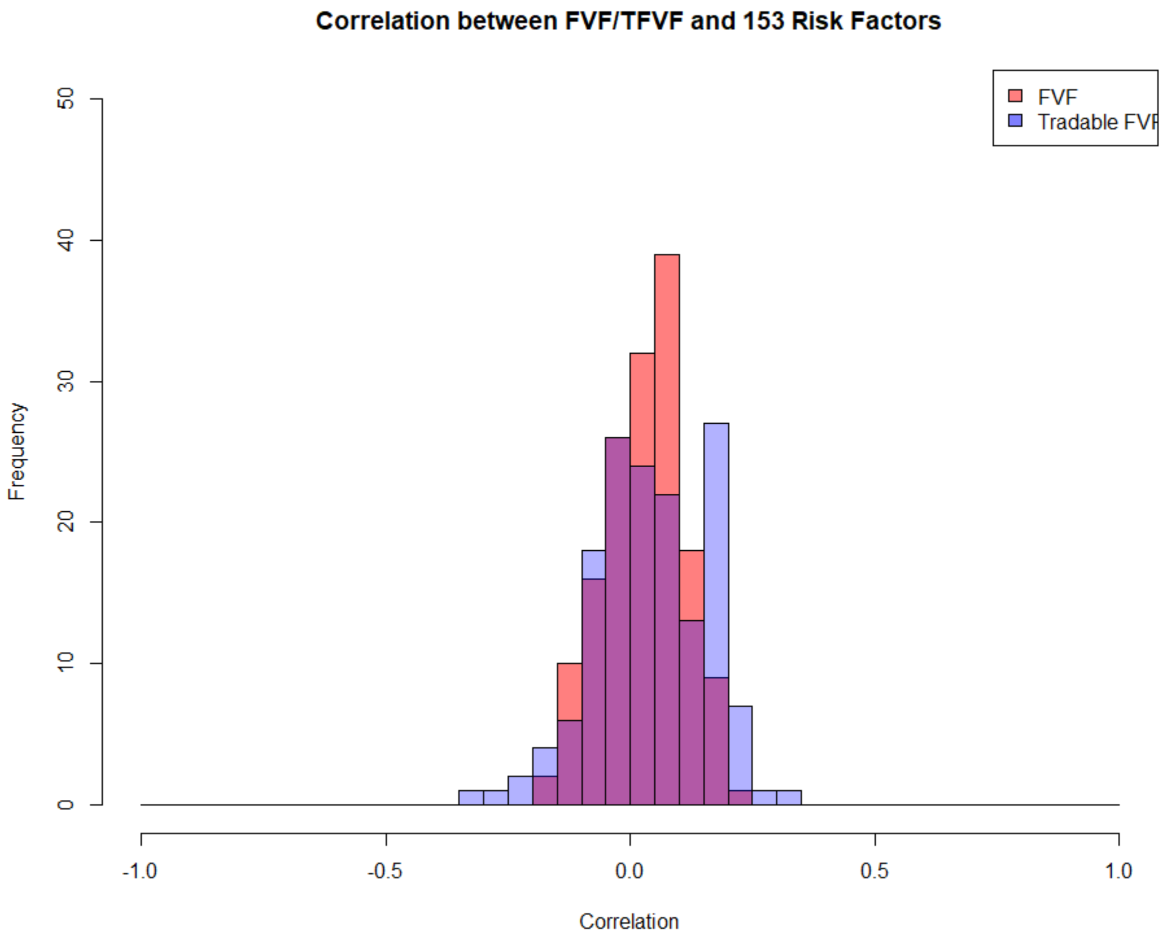



Figura 2.5 – Common Factor Volatility Factor: Histogram of Correlation to Traditional Factors

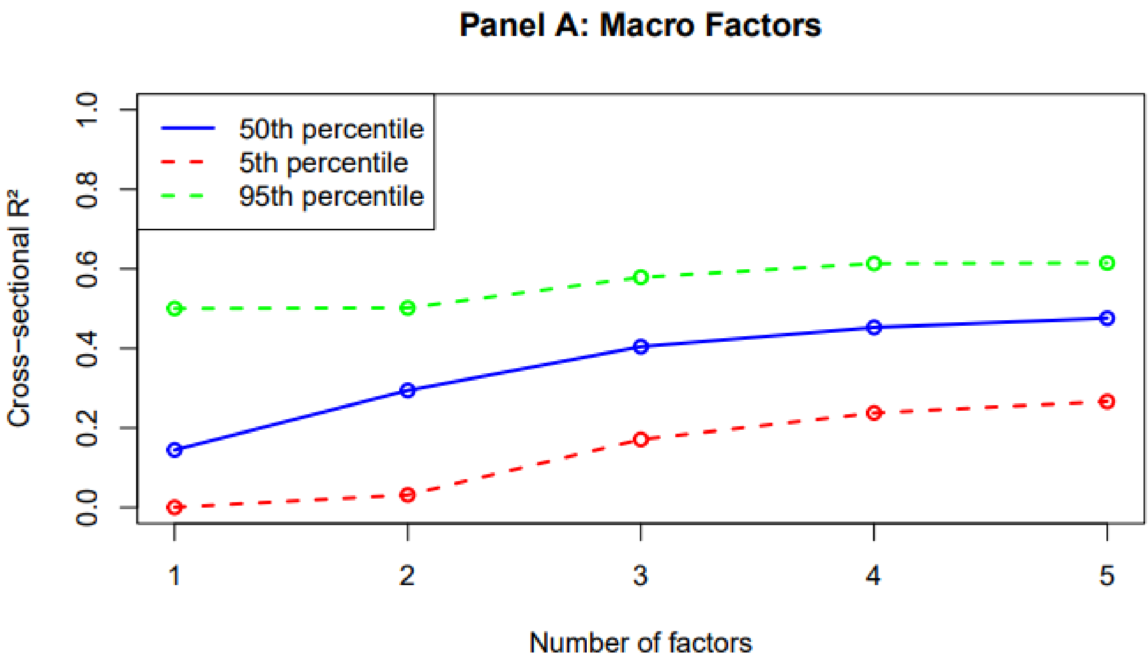



Figura 2.6 – Population R2s for artificial factors. Macro factors are generated by randomly drawing weights for the factors. GLS regressions are used.

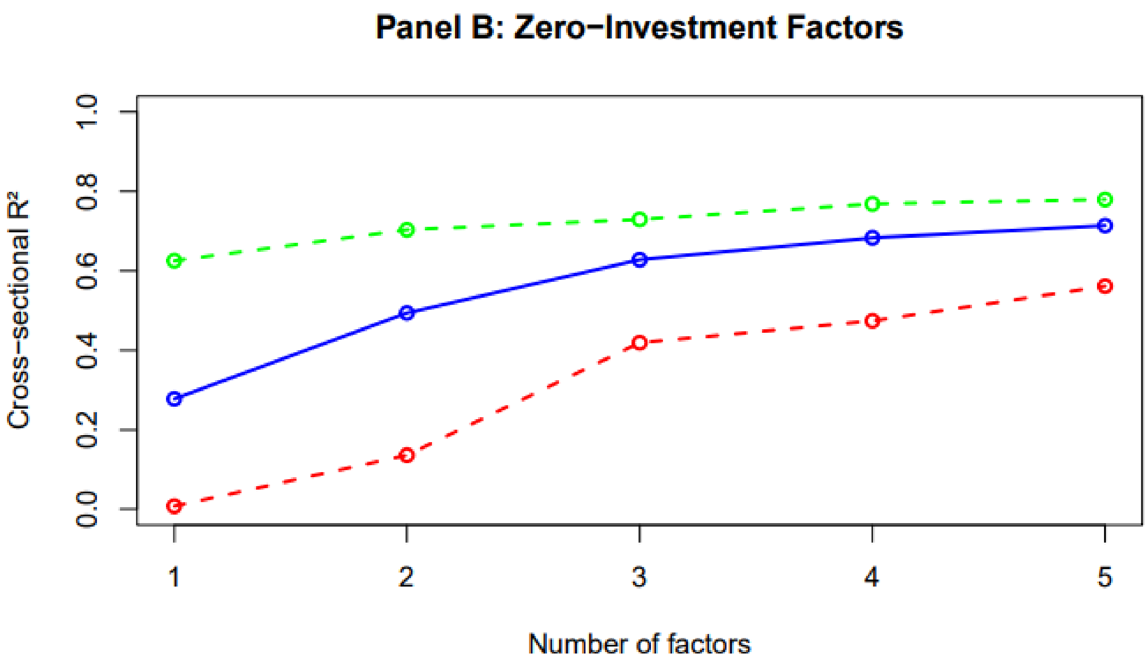



Figura 2.7 – Population R2s for artificial factors. Macro factors are generated by randomly drawing weights for the anomaly portfolios. GLS regressions are used.

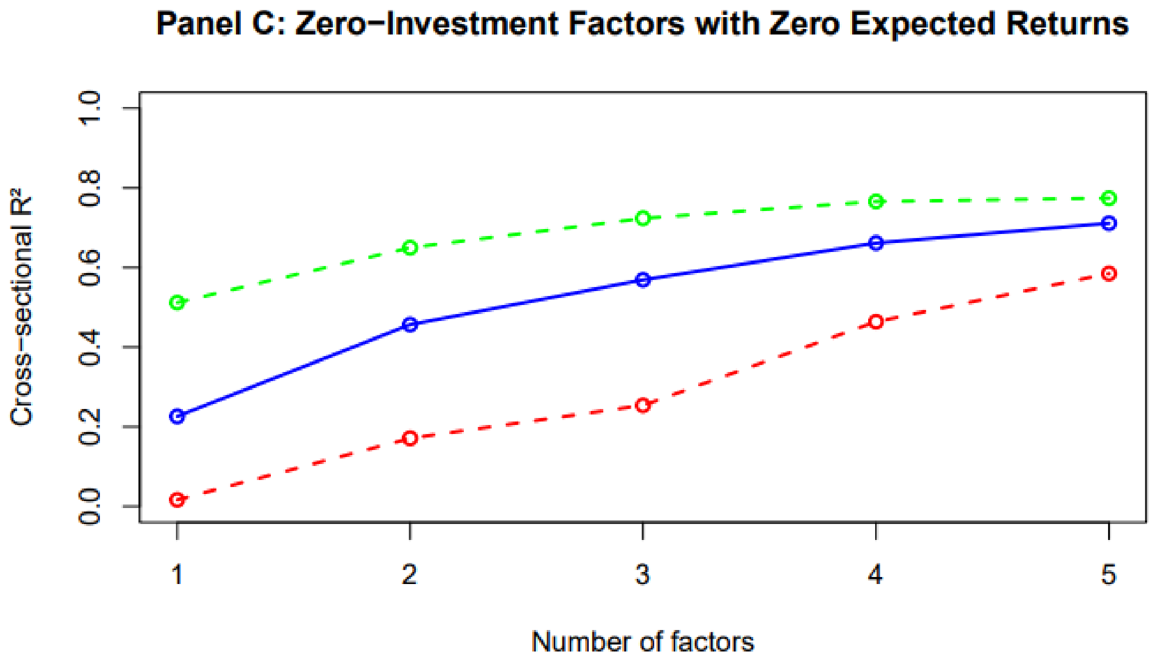



Figura 2.8 – Population R2s for artificial factors. Macro factors are generated by randomly drawing weights for the factors, but only factors with zero expected returns are retained. GLS regressions are used.

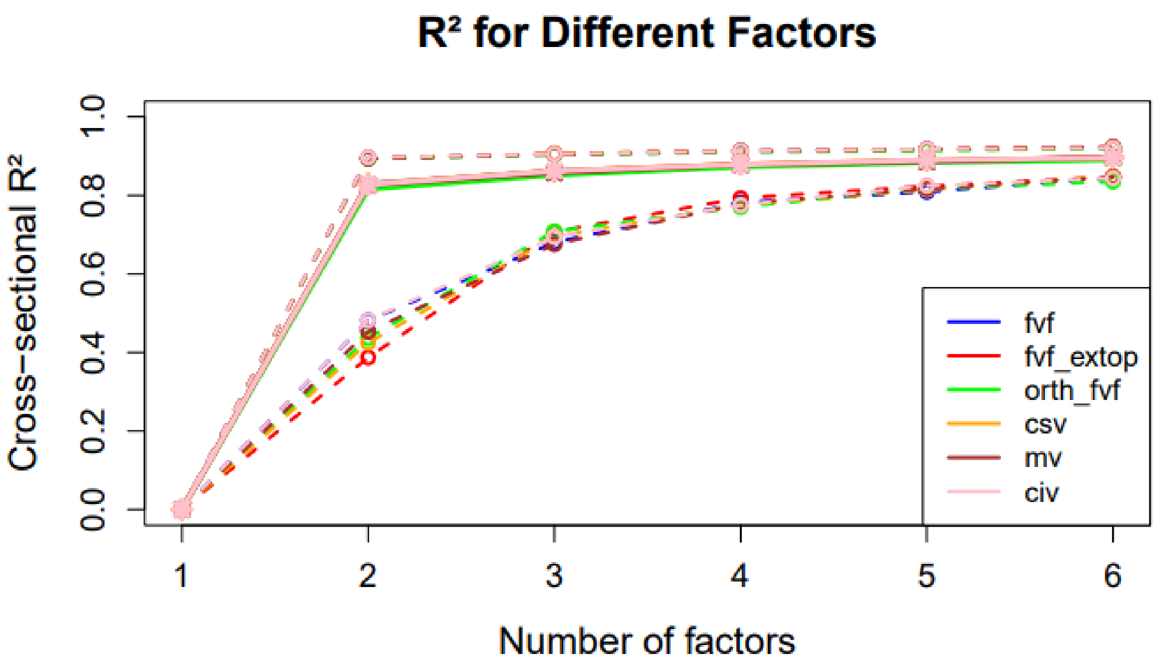



Figura 2.9 – Population R2s for artificial factors. Macro factors are generated by randomly drawing weights for the factors. Cross-Sectional OLS is used.

| Risk Factor | FM Coef. | t-stat. | Risk Factor | FM coef. | t-stat. | Risk Factor | FM coef. | t-stat. |
|---|---|---|---|---|---|---|---|---|
| age | -0.0003 | -2.0800 | fnl_gr1a | -0.0002 | -3.9790 | prc | -0.0003 | -2.4394 |
| aliq_at | -0.0007 | -4.1042 | gp_at | -0.0006 | -4.5952 | prc_highprc_252d | -0.0004 | -1.6783 |
| aliq_mat | -0.0005 | -4.1848 | gp_atl1 | -0.0008 | -5.2633 | qmj | -0.0002 | -1.6227 |
| ami_126d | -0.0005 | -3.6168 | inv_gr1 | -0.0004 | -3.8998 | qmj_growth | -0.0003 | -3.6442 |
| at_be | -0.0001 | -1.1432 | inv_gr1a | -0.0002 | -2.9341 | qmj_prof | 0.0001 | 1.1652 |
| at_gr1 | -0.0007 | -4.9485 | iskew_capm_21d | -0.0003 | -3.0322 | qmj_safety | -0.0007 | -4.6786 |
| at_me | -0.0005 | -2.7094 | iskew_ff3_21d | 0.0000 | -0.6304 | rd5_at | -0.0003 | -1.7303 |
| at_turnover | -0.0004 | -3.6287 | iskew_hxz4_21d | -0.0002 | -2.2541 | rd_me | -0.0001 | -0.8268 |
| be_gr1a | -0.0006 | -4.2382 | ival_me | -0.0003 | -2.1538 | rd_sale | -0.0002 | -1.1043 |
| be_me | -0.0005 | -2.6832 | ivol_capm_21d | -0.0008 | -3.4746 | resff3_12_1 | -0.0001 | -1.1593 |
| beta_60m | -0.0007 | -3.5296 | ivol_capm_252d | -0.0006 | -2.5532 | resff3_6_1 | -0.0004 | -2.7608 |
| beta_dimson_21d | -0.0007 | -3.5990 | ivol_ff3_21d | -0.0008 | -3.5523 | ret_12_1 | -0.0002 | -1.2176 |
| betabab_1260d | -0.0013 | -4.9615 | ivol_hxz4_21d | -0.0008 | -3.5406 | ret_12_7 | -0.0007 | -3.5041 |
| betadown_252d | -0.0012 | -5.2751 | kz_index | -0.0003 | -2.5877 | ret_1_0 | 0.0005 | 2.0599 |
| bev_mev | -0.0005 | -2.7113 | lnoa_gr1a | -0.0001 | -1.6148 | ret_3_1 | 0.0000 | 0.0383 |
| bidaskhl_21d | -0.0006 | -3.2849 | lti_gr1a | -0.0001 | -3.4843 | ret_60_12 | -0.0003 | -2.5832 |
| capex_abn | 0.0000 | -0.2883 | market_equity | -0.0007 | -3.9431 | ret_6_1 | -0.0003 | -1.6180 |
| capx_gr1 | -0.0004 | -3.6033 | mispricing_mgmt | -0.0005 | -3.9185 | ret_9_1 | -0.0001 | -0.7039 |
| capx_gr2 | -0.0004 | -3.9341 | mispricing_perf | -0.0004 | -3.1474 | rmax1_21d | -0.0010 | -3.8471 |
| capx_gr3 | -0.0005 | -4.1624 | ncoa_gr1a | -0.0001 | -1.8256 | rmax5_21d | -0.0011 | -4.0968 |
| cash_at | -0.0003 | -1.7963 | ncol_gr1a | 0.0000 | 0.5754 | rmax5_rvol_21d | -0.0005 | -2.2832 |
| chcsho_12m | -0.0004 | -2.9155 | netdebt_me | -0.0005 | -3.1788 | rskew_21d | -0.0001 | -0.8616 |
| coa_gr1a | -0.0005 | -4.3036 | netis_at | -0.0003 | -2.3891 | rvol_21d | -0.0009 | -3.5635 |
| col_gr1a | -0.0006 | -4.4337 | nfna_gr1a | -0.0003 | -5.5689 | sale_bev | -0.0003 | -2.9929 |
| cop_at | 0.0000 | -0.2401 | ni_ar1 | -0.0002 | -4.6275 | sale_emp_gr1 | -0.0005 | -5.6532 |
| cop_atl1 | -0.0003 | -2.5987 | ni_be | 0.0001 | 1.3233 | sale_gr1 | -0.0006 | -4.1485 |
| corr_1260d | -0.0009 | -5.0664 | ni_inc8q | -0.0002 | -3.3060 | sale_gr3 | -0.0005 | -4.0085 |
| coskew_21d | -0.0002 | -1.4108 | ni_ivol | -0.0004 | -2.4156 | sale_me | -0.0002 | -1.2228 |
| cowc_gr1a | -0.0003 | -4.0680 | ni_me | -0.0006 | -2.9021 | saleq_gr1 | -0.0004 | -2.6767 |
| dbnetis_at | -0.0001 | -2.8418 | niq_at | 0.0004 | 3.0531 | saleq_su | -0.0003 | -3.2140 |
| debt_gr3 | -0.0002 | -4.1795 | niq_at_chg1 | -0.0003 | -4.3231 | seas_11_15an | -0.0004 | -3.5422 |
| debt_me | -0.0004 | -2.7805 | niq_be | 0.0003 | 2.5003 | seas_11_15na | 0.0003 | 2.7915 |
| dgp_dsale | -0.0005 | -5.6448 | niq_be_chg1 | -0.0002 | -3.0853 | seas_16_20an | -0.0004 | -3.2436 |
| div12m_me | -0.0008 | -3.7648 | niq_su | -0.0002 | -2.6119 | seas_16_20na | -0.0002 | -1.9996 |
| dolvol_126d | -0.0007 | -4.6945 | nncoa_gr1a | 0.0000 | 0.0462 | seas_1_1an | -0.0005 | -2.7055 |
| dolvol_var_126d | 0.0003 | 2.1739 | noa_at | 0.0002 | 2.7343 | seas_1_1na | -0.0003 | -1.3449 |
| dsale_dinv | -0.0003 | -5.3531 | noa_gr1a | -0.0001 | -1.0078 | seas_2_5an | 0.0000 | -0.0009 |
| dsale_drec | -0.0001 | -2.3165 | o_score | -0.0001 | -0.7496 | seas_2_5na | -0.0007 | -4.3804 |
| dsale_dsga | -0.0004 | -4.8529 | oaccruals_at | -0.0003 | -3.0675 | seas_6_10an | -0.0006 | -3.9111 |
| earnings_variability | -0.0003 | -2.7414 | oaccruals_ni | -0.0003 | -4.4287 | seas_6_10na | -0.0001 | -0.7721 |
| ebit_bev | 0.0003 | 2.9699 | ocf_at | 0.0003 | 2.7799 | sti_gr1a | -0.0002 | -3.9174 |
| ebit_sale | 0.0000 | 0.1455 | ocf_at_chg1 | -0.0003 | -5.3654 | taccruals_at | -0.0003 | -3.1929 |
| ebitda_mev | -0.0004 | -2.1118 | ocf_me | -0.0002 | -1.3861 | taccruals_ni | -0.0003 | -4.0483 |
| emp_gr1 | -0.0005 | -4.1808 | ocfq_saleq_std | -0.0003 | -2.3551 | tangibility | 0.0002 | 2.2900 |
| eq_dur | -0.0006 | -3.4343 | op_at | 0.0001 | 0.6902 | tax_gr1a | -0.0006 | -5.9482 |
| eqnetis_at | -0.0004 | -2.6323 | op_atl1 | -0.0003 | -2.3376 | turnover_126d | -0.0004 | -2.4572 |
| eqnpo_12m | -0.0005 | -2.8087 | ope_be | 0.0001 | 1.6524 | turnover_var_126d | 0.0001 | 0.6053 |
| eqnpo_me | -0.0007 | -3.6316 | ope_bel1 | 0.0004 | 3.5950 | z_score | -0.0006 | -4.3312 |
| eqpo_me | -0.0005 | -2.3865 | opex_at | -0.0006 | -5.0820 | zero_trades_126d | -0.0005 | -2.6308 |
| f_score | 0.0002 | 2.4563 | pi_nix | 0.0000 | 1.0830 | zero_trades_21d | -0.0007 | -3.5017 |
| fcf_me | 0.0003 | 2.6645 | ppeinv_gr1a | -0.0001 | -1.3376 | zero_trades_252d | -0.0006 | -3.2720 |

This table reports the regression coefficients (Estimates) and t-statistic from a Fama-Macbeth regression that includes Fama-French 5 factors, the risk factors themselves and changes to the risk factor volatility. Risk Factor column is the name of the risk factor added on the Fama-Macbeth regression, FM coef. column displays the coefficient from the Fama-Macbeth regression and the t-stat column is the t-statistic from the Fama-Macbeth regression.

Tabela 2.1 – Fama-Macbeth Regressions of changes to risk factors volatility from 153 risk factor list studied one at a time

| | PC1 | PC2 | PC3 | PC4 | PC5 |
|---|---|---|---|---|---|
| Standard deviation | 0.0636 | 0.0105 | 0.0071 | 0.0064 | 0.0049 |
| Proportion of Variance | 0.9109 | 0.0249 | 0.0114 | 0.0093 | 0.0054 |
| Cumulative Proportion | 0.9109 | 0.9357 | 0.9472 | 0.9565 | 0.9619 |

Summary statistics of the PCA applied to the realized volatility from the 153 risk factors. We can see that the first PC explains almost 91% of the total variance, indicating the presence of a common volatility component among the risk factors.

Tabela 2.2 – PCA on 153 Risk Factor Volatilities

| Parameter | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Intercept | -0.0033 | -0.0033 | -0.0032 | -0.0032 | -0.0033 | -0.0032 | -0.0032 |
| | -22.6494 | -22.8355 | -21.5640 | -21.2922 | -21.6170 | -21.0267 | -20.2791 |
| FVF | -0.0054 | | | | | | |
| | -2.2259 | | | | | | |
| FVF ex top15 | | -0.0043 | | | | | |
| | | -2.1326 | | | | | |
| FVF orth MV | | | -0.0864 | | | | |
| | | | -1.7701 | | | | |
| SVF | | | | -0.0045 | | | |
| | | | | -2.2966 | | | |
| GRFVF | | | | | -0.0013 | | |
| | | | | | -2.4871 | | |
| MV | | | | | | -0.0008 | |
| | | | | | | -2.3629 | |
| CIV | | | | | | | 0.0044 |
| | | | | | | | 0.4682 |
| MKT | 0.0089 | 0.0089 | 0.0088 | 0.0087 | 0.0086 | 0.0087 | 0.0087 |
| | 4.6539 | 4.6495 | 4.6242 | 4.5487 | 4.5597 | 4.5508 | 4.5720 |
| SMB | 0.0017 | 0.0017 | 0.0018 | 0.0017 | 0.0027 | 0.0017 | 0.0018 |
| | 1.2387 | 1.2346 | 1.3103 | 1.2440 | 2.0333 | 1.2501 | 1.3166 |
| HML | 0.0010 | 0.0009 | 0.0008 | 0.0006 | -0.0006 | 0.0006 | 0.0007 |
| | 0.7462 | 0.7019 | 0.5967 | 0.4494 | -0.4766 | 0.4208 | 0.5402 |
| RMW | 0.0029 | 0.0029 | 0.0029 | 0.0031 | 0.0043 | 0.0031 | 0.0030 |
| | 2.6132 | 2.6387 | 2.6496 | 2.7613 | 4.0188 | 2.7839 | 2.7247 |
| CMA | 0.0024 | 0.0024 | 0.0026 | 0.0026 | 0.0025 | 0.0026 | 0.0026 |
| | 2.5385 | 2.5457 | 2.6798 | 2.6871 | 2.7699 | 2.7051 | 2.6762 |
| R2 | 0.4190 | 0.4185 | 0.4135 | 0.4106 | 0.4047 | 0.4095 | 0.4184 |
| RMSE | 0.0159 | 0.0159 | 0.0160 | 0.0161 | 0.0162 | 0.0161 | 0.0159 |

This table reports the regression coefficients (Estimates) of a Fama-Macbeth analysis that relates the anomaly portfolios from Kozak to the market factor (MKT), size (SMB), value (HML), investment (CMA), operating profitability (RMW) and changes to our common volatility measures created. The values bellow the estimates are the t-statistics for the coefficients.

Tabela 2.3 – Pricing analysis (Anomaly portfolios)

| Summary Statistics | FVF 21d | FVF 42d | FVF 63d | FVF 120d | FVF 252d |
|---|---|---|---|---|---|
| Annualized Returns | 0.0276 | 0.0229 | 0.0231 | 0.0123 | 0.0052 |
| Volatility | 0.0736 | 0.0812 | 0.0869 | 0.0949 | 0.1044 |
| Sharpe Ratio | 0.3702 | 0.2796 | 0.2634 | 0.1291 | 0.0500 |
| Corr. MKT | -0.1318 | -0.1042 | -0.1203 | -0.1440 | -0.1786 |
| Alpha CAPM | 0.0318 | 0.0266 | 0.0276 | 0.0182 | 0.0132 |
| Alpha T-Stat CAPM | 2.9361 | 2.2236 | 2.1631 | 1.3115 | 0.8708 |
| Alpha FF3 | 0.0268 | 0.0209 | 0.0205 | 0.0082 | -0.0001 |
| Alpha T-Stat FF3 | 2.6248 | 1.9995 | 1.8898 | 0.7836 | -0.0074 |
| Alpha FF5 | 0.0304 | 0.0196 | 0.0179 | 0.0047 | -0.0079 |
| Alpha T-Stat FF5 | 2.9371 | 1.8699 | 1.6533 | 0.4498 | -0.8081 |

Tabela 2.4 – Summary Statistics of Tradable FVF

| Statistic | FVF | TFVF |
|---|---|---|
| Min. | -0.16 | -0.32 |
| 1st Qu. | -0.02 | -0.02 |
| Median | 0.04 | 0.04 |
| Mean | 0.03 | 0.04 |
| 3rd Qu. | 0.08 | 0.14 |
| Max. | 0.20 | 0.33 |

First PC refers to the First Principal Component of the 153 risk factors volatilities. FVF refers to the Factor Volatility Factor, which is obtained from a long-short portfolio using common volatility exposition of industry portfolios.CIV refers to the Common Idiosyncratic Volatility from Herskovic et al.

Tabela 2.5 – Common Factor Volatility Factors: Correlations to Standard Factors

| Parameter | 1 | 2 | 3 |
|---|---|---|---|
| FVF | | -0.0054 | |
| | | -4.9634 | |
| TFVF | | | -0.0028 |
| | | | -4.7548 |
| Intercept | -0.0032 | -0.0033 | -0.0033 |
| | -14.0375 | -14.6525 | -14.7560 |
| MKT | 0.0087 | 0.0089 | 0.0090 |
| | 36.6954 | 37.5895 | 37.5695 |
| SMB | 0.0017 | 0.0017 | 0.0017 |
| | 4.2946 | 4.3144 | 4.3950 |
| HML | 0.0006 | 0.0010 | 0.0012 |
| | 1.8057 | 2.9883 | 3.3749 |
| RMW | 0.0031 | 0.0029 | 0.0028 |
| | 8.3617 | 7.8360 | 7.6769 |
| CMA | 0.0026 | 0.0024 | 0.0024 |
| | 7.4124 | 6.8726 | 6.8135 |
| R2 | 0.7586 | 0.7677 | 0.7685 |
| RMSE | 0.0015 | 0.0015 | 0.0014 |

This table reports the regression coefficients (Estimates) of a GLS analysis that relates the anomaly portfolios to the market return (MKT), size (SMB), value (HML), investment (CMA), operating profitability (RMW), changes to the non-tradable Common Risk Factor Volatility (FVF) measure and the tradable factor (TFVF). The values bellow the estimates are the t-statistics for the coefficients.

Tabela 2.6 – GLS Pricing analysis (BM, ME, OPP, INV portfolios)

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | tfvf | | | fvf | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Constant | 0.002** | 0.002** | 0.002*** | 0.052*** | 0.052*** | 0.053*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| MKT | 0.038* | 0.026 | 0.035* | −0.132*** | −0.081** | −0.067* |
| | (0.020) | (0.021) | (0.020) | (0.034) | (0.036) | (0.036) |
| SMB | −0.339*** | −0.287*** | −0.258*** | −0.042 | 0.017 | 0.065 |
| | (0.029) | (0.030) | (0.030) | (0.051) | (0.053) | (0.053) |
| HML | 0.226*** | 0.285*** | 0.315*** | 0.070 | −0.089 | −0.039 |
| | (0.029) | (0.038) | (0.037) | (0.051) | (0.067) | (0.066) |
| RMW | | 0.181*** | 0.279*** | | 0.264*** | 0.424*** |
| | | (0.040) | (0.042) | | (0.071) | (0.075) |
| CMA | | −0.193*** | −0.137** | | 0.335*** | 0.427*** |
| | | (0.062) | (0.061) | | (0.109) | (0.108) |
| BAB | | | −0.159*** | | | −0.263*** |
| | | | (0.027) | | | (0.048) |
| Observations | 570 | 570 | 570 | 570 | 570 | 570 |
| $R^2$ | 0.257 | 0.300 | 0.342 | 0.041 | 0.074 | 0.122 |
| Adjusted $R^2$ | 0.253 | 0.294 | 0.335 | 0.035 | 0.066 | 0.112 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the regression coefficients (Estimates) of a linear regression analysis that relates the Factor Volatility Factor (tradable common volatility factor) returns to the market return (MKT), size (SMB), value (HML), investment (CMA), operating profitability (RMW), Betting Against Beta (BAB) factor. The values in the parentheses are standard deviations from coefficients estimates.

Tabela 2.7 – Common Factor Volatility Factors: Spanning Test

| | Earnings Dispersion | Earnings Variance | Employment | Wages | House Prices | Sector | Global |
|---|---|---|---|---|---|---|---|
| FVF | 0.353 | 0.360 | 0.715 | 0.223 | 0.208 | 0.399 | 0.193 |
| CSV | 0.486 | 0.495 | 0.485 | 0.497 | 0.257 | 0.180 | 0.449 |
| CGV | 0.615 | 0.592 | 0.520 | 0.448 | 0.181 | 0.190 | 0.524 |
| MV | 0.489 | 0.485 | 0.532 | 0.434 | 0.226 | 0.193 | 0.429 |
| CIV | 0.433 | 0.435 | 0.586 | 0.294 | 0.274 | 0.363 | 0.255 |

The table shows the correlation between changes in different common volatility measures and growth dispersion innovations for the period 1990-2017.

Tabela 2.8 – Correlation between common volatility and growth dispersion innovations (1990-2020)

| Parameter | 1 | 2 | 3 |
|---|---|---|---|
| Intercept | -0.0032 | -0.0033 | -0.0032 |
| | -20.2625 | -22.7128 | -20.3778 |
| FVF (PC1) | | -0.0054 | |
| | | -2.2448 | |
| FVF (PC2) | | | 0.0004 |
| | | | 0.9563 |
| MKT | 0.0087 | 0.0089 | 0.0087 |
| | 4.5435 | 4.6534 | 4.5421 |
| SMB | 0.0017 | 0.0017 | 0.0017 |
| | 1.2551 | 1.2302 | 1.2577 |
| HML | 0.0006 | 0.0010 | 0.0006 |
| | 0.4300 | 0.7473 | 0.4332 |
| RMW | 0.0031 | 0.0029 | 0.0031 |
| | 2.7877 | 2.6128 | 2.7868 |
| CMA | 0.0026 | 0.0024 | 0.0026 |
| | 2.7095 | 2.5370 | 2.7284 |
| R2 | 0.4053 | 0.4192 | 0.4133 |
| RMSE | 0.0162 | 0.0159 | 0.0160 |

This table presents the Fama-Macbeth regression results for the Second Principal Component Analysis. Parameters include the Intercept, Market Beta (Beta Market), Size Beta (Beta SMB), Value Beta (Beta HML), Profitability Beta (Beta RMW), Investment Beta (Beta CMA), and the first and second principal components of Fama-French volatility factors (Beta FVF PC1 and Beta FVF PC2). The R-squared (R2) and Root Mean Square Error (RMSE) values are reported to evaluate model fit. Each column represents a different regression model, showcasing the impact of each parameter across models. Numbers bellow estimates are t-stats.

Tabela 2.9 – Second Principal Component Analysis - FM Regression

| Parameter | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Intercept | -0.0033 | -0.0033 | -0.0033 | -0.0032 | -0.0033 | -0.0033 |
| | -22.7608 | -22.0366 | -22.6158 | -21.4611 | -22.8367 | -22.3099 |
| FVF | -0.0053 | | -0.0046 | | -0.0046 | |
| | -2.4001 | | -2.4906 | | -2.5080 | |
| FVF orth MV | | -0.0889 | | -0.0719 | | -0.0666 |
| | | -1.8422 | | -1.9022 | | -1.8029 |
| MV | -0.0009 | -0.0008 | | | -0.0009 | -0.0009 |
| | -2.4731 | -2.4045 | | | -2.5474 | -2.5257 |
| CIV | | | -0.0094 | -0.0028 | -0.0095 | -0.0047 |
| | | | -1.3906 | -0.3633 | -1.3949 | -0.6377 |
| MKT | 0.0089 | 0.0088 | 0.0089 | 0.0089 | 0.0089 | 0.0089 |
| | 4.6566 | 4.6236 | 4.6684 | 4.6366 | 4.6678 | 4.6438 |
| SMB | 0.0017 | 0.0018 | 0.0017 | 0.0018 | 0.0018 | 0.0019 |
| | 1.2393 | 1.3038 | 1.2852 | 1.3474 | 1.2937 | 1.3634 |
| HML | 0.0010 | 0.0008 | 0.0011 | 0.0009 | 0.0011 | 0.0009 |
| | 0.7646 | 0.5814 | 0.8165 | 0.6628 | 0.8097 | 0.6738 |
| RMW | 0.0029 | 0.0029 | 0.0028 | 0.0029 | 0.0028 | 0.0028 |
| | 2.6105 | 2.6595 | 2.5598 | 2.6071 | 2.5562 | 2.5747 |
| CMA | 0.0024 | 0.0026 | 0.0024 | 0.0026 | 0.0024 | 0.0025 |
| | 2.5327 | 2.6791 | 2.5102 | 2.6613 | 2.5127 | 2.6393 |
| R2 | 0.4255 | 0.4181 | 0.4302 | 0.4245 | 0.4340 | 0.4292 |
| RMSE | 0.0158 | 0.0159 | 0.0157 | 0.0158 | 0.0157 | 0.0157 |

This table reports the regression coefficients (Estimates) of a Fama-Macbeth analysis that relates the anomaly portfolios from Kozak to the market factor (MKT), size (SMB), value (HML), investment (CMA), operating profitability (RMW) and changes to our common volatility measures created. The values bellow the estimates are the t-statistics for the coefficients.

Tabela 2.10 – Pricing analysis (Anomaly portfolios) - FVF with MV and CIV

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## 2.8 Appendix - Model

## Model Assumptions

We make the following key assumptions:

- **Linear Structure for $m_{t+1} = \ln(M_{t+1})$**: The log of the stochastic discount factor (SDF) $m_{t+1}$ is modeled as:

$$m_{t+1} = \alpha_M + \beta_M Z_{t+1} + \epsilon_{M,t+1}$$

  where $\beta_M$ is the vector of sensitivities of the SDF to the state variables $Z_{t+1}$, and $\epsilon_{M,t+1}$ is an idiosyncratic shock.

- **VAR Structure for $Z_t$ Generating Process**: The state variables $Z_t$, which include economic factors such as the return $r_t$ and a common volatility component, follow a first-order VAR process:

$$Z_{t+1} = \bar{Z} + \Gamma(Z_t - \bar{Z}) + \sigma_t u_{t+1}$$

  where $\bar{Z}$ is the long-run mean, $\Gamma$ is the autoregressive matrix, $\sigma_t$ is a diagonal matrix that represents time-varying volatility, with the first term bein market volatility, and the rest being common volatility, and $u_{t+1}$ is a vector of standard normal shocks.

- **Joint Log-Normality for Payoff $X_{t+1}$ and SDF $M_{t+1}$**: Both the payoff $X_{t+1}$ and the SDF $M_{t+1}$ are assumed to be jointly log-normal:

$$\ln(R_{t+1}) \sim \mathcal{N}(\mu_R, \sigma_R^2(Z_{t+1}))$$

$$\ln(M_{t+1}) \sim \mathcal{N}(\mu_M, \sigma_M^2(Z_{t+1}))$$

## Key Equations

## 1. Innovations to $m_{t+1}$ (SDF)

The innovation in the SDF refers to the unexpected part of $m_{t+1}$, which is the difference between its actual value and the expected value given information at time $t$.

First, we compute the expected value of $m_{t+1}$ given $Z_t$:

$$\mathbb{E}_t[m_{t+1}] = \alpha_M + \beta_M \mathbb{E}_t[Z_{t+1}]$$

From the VAR structure of $Z_t$:

$$\mathbb{E}_t[Z_{t+1}] = \bar{Z} + \Gamma(Z_t - \bar{Z})$$

Thus, the expected value of $m_{t+1}$ is:

$$\mathbb{E}_t[m_{t+1}] = \alpha_M + \beta_M \left(\bar{Z} + \Gamma(Z_t - \bar{Z})\right)$$

Now, the innovation in $m_{t+1}$ becomes:

$$m_{t+1} - \mathbb{E}_t[m_{t+1}] = \beta_M(Z_{t+1} - \mathbb{E}_t[Z_{t+1}]) + \epsilon_{M,t+1}$$

Substituting the VAR structure for $Z_{t+1}$:

$$Z_{t+1} - \mathbb{E}_t[Z_{t+1}] = \sigma_t u_{t+1}$$

Thus, the innovation in $m_{t+1}$ is:

$$m_{t+1} - \mathbb{E}_t[m_{t+1}] = \beta_M^\top \sigma_t u_{t+1} + \epsilon_{M,t+1}$$

# 2. Return Equation Derived from the Asset Pricing Equation

Because of the joint log-normality assumption, we can write the fundamental asset pricing equation as:

$$0 = \ln \mathbb{E}_t \exp\{m_{t+1} + r_{i,t+1}\} = \mathbb{E}_t[m_{t+1} + r_{i,t+1}] + \frac{1}{2}\mathrm{Var}_t[m_{t+1} + r_{i,t+1}]$$

Rearranging this equation:

$$0 = \mathbb{E}_t[m_{t+1}] + \mathbb{E}_t[r_{i,t+1}] + \frac{1}{2}\mathrm{Var}_t[m_{t+1}] + \frac{1}{2}\mathrm{Var}_t[r_{i,t+1}] + \mathrm{Cov}_t[r_{i,t+1}, m_{t+1} - \mathbb{E}_t m_{t+1}]$$

The term $\mathrm{Cov}_t[r_{i,t+1}, \beta_M^\top \sigma_t u_{t+1}]$ indicates that the expected return is affected by how much the return $r_{i,t+1}$ covaries with the shocks to the state variables, including risk factors and common volatility.

# 3. Risk Premia and Common Volatility

Note that the conditional mean of the log SDF innovation is zero, so that:

$$\mathrm{Cov}_t(r_{i,t+1}, m_{t+1} - \mathbb{E}_t m_{t+1}) = \mathbb{E}_t\left[r_{i,t+1}(m_{t+1} - \mathbb{E}_t m_{t+1})\right]$$

and

$$\mathbb{E}_t r_{i,t+1} + \frac{1}{2}\sigma_{it}^2 \simeq (\mathbb{E}_t R_{i,t+1} - 1)$$

Given any reference asset j (which could be but does not need to be the risk-free rate), we can now express the risk premium by rewriting the return equation:

$$\mathbb{E}_t[R_{i,t+1} - R_{j,t+1}] = -\mathbb{E}_t\left[(r_{i,t+1} - r_{j,t+1})(\beta_M^\top \sigma_t u_{t+1} + \epsilon_{M,t+1})\right]$$

## Final Unified Model

- **Innovation in SDF**: The innovation in the SDF $m_{t+1} - \mathbb{E}_t[m_{t+1}]$ is linearly dependent on shocks to risk factors and common volatility.
- **Expected Return Equation**: The expected return $\mathbb{E}_t[r_{i,t+1}]$ is determined by:
  - The expected value of the SDF.
  - Risk (variance) associated with the SDF and the asset returns.
  - The covariance between the returns and the innovation in the SDF, especially the part driven by common volatility.

This combination effectively shows how innovations in the SDF, driven by underlying risk factors and volatility, lead to the emergence of risk premia in expected returns. Assets that covary more with the common volatility component (and thus with the SDF innovations) will require higher expected returns as compensation for the higher risk they represent.

## Empirical Pricing Equation

The empirical form of the pricing equation can be written as:

$$R_{i,t+1} - R_{j,t+1} = \lambda_0 + \lambda_u^\top u_{t+1} + \epsilon_{i,t+1}$$

where:

- $\lambda_0$ is a constant that captures the average excess return.
- $\lambda_u^\top$ represents the loadings (or sensitivities) of excess returns to the shocks $u_{t+1}$, which include common volatility.
- $\epsilon_{i,t+1}$ is an idiosyncratic shock.

# 3 REPUBLICAN STOCKS PUZZLE


**Resumo**

We show that stocks tied to the Republican party consistently outperform those associated with Democrats, using data from 1928 to 2024. This pattern persists even during Democratic governments and is not explained by the business cycle, political cycle, sectoral biases, or other alternative explanations. To better understand these results, we construct a 'Republican Factor' by ranking abnormal stock returns on the day following U.S. elections. Remarkably, the returns generated by this 'Republican Factor' cannot be explained by conventional market factors.

## 3.1 Introduction

This paper explores the connection between politics and stock returns, focusing specifically on whether a firm's political alignment can serve as a predictor of its returns. The phenomenon of Democrat-led administrations being associated with higher excess returns in the US stock market - a puzzle first discussed by Santa-Clara and Valkanov (2003) and known as the "Presidential Puzzle- forms the basis of our inquiry. However, we tackle the cross-sectional implications of the political alignment, while this seminal paper studied the time series relationship. The relevance of this question is underscored by the work of several studies, such as Belo, Gala, and Li (2012), who found that this effect is most pronounced in industries heavily reliant on government spending, and Pástor and Veronesi (2020), who proposed a theoretical model to explain this effect. Meanwhile, studies by Shen and Lin (2015), Boubakri, Guedhami, Mishra and Saffar (2012), and Powell, Shi, Smith, and Whaley (2007) have further explored the links between politics and stock market performance, examining dimensions such as political connections, cost of capital, and the robustness of the "Presidential Puzzle". This paper aims to build on this body of literature, focusing specifically on the predictive power of firms' political leanings.

Our study's principal finding is that stocks associated with firms leaning toward the Republican party outperform those leaning toward the Democratic party, even during Democratic administrations. This finding holds even after accounting for conventional risk factors. This outperformance is typically higher during the second half of political mandates. Controls on legislative composition and close elections do not alter results, with republican firms still being underpriced. While we do not propose a definitive explanation for this puzzle, we do evaluate several alternative explanations associated with other characteristics potentially aligned with political affiliation, such as ESG corporate policies and other equity or macro driving factors.

To test this hypothesis, we propose the construction of a "Republican Factor". This factor aims to isolate and quantify the component of stock returns that remains unexplained by conventional risk factors the day after the U.S. elections. The "Republican Factor" implies maintaining a long position in "Republican" stocks while simultaneously holding a short position in "Democrat" stocks, classified using their abnormal performance. As a robustness to this classification method, we also build an alternative measure of Republican affiliation using political contributions. The alternative method is based on the model used by Luo, Manconi, and Massa (2020), where we define a firm as "Republican"by calculating the ratio $Rep/(Rep + Dem)$, where each stands for the firm's donations to each party. We do find that our "Republican Factor" goes long firms that, on average, contribute more substantially to the Republican party. Another version of our factor accounts just for firms that are persistent on their leanings, such that we constrain portfolio formation to firms that are classified as leaning to the same party for two consecutive elections. Results remains virtually the same, with Republican firms being underpriced.

We also examine alternative explanations that could justify our results, but all failed to explain this apparent anomaly. Firstly, we explore the role of political approval ratings, a variable that could be influencing the market's bias towards Republican candidates. Secondly, we examine business cycle variables such as industrial production, unemployment and recession indicators. Furthermore, we consider the potential influence of political uncertainty on stock returns. We test whether the observed performance around the election date is not necessarily due to their political leaning, but rather their sensitivity to the resolution of political uncertainty that elections bring about. If this were the case, high abnormal returns the day after an election would not necessarily indicate a “Republican” firm, but instead a firm benefiting from the reduction in political uncertainty. We also find no evidence that ESG firms cause the observed alpha. A possibility from the observed results is that Republican firms could be related to “sin stocks”. In order to test this explanation we include an ESG index in our model, however it does not help explaining the observed alpha from the 'Republican Factor'.

We find that our results are not due to the sectoral political biases. We analyze potential sectoral bias in our results by constructing two alternative factors – a Sector-Neutral Factor and a Sectoral Republican Factor. The former provides an intra-sector comparison, aiming to ascertain performance differentials within sectors while maintaining a balanced weight across all sectors. The latter, on the other hand, employs industry portfolios rather than individual stocks, aiming to discern if certain sectors show a preference for a specific political party, which could potentially contribute to generating alpha. Only the first version presents a significant alpha, implying that our results are not related to sectoral biases.

In this research, we explore a phenomenon within the field of political finance, showing that stocks associated with Republican-leaning firms are underpriced compared to their counterparts, resulting in a 'Republican Factor' that generates positive average returns over time. This outcome suggests possible biases in market participants who might undervalue firms based on political leanings, pointing towards inefficiencies in financial markets. Another possible channel is the influence of managers' political orientations on their management styles, potentially affecting company policies and risk profiles. Our study contributes to the existing literature by documenting the discovery of this pricing anomaly and initiating a discussion on potential explanations for its occurrence.

Our study is connected to a research from Chen, Da, Huang and Wang (2023), where they argue that ideology affects stocks performance, with firm's political alignment to incumbent government affecting how investors perceive and price them, with firms aligned to the current government under-performing those that are not. Their main channel, is related to how investors perceive those firms, leading to analysts underpricing or overpricing stocks based on alignment to incumbent government. We find contradictory results, since in our case 'Republican' stocks perform better being contrarians or not to the incumbent government. We run additional tests on our measure together with political donations and considering only persistently aligned firms, and argue that they are not exactly capturing firms alignment to the government. One piece of evidence is that the firms on the lowest decile on the incumbent president betas are also on the lowest decile on the former president betas. What this mean is that as government changes, the same firms continue to be considered contrarians. Moreover, betas on the firms considered aligned with the incumbent government are even higher with former presidents. It seems counterintuitive that firms considered 'Republicans' would be even more aligned with 'Democratic' policies and still be considered 'Republicans'. On the other side, we are selecting firms classified with the same party for consecutive elections and we also show that those firms donate more to the Republican party.

Our research stands also in the context of an evolving body of work that intersects political ideology with corporate management decisions and firm performance. One such strand of literature is exemplified by Kim, Kim, Krueger, and Unsal (2021), who argue that corporate policy decisions often mirror the political ideology of the management, citing evidence that Republican CEOs tend to face more lawsuits from employees, particularly for infringing union rights. Similarly, Karadas, Papakroni, and Schlosky (2022) shed light on how managerial political ideologies shape financial decisions, finding that Republican managers are inclined to reduce leverage amidst periods of high investor sentiment. Colonnelli, Pinho Neto, and Teso (2022) further substantiate the influence of political alignment on management decisions by demonstrating that business owners are more likely to hire and promote co-partisan workers, often paying them higher despite having lesser qualifications.

This study also aligns with investigations on the relationship between political connections, contributions, and firm performance. For instance, Sabherwal, Sarkar, and Uddin (2017) discovered that "sin"stocks, which contribute more to Republican candidates, tend to perform better during Republican presidencies. This performance, they found, was particularly pronounced when there was a Republican majority in Congress. Meanwhile, Boubakri, Cosset, and Saffar (2012) observed that establishing political connections led to an increase in firms' performance and indebtedness. Cooper, Gulen, and Ovtchinnikov (2010) took a different approach by creating a database of firm-level political campaign contributions from 1979 to 2004. They found a statistically significant positive relationship between the number of supported candidates and abnormal returns, noting an incremental effect for Democrats but not for Republicans. Aligning political ideology within the firm's leadership is another factor influencing performance, as evidenced by Lee, Lee, and Nagarajan (2014). Their research suggests that political alignment between a CEO and independent directors can be an indication of similar attitudes and beliefs, which reduces the likelihood of a CEO being fired due to poor performance, albeit at the expense of lower firm valuations, operating profitability, and increased agency conflicts. Lastly, our work is connected to recent findings from Bizjak, Kalpathy, Mihov, and Ren (2022), who studied firm decisions during the COVID-19 pandemic. Their research suggests that the political ideology of CEOs influenced their responses to a public health versus economic activity trade-off, with CEOs favoring the Republican party witnessing relative increases in retail visits, sales, and abnormal stock returns. Interestingly, they also found a correlation between counties with a higher proportion of Republican-led firms and higher COVID-19 transmission rates and fatalities.

In summary, our work joins on the research exploring the profound impact of political ideology on firm decision-making and performance, offering a new perspective on the prediction of stock returns based on firms' political affiliations. The Remainder of the article is organized as follows. In section 2 we describe the data. Section 3 presents our measure of the Republican factor and how it's obtained. Section 4 presents empirical results. Section 5 discuss alternative explanations for the evidence found and section 6 concludes.

## 3.2 Data

The data primarily originates from five major sources: the Center for Research in Security Prices (CRSP), Gallup, the Federal Reserve Economic Data (FRED), the Federal Election Commission (FEC) and Refinitiv. We use monthly data in most of the analysis, however the classification of firms political leanings are built using daily data. Our sample extends from 1928 up until the end of 2024, providing us with a wealth of information spanning several decades, covering a total of 24 U.S. elections.

The CRSP database serves as our principal source for stock returns. To ensure the relevance and applicability of our dataset, we narrowed down our focus to NYSE/AMEX/NASDAQ-listed securities, specifically using CRSP share codes 10 and 11. This allowed us to exclude ADRS, SBIs, Units, REITs, closed-end funds, and companies incorporated outside the USA. Our stock selection relied on two critical criteria: market value and liquidity. On each election day, we identified the top 2000 stocks based on market value. Further refinement of the sample ensued as we excluded stocks that recorded zero traded volume the day after the election and stocks listed after the start of the pre-election period. For Stock data after 2016, we use Refinitiv as the source.

Political approval data, which plays a pivotal role in our analysis, was sourced from Gallup. To maintain consistency and allow for nuanced interpretation, we constructed a monthly series of presidential approval. The approach was straightforward: for each month, we calculated the average of all surveys conducted within that period. In the absence of survey data for a given month, we resorted to a linear approximation centered on the 15th of the respective month.

Our study's macroeconomic scope warranted the inclusion of business cycle variables, for which we turned to the Federal Reserve Economic Data (FRED). This comprehensive resource provided us with datasets on Industrial Production and NBER recession indicator, essential elements in understanding the broader economic context surrounding each election.

The Federal Election Commission (FEC) data was instrumental in building our alternative measure of Republican-leaning firms. Covering the period between 1980 and 2024, the FEC data detailed corporate donations to political parties. This data's application is rooted in the growing body of literature positing that corporate electoral donations serve as a viable proxy for the political leanings of firms and managers. By identifying firms with a pronounced contribution bias towards a particular party, we were able to assign political leanings accordingly.

Regarding risk factors data, we obtained it form Kenneth French data library and Global Factor Data. On robustness checks where we used Fama-French 5 factors, we used excess market returns, value and size factors from French, while investiment and operating profitability came from Global Factor Data, as their data goes back further in time. To start the sample in 1928, we set INV and OPP to zero for the period with no observations.

## 3.3 Republican Factor

Leveraging the methodology of Carvalho, Ribeiro, Terra Neto, and Zilberman (2020), who used cross-sectional stock variation to predict national election results, we develop a "Republican Factor"in this study. Our focus is on the cross-sectional variation observable on the day after an election (D+1).

We begin by calculating abnormal returns for each stock, taking into account market risk factors based on Fama and French's (1993) three-factor model. We use a window of 100 days before the election to estimate the betas for each stock. After obtaining these abnormal returns, we rank firms accordingly. If Republicans win (or lose) the election, we implement a strategy where we buy (or sell) stocks of firms that fall above the 66.66th percentile with value weight, and simultaneously sell (or buy) stocks of firms that fall below the 33.33rd percentile, also with value weight. Essentially, this investment strategy is premised on always taking a long position on what we define as "Republican"stocks—those stocks that show positive performance in response to a Republican election win—while shorting the "Democrat"stocks.

Our strategy can be succinctly summarized with the following equations:

$$r_{it} - RF_t = \alpha + \beta_{i1} MKT_t + \beta_{i2} SMB_t + \beta_{i3} HML_t + \epsilon_i t \tag{1}$$

$$AR_{it} = r_{it} - RF_t - \hat{\beta}_{i1} MKT_t - \hat{\beta}_{i2} SMB_t - \hat{\beta}_{i3} HML_t \tag{2}$$

$$w_i = \frac{1}{(\sqrt{rank_i^d})(\sum^{\{i \in \mathbb{N} | AR_{j,D+1} > AR_{66th,D+1}\}} (1/(\sqrt{rank_j^d})))} * \frac{mkt \quad value_i}{\sum mkt \quad value_j} \tag{3}$$

$$RepFactor_t = \sum w_j AR_{j,t} \tag{4}$$

In Equation (1), we use Fama and French's (1993) three-factor model to estimate the betas. The term $(r_i t - RF_t)$ represents the excess returns of the stock, $MKT_t$ refers to the excess returns of the stock market, $SMB_t$ stands for the return of the Small Minus Big factor, and $HML_t$ corresponds to the return of the High Minus Low factor. We use Equation (2) to calculate abnormal returns $AR_i t$ for each stock. The weighting formula, used to calculate the weight $w_i$ of each stock i in the portfolio, is given by Equation (3). The rank is determined by the rank of abnormal returns. Finally, Equation (4) provides the Republican Factor, which is the sum of weighted abnormal returns of the stocks.

Our alternative methodology for determining a Republican metric follows the model used by Luo, Manconi, and Massa (2020), where the political leaning of a firm is measured by its political contributions. We define a firm as "Republican"by calculating the ratio *Rep*/(*Rep* + *Dem*). Consequently, our measure of Republican firms inherently includes those firms that predominantly contribute to the Republican party. We examine firms that have been identified as Republicans over two consecutive elections using our methodology, along with our alternative Republican measure for the period from 1980 to 2016. This analysis allows us to validate our Republican Factor measure by cross-referencing it with a measure based on political contributions.

We employed two statistical tests to examine the differences in the mean values of firms classified as Republican versus Democrat, with the classification based on the ratio of donations to the Republican party. The first test, a t-test, revealed a statistically significant difference between the two groups, with the mean value for Republican firms (0.2564) being substantially higher than that for Democrat firms (0.0552), yielding a p-value of 0.0075. This result indicates a strong likelihood that the observed difference in means is not due to random chance, thus supporting our hypothesis that Republican firms exhibit distinct characteristics in the measure under investigation. Further reinforcing our findings, the Mann-Whitney test, which compares medians and is non-parametric, thus not assuming normal distribution of the data, also suggested a significant difference between the two groups, as evidenced by a p-value of 0.0354.

In summary, the construction of the Republican Factor allows us to explore and quantify the relationship between stock performance and political outcomes, thereby adding a new dimension to the existing body of literature.

## 3.4 Empirical Results

Our study's principal finding is the consistent and significant alpha of the Republican Factor, a finding that holds its ground even after accounting for conventional risk factors. This factor's robust alpha is observable even during periods of Democratic governance, a surprising result that suggests the Republican Factor might hold predictive power regardless of the current political administration. More intriguingly, our data shows that the alpha is typically higher during the second half of political mandates, implying that the influence of the Republican Factor might increase over time.

Table 3.1 showcases the Republican Factor's alpha and average returns, illustrating a positive performance during Republican presidencies, but with a surprising positive return even during Democratic administrations. This indicates that Republican-leaning firms consistently deliver higher abnormal returns irrespective of the party in power.

Table 3.2 shows the regression analysis of the Republican Factor returns, considering variables such as government type and market conditions. The alpha, significant across different samples, underscores the robustness of the Republican Factor, with a consistently positive performance that transcends political regimes. The regression further highlights the factor's independence from traditional market variables, as evidenced by the significant positive alpha even when controlling for market, size, and value risk factors. These findings suggest a nuanced understanding of political affiliations and their impact on stock performance, with the Republican Factor exhibiting a notable resilience and potential predictive value across varied economic and political landscapes.

To further explore this result, we included additional risk factors (Fama-French 5 factors), the alpha remained positive and significant even in the Democrat sample. This finding, detailed in Table 3.3, underscores the resilience of the Republican Factor across varying time frames and market conditions.

Beyond time frames and presidential administrations, we further investigated the role of legislative control by incorporating detailed political regime configurations into our analysis. Specifically, we examined combinations of party control across the presidency, House, and Senate. As reported in Table 3.4, certain configurations were associated with particularly strong alpha estimates. For instance, the alpha was notably positive and statistically significant under a Democratic President with a Republican House and a Republican Senate, as well as under unified Democratic control across all three branches. Similarly, configurations with a

Democratic President and a Republican Senate, or a Republican President with a Democratic Senate, also yielded statistically significant alphas. These findings suggest that our alpha is robust to a wide range of political environments and tends to remain significant even under divided government. The limited variation in alpha across these regimes reinforces the conclusion that the observed performance is not driven by specific partisan alignments in Congress.

To further test the robustness of our findings, we utilized two different sample sets. The first set exclusively focused on close elections. The rationale behind this choice was the assumption that close elections, due to their inherent uncertainty, would amplify the impact of electoral surprise on stock returns. The results, presented in Table 3.5, confirmed our hypothesis: the alpha indeed strengthened in the sub sample. However, the significant alpha was not exclusive to this sample set, as non-close election samples also yielded a positive and significant alpha, indicating that our results are not merely driven by the surprise element.

Our second alternative sample added a persistence constraint on the firms considered in each election. In this case, only persistent firms were utilized to construct Republican and Democrat portfolios. Specifically, a firm needed to be identified as a Republican in two consecutive elections to be included in a Republican portfolio. This refined selection criterion ensured the consistent alignment of the firms with the Republican ideology over time. Despite the tightened selection criteria, we still observed a robust alpha, indicating the durability of the Republican Factor even among firms with a persistent political orientation. Results can be seen in Table 3.6.

In conclusion, our empirical results underscore the robustness and resilience of the Republican Factor across various conditions, political climates, and election outcomes. By exhibiting a consistent positive alpha over diverse mandates, election closeness, and firm selections, we provide compelling evidence for the potential predictive value and robustness of the Republican Factor. The significant alpha of the Republican Factor, seemingly immune to traditional risk factors, political control, and firm persistence, suggests its potential as a powerful financial tool in predicting stock performance.

## 3.5 Alternative Explanations

To further verify the robustness of our findings, we explored several alternative explanations that might account for the observed positive and significant alpha of the Republican Factor. This section investigate the possibility of political cycle influence, business cycle effects, policy uncertainty, potential sector bias, and the ESG effect. We aim to understand whether these factors are responsible for the performance of our Republican Factor or whether the alpha remains unaffected by them.

In the subsection labeled 5.1, we explore the hypothesis that the political cycle or potential investor bias toward the Republican party could be driving our results. To test this, we devised a measure of "Republican Approval."The logic being that if investors have a consistent bias, expecting the Republican party to always win, it could explain the Republican Factor's significant alpha. We defined the "Republican Approval"measure in two ways - approval during a Republican presidency and disapproval during a Democratic presidency, and alternatively, approval during a Republican presidency and (1-Approval) during a Democratic presidency. The trend of "Republican Approval"is visualized in Figure 3.1, and the corresponding results are presented in Table 3.7. Additionally, we plotted the conditional alpha concerning the Republican dummy and "Republican Approval"in Figure 3.2. The alpha remains positive for the vast majority of the sample, barring three brief periods.

In subsection 5.2, we probe the influence of business cycle variables. If the occurrence of economic crises or variations in industrial production are disproportionately associated with either Republican or Democratic presidencies, these factors could account for our findings. However, our results, summarized in Table 3.8, indicate that business cycle variables do not seem to impact the Republican Factor's alpha.

Next, in subsection 5.3, we test whether our factor is essentially capturing market uncertainty around policy shifts. The idea is that certain firms may gain from the resolution of policy uncertainty and thus exhibit higher abnormal returns after Election Day (D+1). Conversely, firms that benefit from the status quo may experience lower abnormal returns. Our analysis, however, does not support this hypothesis. Results presented in Table 3.9 show no evidence suggesting uncertainty as a driver of our results.

Subsection 5.4 explores the potential bias of specific industry sectors. To eliminate any such bias, we constructed a sector-neutral Republican Factor. We ranked firms by abnormal returns within each industry sector, using two-digit SIC codes, ensuring the inclusion of both Republican and Democratic firms within every sector. Despite reducing the sample size, adding additional risk factors, and creating a sector-neutral Republican Factor, our results remain consistent - the alpha still holds positive and significant, as seen in Table 3.10. Our alternative factor, built using industry portfolios instead of individual stocks, also provided no evidence of sector partisanship (Figure 3.3).

Finally, in subsection 5.5, we investigate the potential impact of ESG (Environmental, Social, and Governance) scores on our results. One could argue that our Republican Factor is essentially capturing the performance of firms that score higher on ESG indexes, depending on their political alignment. However, our data refutes this hypothesis. As seen in Table 3.11, the inclusion of an ESG index does not change much the estimated coefficient, even though the sample is much smaller, suggesting that our factor's performance is independent of ESG effects.

In conclusion, our analysis of these alternative explanations strengthens the robustness of the Republican Factor. Regardless of political cycle influences, business cycle variables, uncertainty effects, sectorial biases, and ESG effects, the Republican Factor continues to show positive alpha. This consistent performance strengthens the argument for the Republican Factor's potential utility in predicting stock returns.

### 3.5.1 Approval driving results

One of the potential explanations for the significant alpha exhibited by the Republican Factor could be tied to the influence of presidential approval ratings. In this subsection, we analyze whether this aspect of political climate could be driving our results. We postulate that if investors, on average, held a bias favoring the Republican party, assuming that it would always secure election victories, it could explain the persistent performance of the Republican Factor.

To test this hypothesis, we formulated a measure termed "Republican Approval."This metric was designed with two scenarios in mind. First, we considered approval ratings during a Republican presidency and contrasted them with disapproval ratings during a Democratic presidency. Alternatively, we examined approval ratings during a Republican presidency against (1-Approval) during a Democratic presidency. This dual perspective allowed us to capture the dynamic nature of investor sentiment across different political regimes.

The trend of the "Republican Approval"is visually represented in Figure 3.1. It provides a graphic overview of public sentiment during Republican and Democratic presidencies. Despite the inevitable fluctuations inherent in such data, the approval ratings offer a valuable insight into the possible political bias among investors.

To further scrutinize the impact of these approval ratings, we plotted the conditional alpha against both the Republican dummy and "Republican Approval"in Figure 3.2. The results were enlightening: while the alpha remains consistently positive for the vast majority of the sample period, there are three brief intervals where it deviates from this pattern.

These findings, detailed in Table 3.7, suggest that although investor sentiment (as reflected in presidential approval ratings) may play a role, it is not the sole driver of the Republican Factor's performance. This implies that even if a pro-Republican bias exists among investors, it doesn't fully account for the significant alpha of the Republican Factor. Hence, while political sentiment is undoubtedly a part of the complex mosaic of factors affecting stock market returns, it doesn't completely elucidate the persistent performance of our Republican Factor.

Consequently, we must look beyond political cycles and approval ratings to uncover other factors that may be at play, contributing to the robust performance of the Republican

Factor.

### 3.5.2 Business cycle variables

The business cycle — the natural rise and fall of economic activity over time — represents another potential influence on the Republican Factor's performance. It is conceivable that economic crises or periods of industrial expansion could coincide with the terms of either Republican or Democratic presidencies, thereby impacting stock returns and the performance of our Republican Factor.

To scrutinize this hypothesis, we analyzed various business cycle indicators. If certain business cycle variables, such as Industrial production and recession indicator, consistently exhibited superior performance during Republican terms, this might explain the significant alpha of the Republican Factor.

However, our empirical analysis did not support this conjecture. We found no convincing evidence of an enduring correlation between business cycle variables and the terms of Republican presidencies that could account for the robust performance of the Republican Factor. These results, detailed in Table 3.8, challenge the idea that the business cycle disproportionately favors one party over the other, at least in terms of observable impact on the stock market returns.

It's important to note that our findings do not dismiss the business cycle's impact on stock market returns altogether. However, they do suggest that the consistent performance of the Republican Factor is not simply a byproduct of favorable economic conditions during Republican presidencies.

### 3.5.3 Uncertainty

In the domain of financial markets, uncertainty can significantly affect investment decisions and market outcomes. Thus, a valid alternative hypothesis to explain the Republican Factor's performance is that our factor is essentially capitalizing on the uncertainty associated with presidential elections.

The logic underlying this hypothesis is as follows: firms that stand to gain from the resolution of policy uncertainty might exhibit the highest abnormal returns immediately after the election (D+1), once the election outcome has removed the uncertainty. Conversely, firms that benefit in some way from the persistence of uncertainty might exhibit the lowest abnormal returns once this uncertainty has been resolved.

To test this hypothesis, we examined the relationship between the uncertainty surrounding the election outcome and the abnormal returns of stocks in the post-election period. Our analysis was designed to identify whether the resolution of uncertainty at D+1 disproportionately favored stocks that were included in our Republican portfolio.

However, the empirical results did not support this hypothesis. As shown in Table 3.9, we did not find any substantial evidence that uncertainty was a key driver behind the significant alpha of the Republican Factor. These results suggest that the performance of the Republican Factor cannot be easily attributed to the dynamics of uncertainty resolution following the election.

### 3.5.4 Sector Neutral Factor

Considering that different sectors may be variably influenced by political outcomes, another alternative explanation that we explore is the potential impact of sectoral biases on our results. For instance, certain sectors might be more inclined to benefit under Republican administrations, skewing the performance of our Republican Factor.

To address this, we embarked on constructing a 'Sector Neutral' Republican Factor. The process of formulating this sector-neutral factor involved ranking firms by their abnormal returns within each sector, using two-digit Standard Industrial Classification (SIC) codes. By doing so, each sector is ensured to comprise both Republican and Democrat firms, thus mitigating any inherent sector bias.

Upon implementing this process and reducing our sample size (starting in 1963 rather than 1929), the inclusion of additional risk factors and the construction of a sector-neutral Republican Factor still resulted in a significant and positive alpha. As evidenced by Table 3.10, these results indicate that our original findings are robust against potential sector biases.

Additionally, we developed an alternative Factor that employs industry portfolios as opposed to individual stocks. The analysis did not reveal evidence of specific sector partisanship, as depicted in Figure 3.3.

By building and testing this sector-neutral Republican Factor, we strive to establish the robustness of our results, assuring that they are not merely reflective of certain sectoral preferences for Republican administrations. This process further enhances the validity and comprehensibility of our research.

### 3.5.5 ESG

Environmental, Social, and Governance (ESG) criteria have increasingly become a consideration for investors who not only focus on financial performance but also on the societal impact of their investments. Thus, we explore another possible explanation for our results: the potential role of ESG factors. Specifically, it may be conjectured that firms favored by either Republican or Democratic administrations could be more likely to score higher on ESG indexes, possibly leading to their superior performance.

To investigate this potential ESG effect, we include an ESG index in our model as a variable. Our aim is to determine whether the inclusion of ESG ratings would have any significant impact on the performance of our Republican Factor.

However, our results, as presented in Table 3.11, reveal that the addition of an ESG index does not alter the positive alpha of our Republican Factor, and does not change much the estimated coefficient, even with a much smaller sample. This suggests that our findings are not merely a byproduct of an ESG effect, thus corroborating the robustness of our results.

By factoring in the potential impact of ESG criteria, we demonstrate that the significant alpha of our Republican Factor is not driven by the ESG performance of the firms. This enhances the credibility of our study by affirming that the results are not subject to the influence of this increasingly pertinent factor in investment decisions.

## 3.6 Conclusion

Our study lends weight to the conception that political affiliation, as manifest in the form of Republican and Democrat-leaning firms, has a significant influence on stock returns. Our finding of a robust, positive alpha persists even after controlling for party in power, mandate year, firm value, and sector bias. This suggests the viability of a unique investment strategy: consistently going long on "Republican"stocks while shorting "Democrat"stocks.

We have constructed a Republican Factor based on this strategy and have found it to demonstrate remarkable resilience, showing positive returns that resist explanation even when a set of risk factors is considered. Intriguingly, the Republican Factor's returns seem to be most robust during Democrat mandates, with an unanticipated concentration in the second half of these mandates.

On analyzing different subsets of data — one focusing on close elections, the other on persistent firms (those maintaining their political alignment for at least two consecutive elections) — the Republican Factor demonstrated an even more significant alpha. These findings bolster our hypothesis, suggesting that the Republican Factor is capturing an inherent characteristic of Republican-affiliated firms. We have also build an alternative measure of Republican leaning using donations data, and have found that our measure indeed capture firms that, on average, donate more to the Republican party.

To ensure the robustness of our results, we scrutinized potential alternative explanations. First, we explored whether a bias towards the Republican party among investors could be driving the observed abnormal returns. However, our examination of a Republican approval measure found no evidence supporting this claim. Second, we assessed if business cycle variables, such as industrial production or recession likelihood, could explain our results. Again, the evidence did not substantiate this notion.

Third, we questioned whether our findings were inadvertently capturing firms' responses to policy uncertainty, with firms benefiting from uncertainty resolution displaying the highest abnormal returns immediately post-election. After controlling for a measure of Economic Policy Uncertainty, it was clear that this factor did not account for our observed returns.

Lastly, we examined the possibility of sectorial bias influencing our results, speculating that certain sectors might benefit more from the economic policy of one party over the other. Our dual-method approach, which involved creating both a sector-neutral factor and a sector-specific factor, demonstrated that sector bias did not influence our findings.

In conclusion, our research identifies a Republican Factor in stock returns that persists independently of conventional risk factors, business cycles, policy uncertainty, sector bias, or ESG indicators. This suggests a strategy for investors: to consistently go long on stocks of firms associated with the Republican party and short those linked to the Democratic party, irrespective of which party is in power. We document this pricing anomaly in political finance and run a series of robustness tests to find possible causes. Future research could explore the underlying mechanisms further, examining the corporate policies and practices that distinguish Republican and Democrat-leaning firms, potentially leading to the observed differences in stock performance, or exploring potential biases among investors.

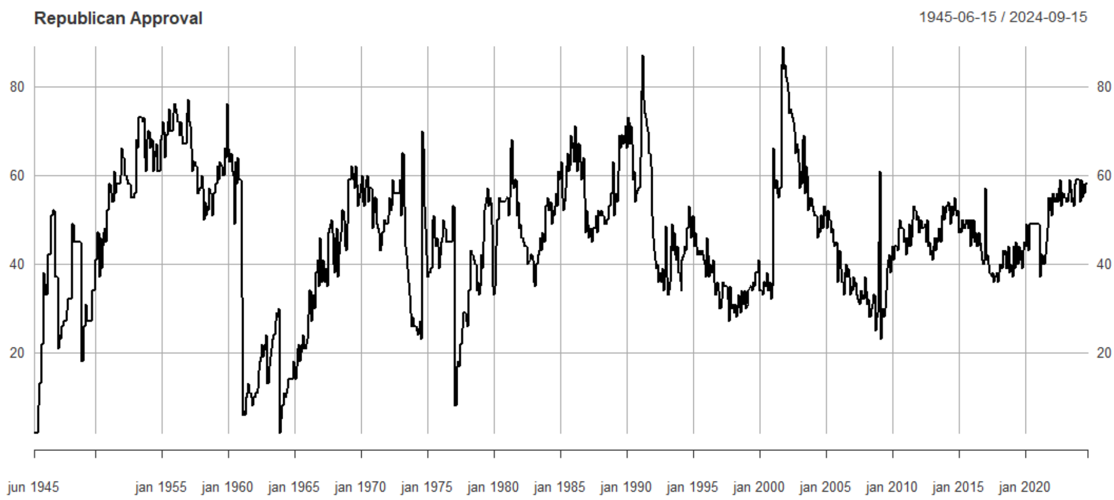


Figura 3.1 – Republican Approval - variable that assumes the value of approval if we have a Republican Presidency and Disapproval if we have a Democrat Presidency

## 3.7 Tables and Figures

The table reports summary statistics for the full sample, a sample with Republican presidencies only and a sample with Democratic presidencies only. On the first row we have average annualized returns of the Republican Factor. Second row we have the mean on monthly returns. Third row we have standard deviation (Std.Dev.) of monthly returns. Fourth row we have the p-value for the null hypothesis that monthly returns are not significantly different from zero. Last row reports the number of observations for each sample.

| | Full sample | Republican Government | Democrat Government |
|---|---|---|---|
| Monthly Alpha (%) | 0.234 | 0.192 | 0.212 |
| Alpha Std. Error | 0.066 | 0.098 | 0.086 |
| Alpha p-value | 0.0004 | 0.049 | 0.014 |
| Mean Monthly Return (%) | 0.162 | 0.171 | 0.154 |
| Return Std. Dev. | 2.269 | 2.417 | 2.137 |
| Mean Return p-value | 0.016 | 0.104 | 0.072 |
| Observations | 1,151 | 528 | 623 |

Tabela 3.1 – Republican Factor - Average Returns

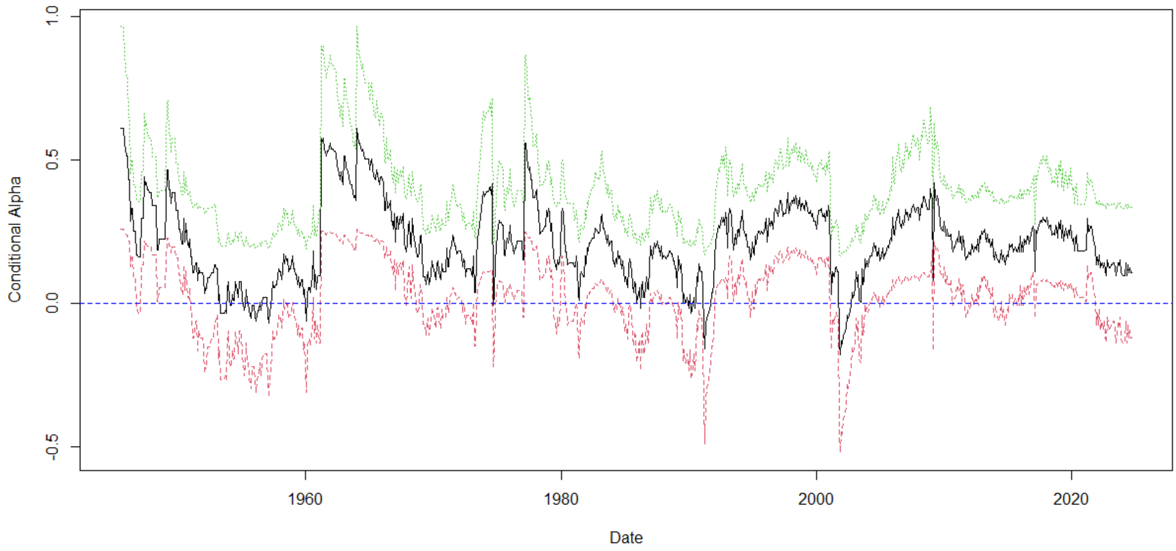


Figura 3.2 – Conditional alpha on Republican dummy and Republican approval - red an green line are 10% confidence intervals

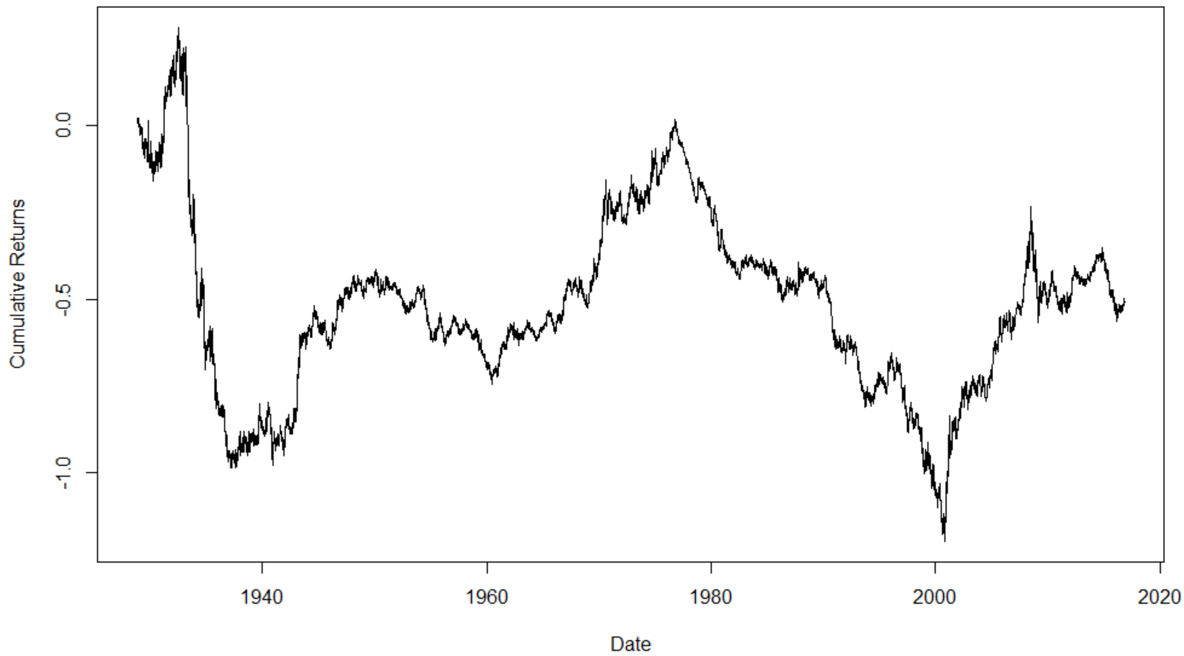


Figura 3.3 – Cumulative Republican Sectorial Factor Returns

The table reports the regression with the Republican Factor returns as the dependent variable. "Republican dummy"is a variable that assumes value 1 when we have a Republican presidency, "First half dummy"is a variable that assumes value 1 when we are on the first and second years of a mandate, "MKT"is the excess return on the market, "SMB"is the size risk factor, "HML"is the value risk factor. The table reports the coefficients and in parenthesis we have the standard deviations. Sample data is from 1928 to 2024.

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Republican Factor Returns | | | | |
| | *Democrat gov* | *Republican gov* | *Full Sample* | *Full Sample* | *Full Sample* |
| | (1) | (2) | (3) | (4) | (5) |
| Alpha | 0.212** | 0.192** | 0.234*** | 0.270*** | 0.343*** |
| | (0.086) | (0.098) | (0.066) | (0.089) | (0.111) |
| Republican dummy | | | | −0.078 | −0.079 |
| | | | | (0.131) | (0.131) |
| First half dummy | | | | | −0.144 |
| | | | | | (0.130) |
| MKT | −0.004 | −0.156*** | −0.087*** | −0.087*** | −0.088*** |
| | (0.019) | (0.018) | (0.013) | (0.013) | (0.013) |
| SMB | −0.070*** | −0.072** | −0.056*** | −0.056*** | −0.057*** |
| | (0.026) | (0.035) | (0.021) | (0.021) | (0.021) |
| HML | −0.066*** | 0.037 | −0.012 | −0.012 | −0.011 |
| | (0.025) | (0.027) | (0.019) | (0.019) | (0.019) |
| Observations | 623 | 528 | 1,151 | 1,151 | 1,151 |
| $R^2$ | 0.032 | 0.151 | 0.062 | 0.062 | 0.063 |
| Adjusted $R^2$ | 0.027 | 0.146 | 0.059 | 0.059 | 0.059 |

*p<0.1; **p<0.05; ***p<0.01

Tabela 3.2 – Controlling the Republican Factor Returns

The table reports the regression with the Republican Factor returns as the dependent variable. "MKT"is the excess return on the market, "SMB"is the size risk factor, "HML"is the value risk factor, "OPP"is the operating profitability risk factor, "INV"is the investment risk factor. The table reports the coefficients and in parenthesis we have the standard deviations. Sample data is from 1928 to 2024.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Republican Factor Returns | | | | | |
| | *Democrat gov* | | *Republican gov* | | *Full Sample* | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| alpha | 0.212$^{**}$ | 0.208$^{**}$ | 0.192$^{**}$ | 0.043 | 0.234$^{***}$ | 0.187$^{***}$ |
| | (0.086) | (0.087) | (0.098) | (0.093) | (0.066) | (0.066) |
| MKT | −0.004 | −0.010 | −0.156$^{***}$ | −0.124$^{***}$ | −0.087$^{***}$ | −0.082$^{***}$ |
| | (0.019) | (0.020) | (0.018) | (0.018) | (0.013) | (0.014) |
| SMB | −0.070$^{***}$ | −0.066$^{**}$ | −0.072$^{**}$ | −0.010 | −0.056$^{***}$ | −0.018 |
| | (0.026) | (0.030) | (0.035) | (0.034) | (0.021) | (0.023) |
| HML | −0.066$^{***}$ | −0.059$^{*}$ | 0.037 | −0.017 | −0.012 | −0.036 |
| | (0.025) | (0.033) | (0.027) | (0.032) | (0.019) | (0.024) |
| OPP | | 0.040 | | 0.383$^{***}$ | | 0.146$^{***}$ |
| | | (0.040) | | (0.047) | | (0.030) |
| INV | | −0.034 | | 0.203$^{***}$ | | 0.039 |
| | | (0.053) | | (0.053) | | (0.038) |
| Observations | 623 | 623 | 528 | 528 | 1,151 | 1,151 |
| $R^2$ | 0.032 | 0.034 | 0.151 | 0.264 | 0.062 | 0.083 |
| Adjusted $R^2$ | 0.027 | 0.026 | 0.146 | 0.257 | 0.059 | 0.079 |

$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Tabela 3.3 – Controlling the Republican Factor - Additional Factors

The table reports regression results where the dependent variable is the monthly return to the Republican factor. All specifications include the Fama-French three factors: "MKT"(market excess return), "SMB"(size factor), and "HML"(value factor). Political alignment is captured through a system of mutually exclusive dummy variables, with no intercept included. As a result, each coefficient reflects the average return conditional on a specific political regime. In Column (1), the specification includes two dummies identifying whether the sitting president is a Republican or a Democrat. In Column (2), four dummies indicate all combinations of presidential party and House majority: Democratic president with Democratic House, Democratic president with Republican House, Republican president with Democratic House, and Republican president with Republican House. Column (3) follows the same structure but for combinations of presidential party and Senate majority. Column (4) includes seven mutually exclusive dummies, each representing a unique configuration of control across the presidency, House, and Senate. To aid interpretation, the final column reports the share of the sample period (1929–2024) during which each political regime was in effect, expressed as a percentage. Coefficients are presented alongside standard errors in parentheses.

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Republican Factor Returns | | | | Share (%) |
| | (1) | (2) | (3) | (4) | |
| ‘Republican President‘ | 0.192** | | | | 45.83 |
| | (0.096) | | | | |
| ‘Democratic President‘ | 0.267*** | | | | 54.17 |
| | (0.089) | | | | |
| ‘Dem Pres + Rep House‘ | | 0.251** | | | 37.50 |
| | | (0.108) | | | |
| ‘Rep Pres + Dem House‘ | | 0.162 | | | 33.33 |
| | | (0.113) | | | |
| ‘Rep Pres + Rep House‘ | | 0.272 | | | 12.50 |
| | | (0.184) | | | |
| ‘Dem Pres + Dem House‘ | | 0.302* | | | 16.67 |
| | | (0.160) | | | |
| ‘Dem Pres + Rep Senate‘ | | | 0.283*** | | 37.50 |
| | | | (0.107) | | |
| ‘Rep Pres + Dem Senate‘ | | | 0.297** | | 29.16 |
| | | | (0.120) | | |
| ‘Rep Pres + Rep Senate‘ | | | 0.008 | | 16.67 |
| | | | (0.159) | | |
| ‘Dem Pres + Dem Senate‘ | | | 0.231 | | 16.67 |
| | | | (0.161) | | |
| ‘Rep Pres + Dem House + Dem Senate‘ | | | | 0.246* | 25.00 |
| | | | | (0.130) | |
| ‘Dem Pres + Rep House + Rep Senate‘ | | | | 0.309*** | 33.33 |
| | | | | (0.114) | |
| ‘Dem Pres + Rep House + Dem Senate‘ | | | | −0.233 | 4.17 |
| | | | | (0.329) | |
| ‘Rep Pres + Rep House + Dem Senate‘ | | | | 0.605* | 4.17 |
| | | | | (0.318) | |
| ‘Rep Pres + Dem House + Rep Senate‘ | | | | −0.092 | 8.33 |
| | | | | (0.225) | |
| ‘Rep Pres + Rep House + Rep Senate‘ | | | | 0.106 | 8.33 |
| | | | | (0.225) | |
| ‘Dem Pres + Dem House + Rep Senate‘ | | | | 0.079 | 4.17 |
| | | | | (0.318) | |
| ‘Dem Pres + Dem House + Dem Senate‘ | | | | 0.375** | 12.50 |
| | | | | (0.184) | |
| MKT | −0.088*** | −0.088*** | −0.087*** | −0.086*** | |
| | (0.013) | (0.013) | (0.013) | (0.013) | |
| HML | −0.012 | −0.012 | −0.012 | −0.014 | |
| | (0.019) | (0.019) | (0.019) | (0.019) | |
| SMB | −0.056*** | −0.055** | −0.057*** | −0.059*** | |
| | (0.021) | (0.022) | (0.022) | (0.022) | |
| Observations | 1,149 | 1,149 | 1,149 | 1,149 | |
| $R^2$ | 0.067 | 0.067 | 0.068 | 0.072 | |
| Adjusted $R^2$ | 0.063 | 0.061 | 0.063 | 0.063 | |
| *Note:* | | | | | *p<0.1; **p<0.05; ***p<0.01 |

Tabela 3.4 – Considering midterm elections

The table reports the regression with the Republican Factor returns as the dependent variable. Columns 1 and 2 report results for a sample considering only close elections, columns 3 and 4 reports results for the full sample except for close election, columns 5 and 6 reports the results for the full standard sample. "Republican dummy"is a variable that assumes value 1 when we have a Republican presidency, "MKT"is the excess return on the market, "SMB"is the size risk factor, "HML"is the value risk factor. The table reports the coefficients and in parenthesis we have the standard deviations. Sample data is from 1928 to 2024.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Republican Factor Returns | | | | | |
| | *Close Elections* | | *Non-Close Elections* | | *Full Sample* | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Alpha | $0.249^{***}$ | $0.374^{***}$ | $0.212^{**}$ | $0.203^{*}$ | $0.234^{***}$ | $0.270^{***}$ |
| | (0.091) | (0.122) | (0.088) | (0.121) | (0.066) | (0.089) |
| Republican dummy | | $-0.280$ | | 0.020 | | $-0.078$ |
| | | (0.181) | | (0.175) | | (0.131) |
| MKT | $-0.135^{***}$ | $-0.137^{***}$ | $-0.038^{**}$ | $-0.038^{**}$ | $-0.087^{***}$ | $-0.087^{***}$ |
| | (0.018) | (0.018) | (0.018) | (0.018) | (0.013) | (0.013) |
| SMB | $-0.062^{*}$ | $-0.065^{*}$ | $-0.077^{***}$ | $-0.076^{***}$ | $-0.056^{***}$ | $-0.056^{***}$ |
| | (0.037) | (0.037) | (0.026) | (0.026) | (0.021) | (0.021) |
| HML | $-0.076^{***}$ | $-0.076^{***}$ | $0.061^{**}$ | $0.061^{**}$ | $-0.012$ | $-0.012$ |
| | (0.026) | (0.026) | (0.026) | (0.026) | (0.019) | (0.019) |
| Observations | 432 | 432 | 719 | 719 | 1,151 | 1,151 |
| $R^2$ | 0.214 | 0.219 | 0.032 | 0.032 | 0.062 | 0.062 |
| Adjusted $R^2$ | 0.209 | 0.212 | 0.028 | 0.027 | 0.059 | 0.059 |

$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Tabela 3.5 – Republican Factor - Close Elections

The table reports the regression with the Republican Factor returns as the dependent variable. Here we use a sample with persistent firms only, such that only firms that remain with the same party two elections in a row (except for first election) are used. "Republican dummy"is a variable that assumes value 1 when we have a Republican presidency, "MKT"is the excess return on the market, "SMB"is the size risk factor, "HML"is the value risk factor. The table reports the coefficients and in parenthesis we have the standard deviations. Sample data is from 1928 to 2016.

| | *Dependent variable:* | |
|---|---|---|
| | Persistent Republican Factor Returns | |
| | (1) | (2) |
| Alpha | 0.303$^{***}$ | 0.328$^{***}$ |
| | (0.093) | (0.127) |
| Republican dummy | | −0.054 |
| | | (0.186) |
| MKT | −0.121$^{***}$ | −0.121$^{***}$ |
| | (0.018) | (0.019) |
| SMB | −0.156$^{***}$ | −0.156$^{***}$ |
| | (0.030) | (0.030) |
| HML | −0.060$^{**}$ | −0.060$^{**}$ |
| | (0.027) | (0.027) |
| Observations | 1,057 | 1,057 |
| $R^2$ | 0.103 | 0.104 |
| Adjusted $R^2$ | 0.101 | 0.100 |

$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

Tabela 3.6 – Persistent Republican Factor

The table reports the regression with the Republican Factor returns as the dependent variable."Republican approval"is a created variable that assumes the value of approval if we have a Republican Presidency and Disapproval if we have a Democrat Presidency, "Republican approval change"is the normalized change in the Republican Approval variable, "Republican dummy"is a variable that assumes value 1 when we have a Republican presidency, "MKT"is the excess return on the market, "SMB"is the size risk factor, "HML"is the value risk factor. The table reports the coefficients and in parenthesis we have the standard deviations. Sample data is from 1945 to 2024.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Republican Factor Returns | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Alpha | 0.210*** | 0.277*** | 0.629*** | 0.628*** | 0.208*** | 0.274*** |
| | (0.068) | (0.097) | (0.217) | (0.219) | (0.068) | (0.097) |
| Republican approval | | | −0.009** | −0.009* | | |
| | | | (0.004) | (0.005) | | |
| Republican approval change | | | | | −0.037 | −0.036 |
| | | | | | (0.028) | (0.028) |
| Republican dummy | | −0.132 | | −0.005 | | −0.129 |
| | | (0.134) | | (0.152) | | (0.134) |
| MKT | −0.094*** | −0.094*** | −0.094*** | −0.094*** | −0.094*** | −0.095*** |
| | (0.016) | (0.016) | (0.016) | (0.016) | (0.016) | (0.016) |
| HML | 0.039 | 0.038 | 0.036 | 0.036 | 0.037 | 0.037 |
| | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) |
| SMB | −0.026 | −0.026 | −0.028 | −0.028 | −0.026 | −0.026 |
| | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) |
| Observations | 952 | 952 | 951 | 951 | 951 | 951 |
| $R^2$ | 0.048 | 0.049 | 0.052 | 0.052 | 0.049 | 0.050 |
| Adjusted $R^2$ | 0.045 | 0.045 | 0.048 | 0.047 | 0.045 | 0.045 |

*p<0.1; **p<0.05; ***p<0.01

Tabela 3.7 – Controlling for Republican Approval

The table reports the regression with the Republican Factor returns as the dependent variable. "Republican dummy"is a variable that assumes value 1 when we have a Republican presidency, "Industrial Production"is percentage change in industrial production from the US, "NBER recession"is a variable that assumes value 1 during NBER defined recessions, "MKT"is the excess return on the market, "SMB"is the size risk factor, "HML"is the value risk factor. The table reports the coefficients and in parenthesis we have the standard deviations. Sample data is from 1945 to 2024.

| | *Dependent variable:* | |
|---|---|---|
| | Republican Factor Returns | |
| | (1) | (2) |
| Alpha | 0.268*** | 0.300*** |
| | (0.075) | (0.093) |
| Republican dummy | | −0.077 |
| | | (0.135) |
| Industrial production | −5.096 | −5.142 |
| | (4.007) | (4.009) |
| NBER recession | −0.145 | −0.120 |
| | (0.192) | (0.197) |
| MKT | −0.087*** | −0.087*** |
| | (0.013) | (0.013) |
| HML | −0.010 | −0.010 |
| | (0.019) | (0.019) |
| SMB | −0.051** | −0.052** |
| | (0.022) | (0.022) |
| Observations | 1,151 | 1,151 |
| $R^2$ | 0.063 | 0.063 |
| Adjusted $R^2$ | 0.059 | 0.058 |
| | | *p<0.1; **p<0.05; ***p<0.01 |

Tabela 3.8 – Controlling for business cycle

The table reports the regression with the Republican Factor returns as the dependent variable. "Republican dummy"is a variable that assumes value 1 when we have a Republican presidency, "EPU"is the uncertainty index from Baker, Bloom and Davis, "MKT"is the excess return on the market, "SMB"is the size risk factor, "HML"is the value risk factor. The table reports the coefficients and in parenthesis we have the standard deviations. Sample data is from 1928 to 2014.

| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | Republican Factor Returns | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| Alpha | 0.282*** | 0.306*** | 0.282*** | 0.307*** | 0.316*** |
| | (0.068) | (0.093) | (0.068) | (0.093) | (0.093) |
| Republican dummy | | −0.053 | | −0.055 | −0.047 |
| | | (0.136) | | (0.138) | (0.138) |
| EPU | | | −0.002 | −0.006 | −0.076 |
| | | | (0.068) | (0.068) | (0.089) |
| EPU*Republican dummy | | | | | 0.170 |
| | | | | | (0.139) |
| MKT | −0.079*** | −0.080*** | −0.079*** | −0.080*** | −0.078*** |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| SMB | −0.070*** | −0.070*** | −0.070*** | −0.070*** | −0.071*** |
| | (0.022) | (0.022) | (0.022) | (0.022) | (0.022) |
| HML | −0.043** | −0.043** | −0.043** | −0.043** | −0.044** |
| | (0.020) | (0.020) | (0.020) | (0.020) | (0.020) |
| Observations | 1,057 | 1,057 | 1,057 | 1,057 | 1,057 |
| $R^2$ | 0.070 | 0.070 | 0.070 | 0.070 | 0.071 |
| Adjusted $R^2$ | 0.067 | 0.067 | 0.066 | 0.066 | 0.066 |

*p<0.1; **p<0.05; ***p<0.01

Tabela 3.9 – Controlling for Uncertainty

The table reports the regression with the Republican Factor returns as the dependent variable. "MKT"is the excess return on the market, "SMB"is the size risk factor, "HML"is the value risk factor, "OPP"is the operating profitability risk factor, "INV"is the investment risk factor. The table reports the coefficients and in parenthesis we have the standard deviations. Sample data is from 1928 to 2024.

| | *Dependent variable:* | |
|---|---|---|
| | Sector Neutral Republican Factor Returns | |
| | (1) | (2) |
| Alpha | $0.093^{**}$ | $0.081^{**}$ |
| | (0.039) | (0.040) |
| MKT | $-0.026^{***}$ | $-0.033^{***}$ |
| | (0.008) | (0.008) |
| SMB | $-0.006$ | 0.002 |
| | (0.013) | (0.014) |
| HML | 0.016 | $0.029^{**}$ |
| | (0.011) | (0.014) |
| OPP | | $0.069^{***}$ |
| | | (0.018) |
| INV | | $-0.043^{*}$ |
| | | (0.023) |
| Observations | 1,150 | 1,150 |
| $R^2$ | 0.012 | 0.026 |
| Adjusted $R^2$ | 0.010 | 0.021 |

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Tabela 3.10 – Sector Neutral Republican Factor

The table reports the regression with the Republican Factor returns as the dependent variable. "MKT"is the excess return on the market, "SMB"is the size risk factor, "HML"is the value risk factor, ESG factor is the excess returns of a ESG portfolio relative to a market portfolio. The table reports the coefficients and in parenthesis we have the standard deviations. Sample data is from 1994 to 2024.

| | *Dependent variable:* | |
|---|---|---|
| | Republican Factor Returns | |
| | (1) | (2) |
| Alpha | 0.210* | 0.197 |
| | (0.125) | (0.126) |
| MKT | −0.199*** | −0.207*** |
| | (0.029) | (0.030) |
| SMB | −0.016 | −0.015 |
| | (0.040) | (0.040) |
| HML | 0.072* | 0.074* |
| | (0.038) | (0.038) |
| ESG Index | | 0.069 |
| | | (0.069) |
| Observations | 414 | 413 |
| $R^2$ | 0.126 | 0.129 |
| Adjusted $R^2$ | 0.120 | 0.120 |
| Note: The ESG Factor is obtained from MSCI KLD 400 | | *p<0.1; **p<0.05; ***p<0.01 |

Tabela 3.11 – ESG Control

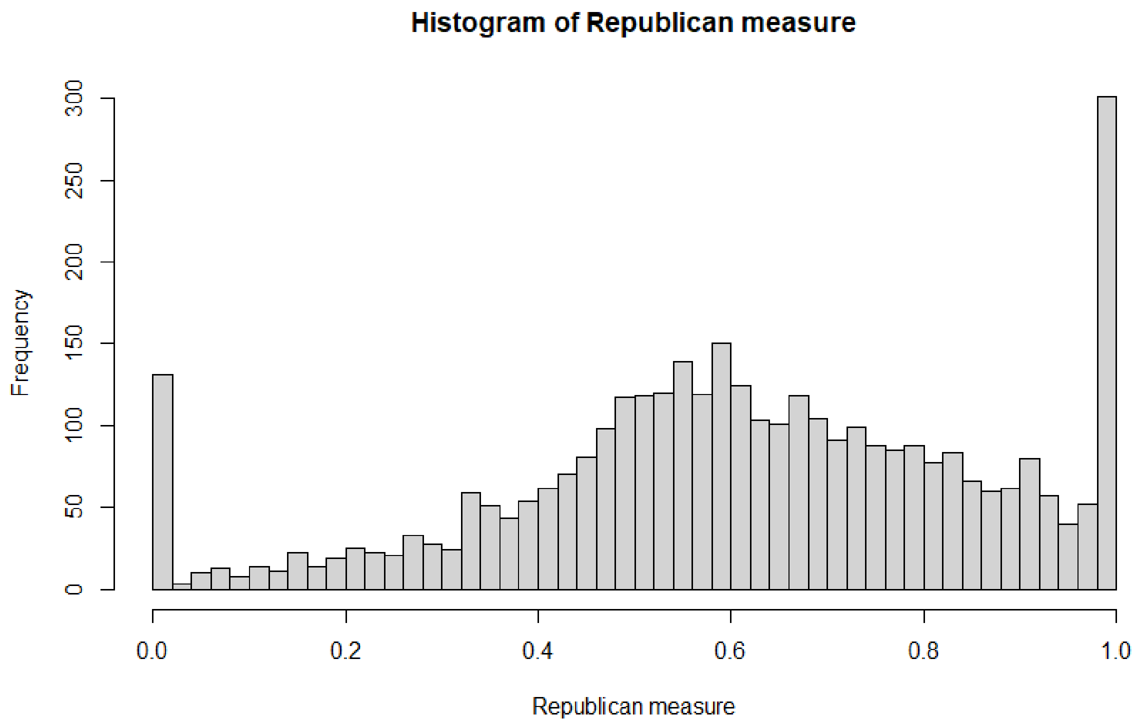


Figura 3.4 – Histogram of Republican measure using contributions data

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## 3.9 Appendix

We want to better understand what is the driver of our returns. We do a variance decomposition to understand the main components of the Republican Factor returns. Following Campbell (1991, EJ), we break unexpected returns into two components: Changes in rational expectations of future dividends (Cash-flow news) and Changes in rational expectations of future return (Discount-rate news). Cash-flow news is the dominant component of the Republican Factor return. This is in line with other anomalies found in the literature, as Lochstoer and Tetlock (2020, JF), in contrast with the stylized fact that DR shocks explain most of market return variance Explanations using changes to investors risk aversion or sentiment would not explain much of the abnormal returns that we find.

- t-test

| Test statistic | df | p-value | Alternative hypothesis | mean of Rep | mean of Dem |
|---|---|---|---|---|---|
| 2.683 | 470.2 | 0.007548** | two.sided | 0.2564 | 0.05518 |

- Mann-Whitney - Median comparison

| Test statistic | P value | Alternative hypothesis |
|---|---|---|
| 37983 | 0.03541 * | two.sided |

# 4 CONCLUSION

This thesis is composed of three self-contained chapters in financial econometrics, with an emphasis on the role of financial risk factors in shaping market dynamics, risk pricing, and asset returns. Each chapter explores a distinct dimension of financial risk: labor income exposure to equity factors, the role of factor volatility in pricing models, and the intersection of politics and asset returns.

The first chapter, "The Value Factor and Labor Income Risk,"investigates how financial risk factors, particularly the Value factor, influence individual earnings growth. By examining labor income exposure to equity risk factors, the chapter highlights the heterogeneity of financial risk across different worker profiles. The findings demonstrate a systematic relationship between earnings skewness and the Value factor, suggesting that certain industries or job types are more exposed to financial market risk. This research bridges the gap between macroeconomic and financial domains, offering insights into risk premia and portfolio hedging strategies.

The second chapter, "A Factor of Factor Volatilities,"expands the understanding of volatility in asset pricing models by focusing on the role of factor volatility rather than traditional factor loadings. The chapter introduces a novel framework that constructs a common volatility factor using principal component analysis on a broad set of risk factor volatilities. The results indicate that changes in factor volatilities significantly impact stock return cross-sections, underscoring the importance of incorporating factor volatility measures into risk assessment and portfolio management strategies.

The third chapter, "The Republican Factor Puzzle,"explores the relationship between political alignment and asset returns. By constructing a "Republican Factor"based on firms' reactions to U.S. elections or their political donation patterns, the study finds that stocks associated with the Republican Party consistently generate excess returns, even under Democratic administrations. The results remain robust after controlling for traditional risk factors, business cycles, and sectoral biases, suggesting the presence of a persistent political anomaly in financial markets. This chapter contributes to the literature on political finance and its implications for investment strategies.

Overall, this thesis provides new insights into financial risk factor modeling by integrating labor income risk, factor volatility dynamics, and political influences in asset pricing. The findings have implications for asset allocation, portfolio construction, and risk management, offering valuable perspectives for both academic research and practical applications in financial markets.