Non-Standard Errors in Portfolio Sorts

This version: August 31, 2022

Abstract

We study the size and drivers of *non-standard errors* (Menkveld et al., 2021) in portfolio sorts across 14 common methodological decision nodes and 40 sorting variables. These non-standard errors range between 0.05 and 0.26 percent and are, on average, larger than standard errors. Supposedly innocuous decisions cause large variation in estimated premiums, standard errors, non-standard errors, and t-statistics. The impact of decision nodes varies widely across sorting variables. Irrespective of choices in portfolio sorts, we find pervasively positive premiums and alphas for almost all sorting variables. This suggests that while the size of these premiums is uncertain, their sign is remarkably stable. Our code is publicly available.

Keywords: Non-standard errors, portfolio sorts, data mining, p-hacking, risk factors, anomalies

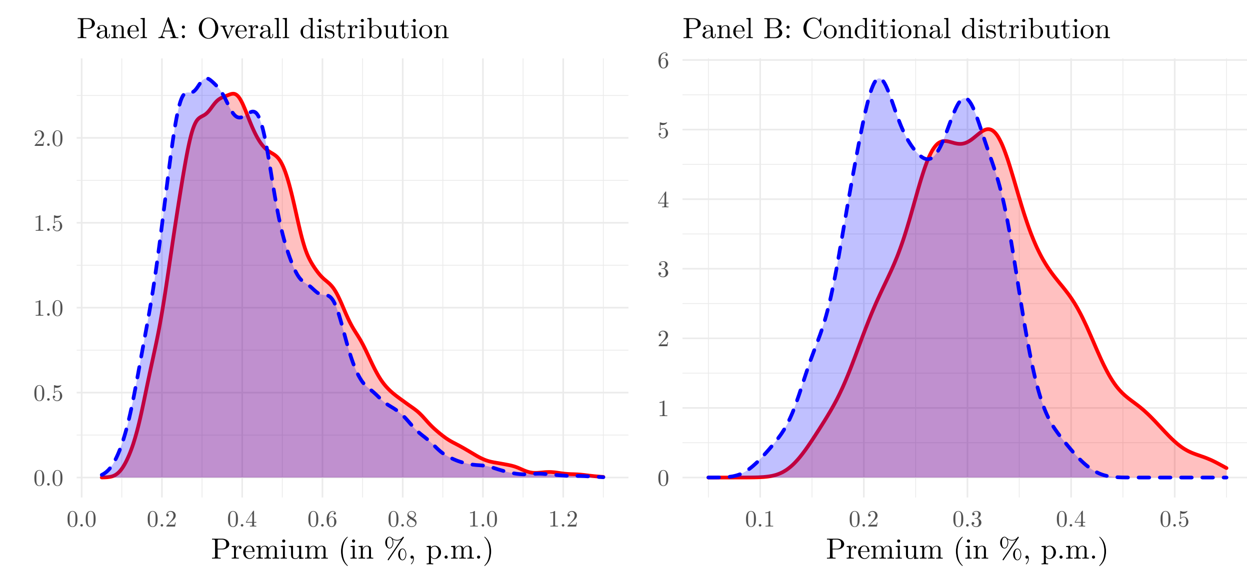
JEL: C58, G10, G11, G12, G14

1 Introduction

In many cases, portfolio sorts are essentially a way to estimate a nonlinear function from stock characteristics to expected returns. Altering seemingly innocuous choices made in a portfolio sort – e.g., the exclusion or inclusion of penny stocks, specific filters on stock characteristics or the market capitalization – is therefore informative of the stability of the estimated functional relationship but also of the underlying drivers of returns.

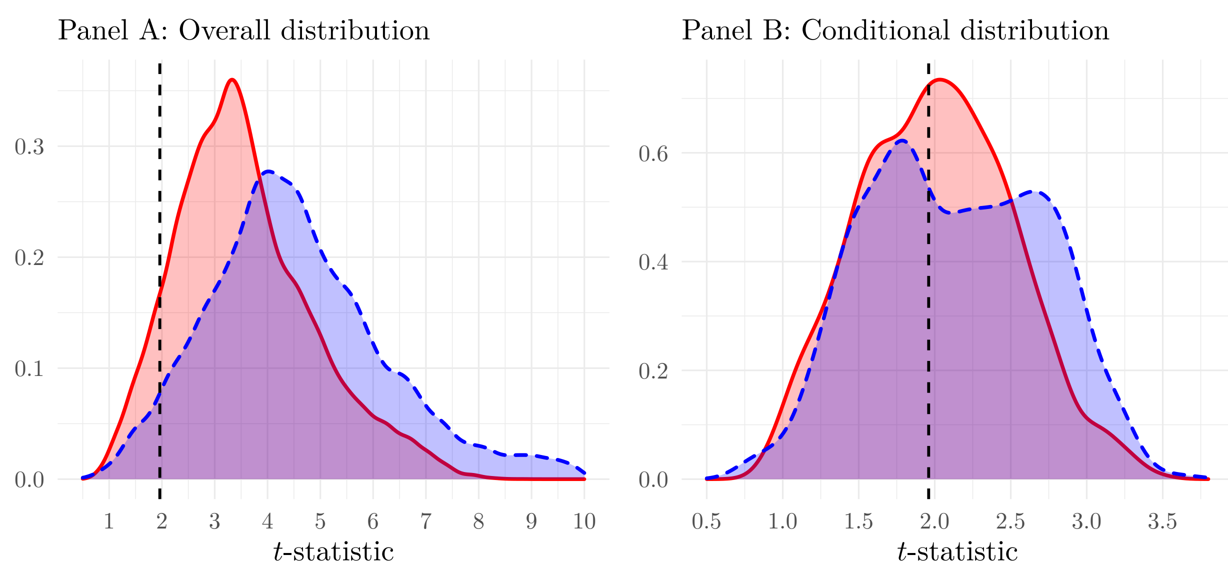
In this paper, we test how much the estimated return premiums vary with these methodological decisions and find that it has a profound impact on the estimates. Figure 1 shows the variation in estimated premiums for the investment anomaly, i.e., the average return differentials between portfolios with high and portfolios with low book asset growth. These *non-standard errors* (see Menkveld et al., 2021, illustrated by the width of the red distribution in Figure 1, Panel A), are hardly reduced by controlling for standard factors (blue distribution), even though, as one would expect, the mean is shifted to the left.

Figure 1: Non-standard errors for portfolios sorted on asset growth.
This figure shows the distribution of estimated premiums (i.e., the time-series average of high-minus-low portfolio returns) over all possible specifications across 14 methodological decision nodes. Panel A shows all possible specifications, and Panel B only considers variation across ten decision nodes, conditional on deciles, NYSE breakpoints, and value-weighted returns from single sorts. Each panel shows premiums (red, solid line) and alphas of the Fama and French (1992)-model (blue, dashed line).



The estimated premium varies widely depending on the choices made at each of the fourteen decision nodes. While the variation is largest when we allow for variation at all decision nodes (Panel A), it is still substantial when keeping some of them constant. In particular, when we keep the more obviously decisive decision nodes constant (i.e., only consider decile portfolios based on NYSE breakpoints, value-weighted returns, and single sorts), the remaining ten decision nodes still produce sizeable non-standard errors, as shown in Panel B of Figure 1.

Figure 2: Variation in t-statistics for portfolios sorted on asset growth.
This figure shows the distribution of t-statistics of the estimated premiums (i.e., the time-series average of high-minus-low portfolio returns) over all possible specifications across 14 methodological decision nodes. We use Newey and West (1987) standard errors with automatic lag selection as in Newey and West (1994). Panel A shows all possible specifications, and Panel B only considers variation across ten decision nodes, conditional on deciles, NYSE breakpoints, and value-weighted returns from single sorts. Each panel shows premiums (red, solid line) and alphas of the Fama and French (1993)-model (blue, dashed line). A t-value of 1.96 is indicated by the vertical dashed line.



The focus of this paper is not the size of specific premiums per se, although we do find that supposedly innocuous choices can have huge impacts on the size and statistical significance of the premiums (see, for instance, Figure 2). Rather, we provide estimates of how much the estimated premiums vary conditional on what decisions are taken at each specific node. Thereby, we disentangle the drivers of non-standard errors in portfolio sorts. In particular, we find that the number of portfolios, the weighting (value vs equal), the decision to include stocks with positive earnings, the stock exchanges used to define breakpoints as well as the exclusion of financial firms has a huge impact on how much the estimate premiums and alphas vary.

The impact of these decision nodes varies widely across sorting variables. For instance, the inclusion or exclusion of financial firms has a great impact on estimated premiums for profitability variables, the frequency of rebalancing matters greatly for investment variables and size restrictions for trading friction variables.

That said, we find that premiums are very robust and the link between sorting variables and subsequent returns does not depend on specific samples for the vast majority of sorting variables. In fact, while the size of estimated premiums varies, they are almost always positive and in most cases have a t-statistic above 1.96.

Our paper is related to different strands of the literature. Our paper is closely related to the paper by Menkveld et al. (2021) who introduce the term "non-standard errors" for the variation in estimates that is driven by the choices that researchers make when trying to investigate a question. We study a specific instance when non-standard errors occur, namely portfolio sorts and formalize the process by studying the impact of decisions typically taken when asset-pricing researchers study the returns on sorted portfolios. In a similar spirit, Mitton (2022) analyzes methodological variation in corporate finance regressions and finds that the selection and transformation of variables and outlier treatment are the main drivers of significance.

Investigating non-standard errors in finance is a dynamic field. In a concurrent paper, Soebhag et al. (2022) analyse effects of the portfolio construction mechanism and investigate its relevance for model selection in factor models. Our paper can be understood as complementary to Soebhag et al. (2022) since we focus on the impact of individual decision nodes and their economic interpretation. Coqueret (2022) studies "forking paths" in finance research (corresponding to nodes in our paper), and studies the statistical significance of portfolio strategies as an application. In line with our findings, he finds a large variation in t-statistics that can be used for p-hacking. Our interpretation is different. To us, a persistently positive premium shows that an anomaly is pervasive across stocks and evidence in favor of the existence of the anomaly from an economic point of view. That said, we also find large variation in the size of the premiums, i.e., non-standard errors.

We also contribute to the literature in empirical asset pricing discussing p-hacking and data mining. Prominently, Harvey (2017) discusses these issues and proposes a higher p-value threshold of 3 for subsequent return anomalies. Moreover, the vast number of asset pricing return anomalies received extensive scrutiny (in, e.g., Cochrane, 2011; Harvey et al., 2016; Linnainmaa and Roberts, 2018; Chordia et al., 2020; Feng et al., 2020, among others). McLean and Pontiff (2016) show the (lack of) robustness of anomalies after their publication. In contrast, we do not consider the time frame to be at the discretion of researchers in this study. Hou et al. (2020) advocate holding certain decision nodes constant for future publications and show that many published anomalies fail significance tests in their setting. In essence, the aforementioned studies show that data mining is a problem in empirical asset pricing. Yet this problem is even further increased by the fact that there is a strong bias towards publishing significant results over insignificant ones in most journals, i.e., the *file drawer problem* of Rosenthal (1979). For example, Kim and Ji (2015) and Morey and Yadav (2018) discuss the publication bias for financial economics specifically.

Our contribution to the discussion about a "replication crisis" in empirical asset pricing (see, e.g., Harvey, 2019; Jensen et al., 2021; Chen, 2022, for discussions) is twofold. Mainly, we highlight the critical decision nodes where data mining is most likely to yield significant results and peer reviewers will want to pay close attention to them. Secondly, we suggest that when testing whether a return premium exists, one may rather try out different sorting specifications than to check if a return differential should clear ever-increasing t-hurdles. The evidence in our paper is reassuring in the sense that almost all considered sorting variables yield positive premiums irrespective of the choices made. This looks a little less positive for t-statistics which are in about one third of cases across anomalies below commonly used cutoff points for t-statistics. The asset growth anomaly shown in Figures 1 and 2 is representative of both of these stylized facts. Which of these two pieces of evidence looms larger is debatable. In any case, most of the premiums we investigate are remarkably stable in terms of their sign and significance but still exhibit a wide variation that cast doubt if not on the existence of the premium but on their size, economic source and significance.

2 Data and methodology

We analyze commonly available data used in most empirical asset pricing studies from 1968 until 2021. In particular, we use daily and monthly returns from the Center for Research in Security Prices (CRSP) on common equity of US-based enterprises from NYSE, AMEX, and NASDAQ. Additionally, we acquire information on the shares outstanding, adjusted prices, industry classifications, and trading volume from CRSP alongside delisting returns, which we adjust according to Shumway (1997)[1]. Accounting data are from Compustat's North America Fundamentals Annual file. Moreover, we obtain the return time series for the Fama and French (1993) factors and the risk-free rate from Prof. French's homepage.

In recent years, many studies have discussed the need for reproducibility and the need for sharing code. Therefore, we share our code publicly in the following Github repository and refer the reader to tidy-finance.org for insights into the code design.

2.1 Sorting variables

We investigate 40 sorting variables suggested by previous studies to predict the cross-section of equity returns. They cover a wide range of suggested underlying economic mechanisms. Among them are well-known sorting variables such as size, the book-to-market ratio, asset growth, gross profits-to-assets, momentum, and idiosyncratic volatility. We provide the full list in Table 1. To enhance comparisons, we assign all sorting variables to one out of seven groups: momentum, size, valuation, investment and financing, profitability, intangibles, and trading frictions. The construction of these sorting variables closely follows Hou et al. (2020) and details can be found in Appendix A.

We acknowledge that researchers also have to make choices when constructing sorting variables from COMPUSTAT or CRSP data, such as the treatment of missing data or the

[1]Missing delisting returns for firms delisted for cause (delisting codes 400 - 591) are set to -30%.

choice of estimation windows. Although these decisions can also induce variation in results, we focus in the next section on the choices researchers have to make when mapping these sorting variables into expected returns, i.e., we treat the definition of sorting variables as given.

Table 1: List of sorting variables

We document the category, data frequency, abbreviation, description and authors for all 40 sorting variables.

Category	Data freq.	Abb.	Description	Publication
Momentum	monthly	MOM6	Return momentum (6-month formation period)	Jegadeesh and Titman (1993)
	monthly	MOM	Return momentum (11-month formation period)	Fama and French (1996)
	monthly	E6	Residual momentum (6-month formation period)	Blitz et al. (2011)
Size	monthly	ME	The natural logarithm of market equity in $	Banz (1981)
Profitability	yearly	ATO	Asset turnover	Soliman (2008)
	yearly	CBOP	Cash-based operating profitability	Ball et al. (2016)
	yearly	CTO	Capital turnover	Haugen and Baker (1996)
	yearly	GPA	Gross profits to assets	Novy-Marx (2013)
	yearly	O	Ohlson's O-score	Ohlson (1980), Dichev (1998)
Valuation	yearly	BM	Book equity scaled by market equity	Davis et al. (2000)
	yearly	CFP	Cash flows scaled by market equity	Lakonishok et al. (1994)
	yearly	DM	Debt scaled by market equity	Bhandari (1988)
	yearly	EP	Earnings scaled by market equity	Basu (1983)
	yearly	NPY	Net payout yield	Boudoukh et al. (2007)
	yearly	OCP	Operating cash flows scaled by market equity	Desai et al. (2004)
	yearly	SP	Sales scaled by market equity	Barbee Jr et al. (1996)
Investments and Financing	yearly	AG	Asset growth	Cooper et al. (2008)
	monthly	CSI	Composite share issuance	Daniel and Titman (2006)
	yearly	dNCA	Change in non-current operating assets	Richardson et al. (2005)
	yearly	dNCO	Change in net non-current operating assets	Richardson et al. (2005)
	yearly	dPIA	Change in property, plant, and equip. scaled by book assets	Lyandres et al. (2008)
	yearly	dWC	Change in net non-cash working capital	Richardson et al. (2005)

Continued on next page

Table 1 continued: List of sorting variables

	yearly	IG	Investment growth	Xing (2008)
	yearly	IVA	Investments scaled by assets	Lyandres et al. (2008)
	yearly	IVC	Inventory changes	Thomas and Zhang (2002)
	yearly	IVG	Inventory growth	Belo and Lin (2012)
	yearly	NOA	Net operating assets	Hirshleifer et al. (2004)
	yearly	OA	Operating accruals	Sloan (1996)
	yearly	POA	Percent operating accruals	Hafzalla et al. (2011)
	yearly	PTA	Percent total accruals	Hafzalla et al. (2011)
Intangibles	yearly	ADM	Advertisement expenses scaled by market equity	Chan et al. (2001)
	yearly	EPRD	Earnings' predictability	Francis et al. (2004)
	yearly	OL	Operating leverage	Novy-Marx (2011)
	yearly	RER	Real-estate ratio	Tuzel (2010)
	yearly	RDM	R&D expenses scaled by market equity	Chan et al. (2001)
Trading frictions	monthly	DTV	Dollar trading volume	Brennan et al. (1998)
	monthly	ISCC	Idiosyncratic skewness rel. to the CAPM	Bali et al. (2016)
	monthly	ISCFF	Idiosyncratic skewness rel. to the Fama and French (1993) model	Bali et al. (2016)
	monthly	IVOLC	Idiosyncratic volatility rel. to the CAPM	Ang et al. (2006)
	monthly	IVOLFF	Idiosyncratic volatility rel. to the Fama and French (1993) model	Ang et al. (2006)

2.2 Decision nodes

Researchers and practitioners have to make several decisions when constructing portfolio sorts. We follow the operations research literature (see, e.g., Kamiński et al., 2018), and label each decision as a decision *node*. From each node, the investigator's decision leads through two or three *branches* that subsume all subsequent nodes. At the end, each path ends in a *terminal node*, which we also refer to as a *specification*. In order to assess the impact of a specific decision node, we compare the *specifications* from all paths conditional on a specific choice of this decision node. Therefore, we introduce the term *branch* which subsumes all possible specifications conditional on a specific choice of the decision node under investigation.

We consider 14 common methodological decision nodes depicted as a flowchart in Figure 3 alongside their corresponding branches. In general, these decision nodes can be grouped into sample construction and portfolio construction nodes. Following this distinction, we present the seven sample construction nodes in Subsection 2.3 and the seven portfolio construction nodes in Subsection 2.4, respectively.

2.3 Sample construction

Before forming portfolios, researchers have to decide which sample of stocks to analyze. We discuss seven sample construction decision nodes and analyze their impact on return premiums. Theoretically, our choice to focus on common stocks from the United States (as a natural candidate) is in fact also a choice node. Conditional on only considering US common stocks, we analyze the following decision nodes throughout the sample construction.

Size filter. Researchers often limit their sample by excluding small stocks based on quantile breakpoints of NYSE market equity. In our analysis, we either consider all stocks or exclude the 5% or 20% of stocks with the lowest market capitalization in each month at the NYSE. This decision node might be particularly important, because stocks below the 20%-NYSE-threshold account on average for 50% of all stocks in our sample, although they only for a small fraction of the overall market capitalization. Therefore, this decision node is informative to which degree small (and illiquid) stocks drive the relation between the sorting variable and subsequent mean returns.

Financials. The exclusion of stocks belonging to the financial sector with standard industrial classification (SIC) codes between 6000 and 6999 is another frequently considered choice variable. This might be particularly relevant, because financial stocks have different balance sheet patterns compared to industrial firms and a larger exposure to periods of financial instability. Banks, in particular, face additional stringent regulation on their business activities. Moreover, firms in the financial industry make up roughly 15% of the number of stocks and the total market capitalization in our sample. Thus, this decision node reveals to which extent the relation between the sorting variable and subsequent mean returns (premiums) is exposed to the financial sector.

Utilities. We also study the effects of excluding stocks of utility firms with SIC codes between 4900 and 4999. Although utility stocks make up only about 5% of our sample, there are important reasons to consider this decision node. Firstly, stocks in the utility sector are typically heavily regulated and secondly depend often on the price development of underlying commodities. However, it is not always clear to what extent this restricts the proposed relation between a stock characteristic and stock returns.

Negative book equity. Even though limited liability ensures that the market value of equity cannot become negative, firms can have negative book equity values in the Compustat database. Nevertheless, book equity can become negative, e.g. if firms have sufficiently negative earnings, or high goodwill impairments. Interestingly, Luo et al. (2021) show that the share of negative book equity stocks has increased steadily from 1% in 1980 to about 4% of all Compustat stocks in 2012. The authors moreover reject the common perception that all negative book equity stocks are in distress, since roughly 50 % of stocks also show strong balance sheet patterns such as positive earnings. In the light of these findings, the decision to exclude negative book equity stocks is worthwhile to consider and is potentially important for sorts on valuation characteristics.

Negative earnings. Moreover, we analyze the exclusion of stocks which report negative earnings(indicated by Compustat item IB, income before extraordinary items) below zero. This decision node can have a large impact on the results of mapping sorting variables into mean returns, since over time, roughly 28% of stock-months have negative earnings. Investigating this decision node might help researchers to understand whether stocks with negative earnings impact return premiums. This is particularly interesting since such firms may be young firms with low profitability which have been associated with high average returns (Hou et al., 2014).

Stock age filter. Banz and Breen (1986) noted that Compustat often adds new firms with their full history of data to the database although the full history was not known at each respective point in time. This introduces a backfill bias which impacts the information availability for investors. Fama and French (1993) investigate this concern and claim that Compustat rarely adds firms with more than 2 years of historical data. Therefore, researchers typically require at least two years of previous observations for all firms in the Compustat database. We consider this decision node for two reasons: firstly, this node affects on average roughly 12% of firm-year observations. Secondly, while investors might be particularly concerned by this bias, researchers are often interested in the relationship per se and might not decide for a minimum listing age. Therefore, this node is particularly useful for investors, since it shows whether the mapping from sorting variables to mean returns can be replicated in real world markets.

Price filter. Lastly, researchers often consider excluding so called "penny stocks" with low absolute share prices. We consider no exclusion, or excluding stocks which trade below either 1$ or 5$. This decision node might help researchers to understand to which degree the functional relation between the sorting variable and mean returns is driven by small, illiquid, and highly volatile stocks that can potentially not be traded without frictions.

2.4 Portfolio construction

The sample construction constitutes only one layer of non-standard errors. Once the underlying sample is specified, researchers have to specify how to construct the portfolio. Again, we investigate seven decision nodes for portfolio construction:

Lagging of sorting variable. When forming portfolios, researchers need to make an assumption of how new the used information should be. For annual accounting data from Compustat, researchers prefer sufficiently long lags of at least 6 months. This ensures that the respective information was available to actual investors when portfolios are formed. Nonetheless, lags of 6 or more months do not allow the researcher to evaluate the short-term relationship between the sorting variable and mean returns throughout the first six or even more months. Therefore, we investigate a lag of exactly 3 months, 6 months or as in Fama and French (1992) of at least 6 months. This option depends on the data frequency of the sorting variables and is only available for yearly Compustat variables. We indicate the frequency of sorting variables in Column 2 of Table 1 where we group our sorting variables into high- and low-frequency variables depending on whether new information becomes available on a monthly or annual basis. This decision node might help researchers to understand whether the mapping from the sorting variable into mean returns is rather short-term or persistent.

Rebalancing frequency. We consider rebalancing portfolios on a monthly and yearly basis as it is common in most portfolio sorts. Whether there is an option for the frequency of rebalancing depends on data availability and is so far only available for yearly sorting variables (see Table 1, Column 2). Therefore, the effects from this decision node can be mainly attributed to the differences in fiscal year ends for distinct stocks. This choice node might help to understand how persistent the relation between high frequency variables and mean returns is. Moreover, it can also indicate to which degree the underlying relationship depends on transaction cost which are high for frequent rebalancing.

Breakpoints: Quantiles (main). Which quantiles are used for portfolio breakpoints is an obvious driver of estimated premiums, both in terms of means as well (non-)standard errors. From an economic perspective, it may be indicative about the degree of monotonicity in the underlying functional relationship between stock characteristics and mean returns. Having a larger premium when using more extreme breakpoints is of course natural but it is moreover possible that more extreme breakpoints have an impact on the effect of other decision nodes. In this paper we consider either quintiles or deciles to determine the breakpoints of portfolios.

Double sorting. In general researchers are interested between the relationship of a single sorting variable and mean returns (single sorts). Nonetheless, many researchers investigate the robustness of this relationship conditional on other sorting variables such as size. Therefore, we consider independent and dependent double sorts with size as secondary sorting variable. Dependent double sorts condition on the portfolios of the primary sorting variable, whereas independent double sorts compute size breakpoints independently of the level of the primary sorting variable. This decision node is informative whether the relationship between the primary sorting variable and mean returns is robust to specific groups of the secondary sorting variable, i.e., size groups.

Breakpoints: Quantiles (secondary). Conditional on investigating double sorts, a researcher has to decide how many secondary portfolios to choose. We allow for 2 or 5 secondary portfolios. From an economic perspective, the granularity of secondary breakpoints indicates to which extent the relationship between the primary sorting variable and mean returns is robust or limited to extreme observations of the secondary variable. This becomes highly relevant if researchers are concerned that the primary sorting variable is closely related to other characteristics which are known to predict the cross-section of stock returns.

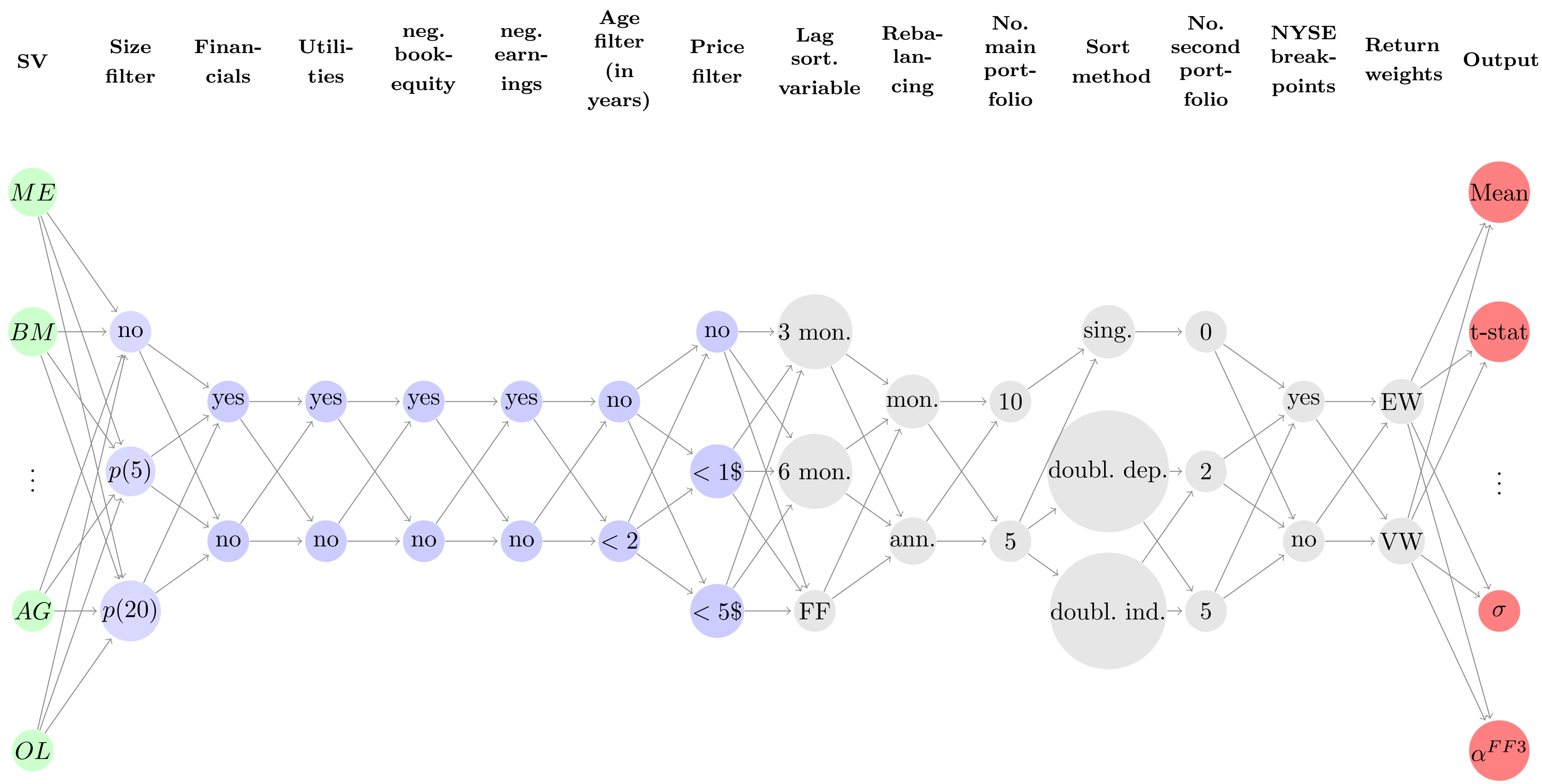
Breakpoints: Exchanges. To mitigate the impact of small stocks, it is common to compute breakpoints for the primary but also secondary sorting variable based on stocks listed on the New York Stock Exchange (NYSE). In detail, NYSE stocks have an average market capitalization of roughly 5bn$ compared to 1bn$ for stocks listed on Nasdaq and 4bn$ for stocks listed on Amex. This choice of breakpoints allows for an interesting interpretation: If we observe large non-standard errors alongside this choice node, the primary sorting variable is likely to be systematically related to size in terms of Spearman rank correlations.

Weighting scheme. After assigning stocks to their respective portfolio, a researcher has to decide how to form an average over all stock returns in each portfolio. We consider either equally weighted average returns or returns weighted with the market capitalization of the corresponding stock (value weights). This decision node shows to which degree the relationship between the sorting variable and mean returns depends on returns from small stocks.

Overall these 14 decision nodes imply 69,120 specifications for annual and 11,520 specifications for monthly sorting variables. This amount of potential specifications underlines that non-standard errors might be particularly relevant in portfolio sorts. Given that we analyze 40 sorting variables, we report the outcomes for 2,188,800 specifications in the following sections.

Figure 3: Flowchart of decision nodes for portfolio sorts.

After constructing 41 sorting Variables (SV) we consider the paths of 14 decision nodes for portfolio sorts until the final nodes, i.e., the output. The first seven decision nodes are sample construction nodes: include large stocks dependent on market equity quantiles (all, larger then p(5) or p(20)), include financials (yes or no), include utilities (yes or no), firm-months with negative book equity (yes or no), firm-months with negative earnings (yes or no), stocks-age filters (at least two years or all), and stock prices (larger than \$1, \$5, or all). The ensuing seven decision nodes belong to the portfolio construction nodes: the lag of the sorting variables (three months, six months, or a Fama-French lag), the portfolio rebalancing (monthly or annually), the number of main portfolios (5 or 10), the sorting method (single sorts, independent or dependent double sorts), the number of secondary portfolios for double sorts (2 or 5), the exchanges for breakpoints (NYSE or all), and the weighting scheme (equal- or value-weighting).



There are some potential nodes we keep constant in this paper and hence do not consider as decision nodes. First, we do not change the sequence of the decision nodes, even though we could partly reshuffle the present order. In particular, excluding a fraction of small firms, which depends on the sample composition, might induce non-standard errors. Nevertheless, we find that the sequence does not impact our conclusions in this case. Second, the exact definition of each sorting variable is, in principle, another decision node. We do not consider it here separately as there are no standardized procedures for a large set of different sorting variables. However, the impact of sorting variable variation should not be disregarded as a source of non-standard errors. Moreover, we also keep the sample period constant, since it is not necessarily at the discretion of researchers interested in new return anomalies and again is hard to standardize. Finally, we do not study the impact of coding errors on the outcome of portfolio sorts. It seems arbitrary to include mistakes in some code by design even though it may have a potentially huge impact.

2.5 Empirical methodology

For each specification of the portfolio sorting procedure, we compute the average return differential between the two extreme portfolios (i.e., high-minus-low portfolio returns), which we refer to as *premium*.[2] In particular, we compute

$$r_s^v = \frac{1}{T}\sum_{t=1}^{T}\left(\bar{r}_{t,s}^{v,\text{High}} - \bar{r}_{t,s}^{v,\text{Low}}\right), \tag{1}$$

where v denotes the sorting variable, s references the specification, and t is a time indicator from period 1 up to T. $\bar{r}_{t,s}^{v,\text{High}}$ and $\bar{r}_{t,s}^{v,\text{Low}}$ specify the extreme portfolios' returns in the time series, such that the sign is normalized to yield a positive premium in line with the results of the original paper that proposed the anomaly. The extreme portfolios' returns are weighted according to the specification's weighting scheme. In the case of double sorts, the extreme

[2]We are deliberately loose with the term 'premium'. Not all considered return differentials were originally referred to as premiums in the asset-pricing sense of a (risk) premium. Moreover, strictly speaking, the expected value of the long-short-portfolio return is the premium, whereas the average long-minus-short portfolio return is an estimate.

portfolios' returns are then equally weighted (i.e., $\bar{r}^{v,\cdot}_{t,s}$ is always an extreme portfolio's return for a particular specification, sorting variable, and time).

All results shown in this paper are based on monthly returns in percent. Furthermore, we also adjust the monthly returns accounting for the exposure to the factors of the Capital Asset Pricing Model (CAPM) and the Fama and French (1993)-Model (FF3) for some tests. Whenever we present summary statistics of the premiums produced by different specifications, we take an average over the (sub-)sample of premiums for each sorting variable, before averaging across sorting variables. The removal of outliers does not impact our results, and we do not truncate or winsorize our samples.

We also consider t-statistics and the respective time series' standard errors in some tests. Throughout the paper, we report Newey and West (1987) standard errors with automatic lag selection following Newey and West (1994). These corrected errors are also used for t-statistics. We aggregate t-statistics by counting the number of specifications larger than 1.96 relative to the total number of specifications within a test. We also compute average standard errors, by taking the average across specifications.

Finally, we define *non-standard errors* in line with Menkveld et al. (2021) as the standard deviation of estimates across specifications. Specifically, in our case, we take

$$\mathrm{NSE}^v = \sqrt{\frac{1}{n-1}\sum_s (r^v_s - \bar{r^v_s})}, \tag{2}$$

where n denotes the number of specifications s considered, which can vary for different questions.

3 Decision node impact across sorting variables

In this section, we study whether the variation in the outcome of portfolio sorting strategies varies with the sorting variable, i.e. whether for some sorting variables, the overall non-standard error is larger than for others.

The 14 suggested decision nodes in portfolio sorts imply that researchers can take many different paths even though they intend to infer the same relation between a given sorting variable and expected returns. To study this source of variation, we aggregate the outcomes such as premiums and t-statistics over all specifications into distributions. Figure 4 shows these distributions of premiums from all possible specifications for each sorting variable. The shape of the distribution varies widely across sorting variables and the average variation depicted by these box plots is substantial. For very few sorting variables which are known to be significant predictors of equity returns such as investments-to-assets (IVA) or residual momentum (E6), this variation is even large enough that a non-positive premium can be observed. This might be less surprising for sorting variables such as asset turnover (ATO), capital turnover (CTO) or the debt-to-market ratio (DM) which have been shown to be only marginally statistically significant (Hou et al., 2020). Importantly, Figure B.1 shows that this variation in premiums also translates into variation in t-statistics of these premiums. In fact, some specifications for investments-to-assets (IVA) or residual momentum (E6), which are both known to be significant cross-sectional predictors, yield insignificant premiums. Nevertheless, it is remarkable that we observe only for a few sorting variables in Figure 4 a non-positive premium and in Figure B.1 a t-statistic below the 10% significance level. This confirms that the asset pricing findings of these sorting variables are most likely robust.

Interestingly, the larger the average premium of a sorting variable, the more variation can be observed in Figure 4. For example, different versions of the momentum anomaly (MOM6 or MOM) or earnings' predictability (EPRD) show the largest variation and tend to have the largest average premium across sorting variables. In contrast, the real estate ratio (RER) or the Ohlson (1980) O-score (O) have both low average premiums and a low variation across specifications. This might imply that sorting variables which are associated on average with a large absolute premium might be often based on extreme observations. Thus, slightly altering the choices in portfolio sorts can have a huge impact on results.

Overall, we find the largest variation in premiums for sorting variables belonging either to investments and financing or to the momentum group. The picture for all other groups of sorting variables is mixed in the sense that they are comprised of sorting variables with either relatively high or low variation in their distribution. For example, among the sorting variables categorized as “trading frictions”, the distributions of different versions of idiosyncratic skewness (ISCC and ISCFF) can be characterized by lower variation compared to the relatively large variation in distributions of distinct versions of idiosyncratic volatility (IVOLC and IVOLFF).

Figure 4: Non-standard errors across sorting variables.
This figure shows the estimated premiums (in %) in boxplots for all sorting variables across all decision nodes. The vertical axis shows the associated sorting variable, while the color scheme connects each sorting variable to the respective group.

Moreover, we quantify the variation of these distributions in Table 2 where we show corresponding moments such as the mean, skewness, kurtosis and non-standard errors. The average premium across all 40 sorting variables is around 0.37% per month and the average non-standard error is a sizable 0.15%. What does a non-standard error of 0.15 tell us? It implies that a change of one standard deviation from the mean captures premiums from 0.22% to 0.52% per month. Adding one more standard deviation we observe premiums in the interval from 0.07% to 0.67%. These are sizeable and important differences once we consider that the mean premium across sorting variables is 0.37% per month. Interestingly, the average non-standard error for all sorting variables tends to be with 0.15 even slightly larger than the average standard error of 0.14. Therefore, the ratio of the non-standard errors to standard errors which are commonly used to evaluate statistical significance is for most sorting variables larger than 1.

Similar to Figure 4, non-standard errors tend to be considerably large for sorting variables belonging to the groups investments and financing, momentum and trading frictions. On average, we observe non-standard errors around 0.15, 0.21 and 0.16 for these groups. In contrast, sorting variables from the groups valuation, profitability and intangibles tend to have relatively low non-standard errors with on average 0.12, 0.11 and 0.11 respectively. Interestingly, Table 2 indicates that the distributions from Figure 4 show an kurtosis of roughly 3.96 and are positively skewed. The choices in portfolio sorts tend to induce particularly large outliers in premiums for sorting variables from the groups trading frictions, intangibles and profitability. Table 2 also confirms the observation that most premiums across sorting variables are remarkably stable for all portfolio specifications. On average we observe only for 2% of all specifications a non-positive premium and for 35% of all observations a premium with statistical significance below the 95% level.

Summing up, there are two main takeaways from this section. Firstly, we find that the choices in portfolio sorts induce considerably large variation in average premiums and t-statistics. Secondly, although we find large non-standard errors, most premiums are pervasively positive.

Table 2: Non-standard errors across sorting variables.
This table shows summary statistics for all sorting variables grouped by the respective category. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums across all decision nodes for each sorting variable. Furthermore, it contains the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and t-statistics larger than 1.96 (Sig.) scaled by the number of premiums, respectively.

Group	SV	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Int.	ADM	0.22	0.10	0.17	0.56	0.67	3.50	1.00	0.10
Int.	EPRD	0.75	0.16	0.16	1.01	0.42	2.40	1.00	1.00
Int.	OL	0.30	0.10	0.15	0.71	0.97	3.79	1.00	0.52
Int.	RDM	0.42	0.13	0.16	0.80	0.89	4.60	1.00	0.85
Int.	RER	0.17	0.05	0.06	0.87	1.07	4.75	1.00	0.90
Inv.	AG	0.47	0.20	0.13	1.51	0.93	4.06	1.00	0.91
Inv.	CSI	0.47	0.14	0.14	0.95	0.55	2.89	1.00	0.99
Inv.	DNCA	0.47	0.18	0.11	1.66	0.73	3.52	1.00	0.98
Inv.	DNCO	0.49	0.17	0.10	1.70	0.73	3.56	1.00	0.99
Inv.	DPIA	0.49	0.19	0.11	1.67	0.79	3.81	1.00	0.95
Inv.	DWC	0.45	0.16	0.09	1.74	0.54	2.81	1.00	1.00
Inv.	IG	0.34	0.11	0.09	1.25	0.73	3.66	1.00	0.96
Inv.	IVA	0.25	0.17	0.13	1.33	0.99	4.09	0.99	0.47
Inv.	IVC	0.43	0.16	0.10	1.70	0.59	2.67	1.00	1.00
Inv.	IVG	0.40	0.14	0.09	1.52	0.37	2.46	1.00	0.96
Inv.	NOA	0.52	0.16	0.12	1.26	0.72	3.75	1.00	1.00
Inv.	OA	0.40	0.15	0.10	1.52	0.63	2.84	1.00	0.91
Inv.	POA	0.44	0.13	0.09	1.42	0.46	2.53	1.00	0.99
Inv.	PTA	0.31	0.10	0.09	1.11	0.32	2.65	1.00	0.92
Mom.	E6	0.26	0.16	0.12	1.31	0.15	2.50	0.95	0.57
Mom.	MOM	0.87	0.21	0.23	0.91	0.35	2.71	1.00	1.00
Mom.	MOM6	0.65	0.26	0.20	1.32	0.43	2.80	1.00	0.88
Pro.	ATO	0.11	0.09	0.12	0.73	0.51	2.73	0.91	0.09
Pro.	CBOP	0.45	0.16	0.12	1.27	0.95	4.09	1.00	0.93
Pro.	CTO	0.14	0.09	0.15	0.62	0.79	4.00	0.97	0.04
Pro.	GPA	0.35	0.15	0.14	1.05	0.79	3.25	1.00	0.66
Pro.	O	0.07	0.07	0.13	0.56	0.44	3.93	0.85	0.03
Siz.	SIZE	0.28	0.23	0.18	1.25	3.45	19.70	0.99	0.15
Tra.	DTV	0.27	0.16	0.19	0.85	1.37	7.00	0.98	0.20
Tra.	ISCC	0.10	0.11	0.07	1.70	−0.21	3.80	0.86	0.42
Tra.	ISCFF	0.01	0.11	0.07	1.65	−0.59	4.45	0.62	0.13
Tra.	IVOLC	0.45	0.22	0.22	1.02	0.71	3.65	0.99	0.51
Tra.	IVOLFF	0.44	0.21	0.21	1.01	0.72	3.78	0.99	0.51
Val.	BM	0.33	0.17	0.19	0.91	1.25	4.85	1.00	0.31
Val.	CFP	0.35	0.13	0.18	0.71	0.56	3.18	1.00	0.46
Val.	DM	0.10	0.08	0.18	0.43	0.51	3.22	0.92	0.00
Val.	EP	0.36	0.10	0.16	0.62	0.82	3.85	1.00	0.65
Val.	NPY	0.43	0.12	0.16	0.76	0.74	3.44	1.00	0.85
Val.	OCP	0.44	0.10	0.17	0.58	0.42	3.01	1.00	0.85
Val.	SP	0.42	0.16	0.20	0.80	1.13	4.13	1.00	0.52
Mean		0.37	0.15	0.14	1.11	0.71	3.96	0.98	0.65

4 The impact of individual decision nodes

The main goal of this study is to investigate the impact of 14 portfolio sort-specific methodological decision nodes. We study the nodes' impacts on two levels with various tests. First, we analyze the effects of each node on a time-series level. Specifically, we compare return time-series between specifications that differ only in the respective node, i.e., we compare pairs of specifications across branches. Second, we analyze the distribution of premiums within each branch of a decision node.

4.1 Impact across branches

In this section, we focus on two main outcome variables, the mean absolute difference in premiums' time series and the average correlation of long-short-return differentials. Table 3 shows the mean absolute differences across decision nodes in Panel A, i.e., the mean of pairwise absolute differences between premiums' time series with specifications that are identical except for one decision node (specified in the first column of Panel A). For instance, row 1 shows the difference between the premiums in all terminal nodes that are computed using identical decisions in all nodes except for the choice of quantile breakpoints (i.e., quintiles or deciles).

Overall, we find large impacts in terms of mean absolute differences, which in most cases exceed half a percentage point per month. A few cases stand out. As expected, the number of portfolios has a huge impact on non-standard errors. The weighting scheme is similarly important as conditioning on positive earnings, the exchanges used for setting quantile breakpoints (particularly so for sorts on size), the size restriction itself, and the exclusion of financial firms. Interestingly, the effects on mean absolute differences vary across groups of sorting variables. Perhaps not surprisingly, since it is related to earnings, profitability anomalies have huge mean absolute deviations depending on whether only firms with positive earnings are included. Similarly, the exclusion of financial firms has a strong effect on profitability-related return differentials. While the exclusion of utilities does not have a strong impact on sorts relying on intangibles, investment and financing, and momentum, its effect amounts to more than half a percentage point for profitability, size, and valuation sorts.

Panel B of Table 3 shows the correlation of the realized time-series of return differentials where, again, as in Panel A, the decisions in all nodes but the node specified in the first column are kept constant. For instance, the second row in Panel B shows the average pairwise correlation between return time series that only differ in whether they include or exclude firms with negative earnings. A low degree correlation between return differentials indicates a strong impact on the respective decision node. From an economic perspective, stable correlations across branches provide important information on whether an anomaly represents a (risk) factor. The ranking is similar to that from Panel A, which was based on mean absolute differences. Comparing across groups of sorts, momentum stands out in its non-susceptibility with respect to changes in decision nodes when measured in terms of correlations, which remain high across decision nodes. This indicates that irrespective of the nodes, momentum sorts exhibit a great deal of common variation, even when the mean absolute differences are large, as shown in Panel A. This points to momentum having a strong factor structure robust to the exact choices of portfolio formation and sorting procedures that applies to all stocks irrespective of sample composition or sorting procedures. At the opposite end of the spectrum in terms of stability are investment and financing anomalies, which are particularly susceptible to losing correlation when altering choices about rebalancing or excluding stocks with negative earnings.

Table 3: Mean absolute differences and correlations across decision nodes.
This table shows mean absolute differences (Panel A, in %) and correlations (Panel B) of the premiums' time series across individual decision nodes. For each decision node, we compare time-series pairs that differ only in the specific node. Then, we take the mean for each node-sorting variable combination. The two panels show means for all categories together (Overall) and individual categories separately. Moreover, the nodes are arranged by impact. By construction, some entries do not produce variation and are left empty.

Panel A: Mean absolute differences

Node	Overall	Int.	Inv.	Mom.	Pro.	Siz.	Tra.	Val.
BP: Quantiles (main)	1.04	1.09	0.99	1.17	0.97	0.77	1.24	1.00
Weighting scheme	0.99	1.09	0.96	1.05	1.01	0.64	0.88	1.06
Positive earnings	0.91	0.87	0.86	0.86	1.09	0.91	1.00	0.88
Size restriction	0.83	0.82	0.73	0.84	0.76	1.53	1.08	0.78
BP: Exchanges	0.82	0.82	0.73	0.76	0.75	1.08	1.08	0.83
Financials	0.74	0.83	0.54	0.63	1.43	0.62	0.67	0.72
BP: Quantiles (second)	0.65	0.66	0.59	0.60	0.57		1.01	0.59
Rebalancing	0.63	0.53	0.71		0.50			0.61
Double sort	0.62	0.60	0.55	0.51	0.44		1.26	0.50
Utilities	0.45	0.18	0.38	0.43	0.68	0.43	0.53	0.57
Sorting variable lag	0.43	0.34	0.51		0.32			0.42
Stock-age restriction	0.41	0.33	0.45	0.27	0.41	0.46	0.50	0.39
Price restriction	0.35	0.36	0.33	0.33	0.33	0.53	0.45	0.32
Positive book equity	0.21	0.24	0.20	0.19	0.21	0.21	0.22	0.21

Panel B: Correlations

Node	Overall	Int.	Inv.	Mom.	Pro.	Siz.	Tra.	Val.
Weighting scheme	0.86	0.82	0.83	0.93	0.87	0.97	0.87	0.91
Positive earnings	0.88	0.89	0.85	0.96	0.79	0.85	0.90	0.94
BP: Quantiles (main)	0.90	0.87	0.87	0.96	0.92	0.92	0.88	0.95
Size restriction	0.91	0.90	0.90	0.96	0.93	0.71	0.89	0.96
Financials	0.91	0.87	0.94	0.98	0.75	0.92	0.96	0.96
Rebalancing	0.92	0.94	0.87		0.95			0.96
BP: Exchanges	0.92	0.91	0.91	0.97	0.93	0.81	0.91	0.96
BP: Quantiles (second)	0.94	0.93	0.93	0.98	0.96		0.92	0.97
Sorting variable lag	0.95	0.97	0.91		0.98			0.98
Double sort	0.95	0.95	0.94	0.99	0.97		0.90	0.98
Utilities	0.97	0.99	0.97	0.99	0.92	0.93	0.97	0.97
Stock-age restriction	0.97	0.98	0.96	1.00	0.97	0.93	0.97	0.99
Price restriction	0.97	0.97	0.97	0.99	0.98	0.93	0.97	0.99
Positive book equity	0.99	0.99	0.99	1.00	0.99	0.98	0.99	1.00

4.2 Effects within branches

We now turn to the impact of individual nodes on the distribution in the branches they create. We study variation in terms of mean premiums, standard errors (average standard errors, ASE) and non-standard errors (non-standard error) within one branch when keeping one node constant. We also report the ratio of non-standard errors to ASEs as well as the skewness, kurtosis, share of end notes with a positive premium and the share of end notes with a Newey and West (1987) t-statistic above 1.96. We focus on the nodes with the largest impact in terms of mean absolute differences in premiums in Table 3. All Tables are presented in Appendix C.

Impact of: Breakpoint quantiles (main). Table C.1 shows the results for the first node, the breakpoint quantiles. Across all sorting variable groups, non-standard errors are higher for the more extreme decile breakpoints. non-standard errors tend to increase more than ASEs when breakpints are more extreme. The only exception are trading friction anomalies where the ratio of non-standard error to ASEs decreases. Overall this is not surprising since if the sorts correspond to a monotonically increasing of stock characteristics, premiums should be higher for more extreme values. Since this likely impacts all other decision nodes, higher non-standard errors (and ASEs) are to be expected.

Impact of: Weighting scheme. Next, we turn to the impact of different weighting schemes with results presented in Table C.2. As one would expect, mean premiums are higher for equally weighted returns, as are non-standard errors. This is probably the case because smaller firms have more exposure to a variety of priced risks (and potential mispricing). These stocks get a smaller weight in value-weighted sorts.

Impact of: Positive earnings filter. Table C.3 shows the results for the decision node that considers restricting the sample to firms with positive earnings only. For most groups of sorting variables, getting rid of stocks of firms with negative earnings leads to lower mean premiums, with the strongest effect for profitability. This is intuitive since the profitability anomaly has low profitability stocks in its short leg, some of which have negative earnings. Interestingly, we see the opposite effect for the size anomaly, i.e. when excluding negative-earnings stocks, the size premium is higher on average. Excluding stocks with negative earnings reduces non-standard errors for all sorting variable groups.

Impact of: Size restriction. As one would expect, mean premiums are smaller when excluding the smallest 20% of stocks at each formation time, as shown in Table C.4. Moreover, non-standard errors are lower, as are ASEs. This suggests that most anomalies are related to market capitalization. Obviously, the effects are strongest for sorts on size which generates most of the premium from the smallest 20 percent of stocks. Results are similar for trading friction anomalies where the distribution becomes slightly left-skewed.

Impact of: Breakpoint exchanges. We find similar effects when considering the decision node which stock exchanges to base the breakpoints on (see Table C.5). Overall, mean premiums are higher when basing breakpoints on all stock exchanges rather than just NYSE. A look at Panel E (size) suggests that this seems to be again related to smaller stocks being listed on non-NYSE exchanges.

Impact of: Financials. It is common to exclude financial firms in portfolio sorts. We present the effects of this decision in Table C.6. Interestingly, the in-or exclusion of financial firms has hardly any impact on most sorting variable groups. However, the impact is profound when considering profitability anomalies. Sorts on profitability variables have markedly lower premiums when including financial firms. Following Novy-Marx (2013), most papers on profitability exclude financial firms. Financial firms tend to have higher leverage which reduces the denominator in many measure of profitability (see Appendix A). Such estimates of "profitability" may not be comparable to those of others firms.

Impact of: Breakpoint quantiles (secondary). We also consider different break points for secondary sort acccording to size. The results are presented in Table C.7. Interestingly, there are hardly any effects.

Impact of: Rebalancing frequency. We also consider results when either rebalancing yearly in July or at a monthly frequency. The results in Table C.8 show only modest differences except for investment and financing anomalies where using "fresher" data leads to higher premiums and slightly higher non-standard errors. This may be due to the lower persistence of these variables which makes newer information more valuable.

Impact of: Double sorts. We now turn to the effects of double-sorting on a sorting variable and size (market capitalization). Table C.9 shows that sorting additionally on size leads to higher premiums, particularly for trading friction and momentum anomalies, suggesting that both effects tend to be driven by small, hard-to-trade stocks.

Impact of: Other nodes. Finally, we consider those decision nodes that had a mean absolute difference across branches of below 0.5 percentage points in Table 3. Including or excluding utilities has only smaller effects on the distribution within branches (see Table C.10), lagging the sorting variable has a strong effect on investment and financing sorts (in line with the results on rebalancing discussed above, see Table C.11 for results). Concerning the stock-age restriction, the results in Table C.12, we find the greatest effects for the size and momentum sorting variable groups. Including more established companies only lowers the momentum premiums and increases the size premium. The exclusion of penny stocks with prices below five or one dollar only has a marked effect on non-standard errors and premiums of sorts on size (see Table C.4. Table C.14 shows that the exclusion of stocks with negative book equity has very negligible effects.

Overall, our analysis of comparing the distribution of premiums across nodes showed very broad and homogeneous effects for some node such as the size restriction and heterogeneous effects depending on what group of sorting variables we consider for others. For instance, the impact of including financial firms is particularly strong for profitability anomalies, investing and financing anomalies.

Note that this may mask the differences between otherwise identical specifications in each of the branches. This may be the case when there is a lot of volatility in the time series such that when comparing specifications that only differ in one node, one frequently ends up with rather different premium estimates (as shown in Table 3) even though the overall distribution of premiums may look rather similar, as is often the case in Tables C.1-C.14. Strikingly, almost all specifications yield positive premiums.

5 Adjusted returns

It is a standard procedure in asset pricing to control for factor models in order to find out how much of the measured premiums are actually due to exposure to other, well-established risk factors. In particular, some return differentials can be fully explained by other risk factors, i.e., they represent an indistinguishable return pattern. In this section, we investigate the relation between the variation in premiums that can be explained by two prominent factor models, namely, the CAPM and the Fama and French (1993) three-factor model. Similar to the return patterns, non-standard errors could be driven by premiums' exposure to existing factors.

For estimating the CAPM alphas α^{CAPM}, we regress the time-series of return differentials $r^v_{t,s}$ for each sorting variable v and specification s on the market return r^M_t, i.e.,

$$r^v_{t,s} = \alpha^{\mathrm{CAPM},v}_s + \beta^{\mathrm{M,CAPM},v}_s r^M_t + \varepsilon^{\mathrm{CAPM},v}_{t,s}. \tag{3}$$

Additionally, for estimating the Fama and French (1992) alphas α^{FF3}, we regress the time-series of return differentials $r^v_{t,s}$ on the market return r^M_t, the size factor returns r^{SMB}_t, and the value factor returns r^{HML}_t,i.e.,

$$r^v_{t,s} = \alpha^{\mathrm{FF3},v}_s + \beta^{\mathrm{M,FF3},v}_s r^M_t + \beta^{\mathrm{SMB},v}_s r^{\mathrm{SMB}}_t + \beta^{\mathrm{HML},v}_s r^{\mathrm{HML}}_t + \varepsilon^{\mathrm{FF3},v}_{t,s}. \tag{4}$$

5.1 Alphas across sorting variables

To investigate the distribution of model-adjusted premiums, we estimate Equations (3) and (4) for each specification and sorting variable separately. Then, we show the distribution of α^{CAPM} and α^{FF3} in boxplots for each sorting variable across all specifications.

Figure 5 shows that non-standard errors in CAPM-alphas are, on average, sizeable and comparable to their unadjusted counterparts shown in Figure 4. For the majority of sorting variables, the variation in CAPM-alphas even exceeds the variation observed in the premiums originally. We also show that this increase in non-standard errors is accompanied by a slight decrease in average standard errors.[3] This also leads to an increase in the non-standard error to average standard error ratios on average.

While adjusting premiums for their market exposure does not explain a significant part of non-standard errors, it affects their levels. In particular, the adjustment positively affects CAPM alphas, which are larger than the respective premiums. Nonetheless, the effect is non-monotonic, and some premiums' CAPM alphas drop close to zero. However, even for sorting variables with low CAPM alphas (e.g., ATO, CTO, and SIZE), non-standard errors increase.

We also show the effects of the Fama and French (1993)-model on variation in premiums with a boxplot in Figure 6. We see a drop in the estimates compared to CAPM alphas. This is largely concentrated in the valuation and size group, which are related to the additional factors of the three-factor model. Again, non-standard errors remain large and actually increase relative to average standard errors across most sorting variables.

In a further analysis[4], we also show that the fraction of positive t-statistics increases on average when adjusting only for market risk (compared to premiums themselves), but decreases again when adding the factors size and value. The overall variation in t-statistics across different portfolio sorting approaches is large. Moreover, the same is true for variation in standard errors. Nevertheless, most of the sorting variables presented here have statistically significant α^{CAPM} and α^{FF3}. The overall fraction of positive t-statistics is 73% for the CAPM and 70% for the three-factor model, and, on average, over 90% of alphas are positive.

Overall, we conclude that the adjustment for factor models does not decrease non-standard errors. On the contrary, variation in alphas can exceed the variation in premiums themselves across a researcher's decision spectrum. Additionally, irrespective of the model, most sorting

[3] We provide summary statistics for the CAPM and FF3 alphas in the Internet Appendix in Table 4 and in Table D.1, respectively.

[4] We present boxplots for t-statistics and standard errors for premiums, CAPM alphas, and FF3 alphas in the Internet Appendix in Section II.

variables remain pervasive. Similar to premiums, alphas are consistently positive and statistically significant. While most return differential time series feature a significant orthogonal component irrespective of the specification, differences in return patterns induced by methodological choices lead to unexplained and sizeable non-standard errors.

Figure 5: CAPM alphas: Non-standard errors across sorting variables.
This figure shows the estimated average premiums (in %) adjusted for the CAPM-model in boxplots for all sorting variables across all decision nodes. The vertical axis shows the associated sorting variable, while the color scheme connects each sorting variable to the respective category.

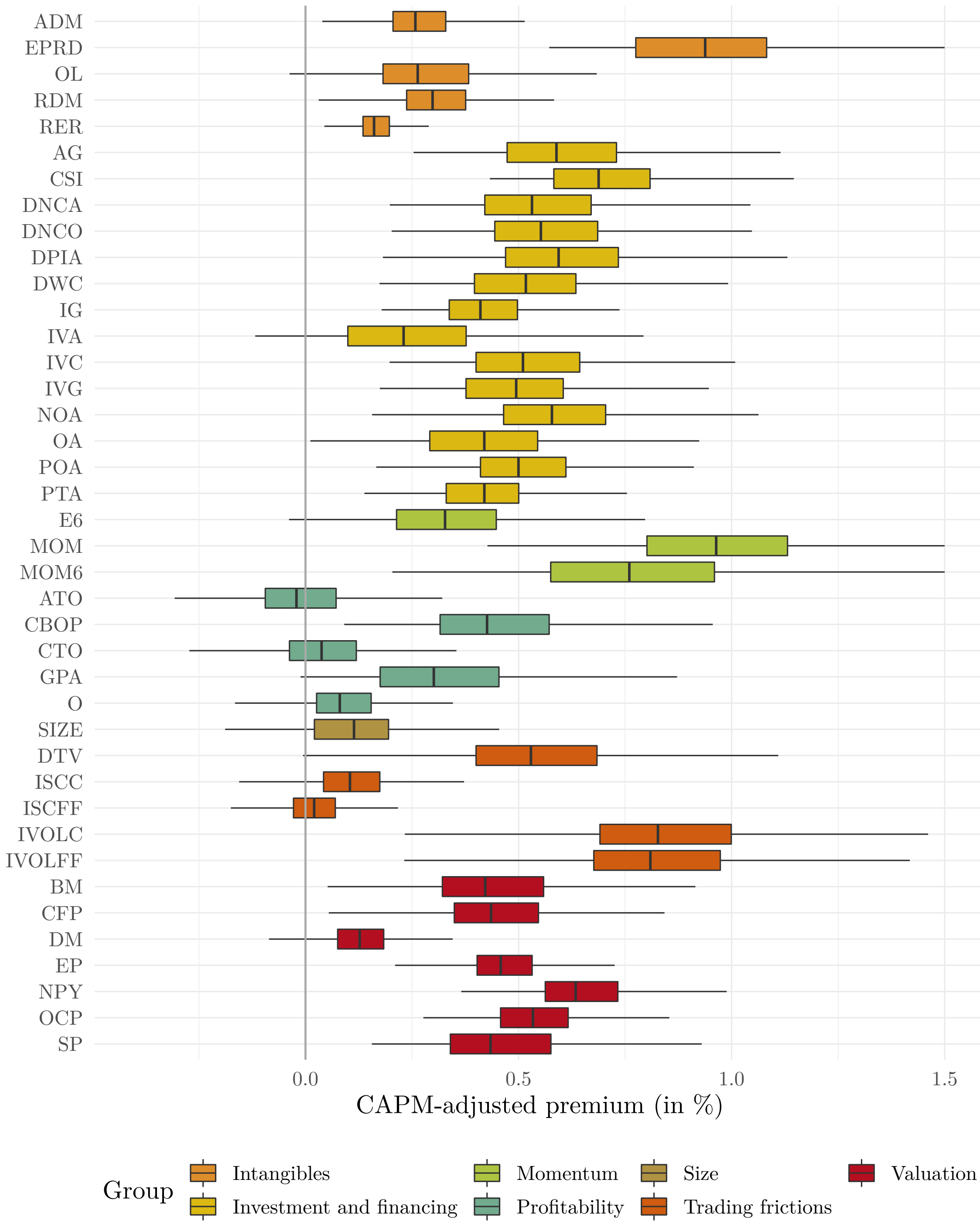
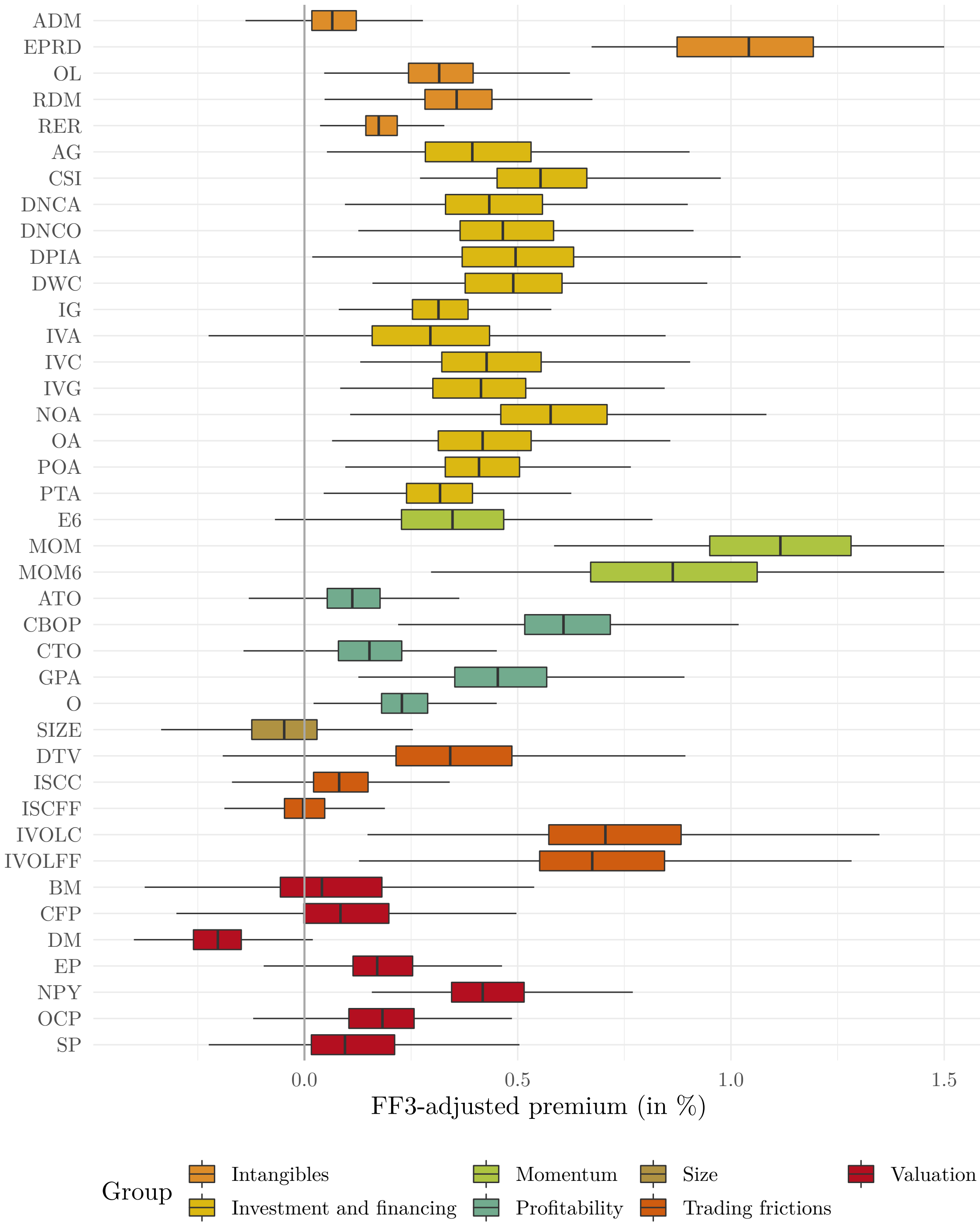


Figure 6: FF3-adjusted returns: Non-standard errors across sorting variables.
This figure shows the estimated average premiums (in %) adjusted for the Fama and French (1992)-model in boxplots for all sorting variables across all decision nodes. The vertical axis shows the associated sorting variable, while the color scheme connects each sorting variable to the respective category.



5.2 The impact of individual decision nodes on alphas

In the last empirical analysis, we investigate which nodes drive the variation in adjusted returns in the time series and how large non-standard errors in alphas are in the respective node's branch. To analyze the effect of each node on the time series of adjusted returns, we add the respective intercept and the residuals of Equations (3) and (4) for particular sorting variables' specifications, i.e., we define the *adjusted return* time series

$$\tilde{ar}_{t,s}^{\mathrm{m},v} := \tilde{\alpha}_s^{\mathrm{m},v} + \tilde{\varepsilon}_{t,s}^{\mathrm{m},v}, \tag{5}$$

for model $m \in \{\mathrm{CAPM}, \mathrm{FF3}\}$. The time series variation is then driven by the residuals and the level difference in alphas, respectively.

In Table 4, we show the effects of the individual decision nodes on the time-series of CAPM alphas.[5] Exactly as in Section 4 above, we only compare time-series that differ in exactly one decision node. The overall mean absolute differences in alphas are not significantly different from the differences in premiums per se. Moreover, the decision node's effect on the average correlations is also not markedly changed by controlling for the market risk exposure. Given that the anomaly status is typically defined relative to the CAPM, this is not surprising.

Hence, we find that the same decision nodes show the highest mean absolute differences and correlations in alphas as in the unadjusted premiums. In particular, the number of quantiles, the definition of the exchange for which quantiles are computed, and the weighting scheme remain the most important nodes in the portfolio construction category. Moreover, in the nodes concerned with sample construction the earnings filter, the size restriction, and the decision to include financial stocks have the highest impact.

[5]We show results for the Fama and French (1993)-alphas in the Appendix in Table D.1. Additional summary statistics for both models are in Internet Appendix Section V.

Table 4: CAPM-adjusted returns: Mean absolute differences and correlations.
This table shows mean absolute differences (Panel A, in %) and correlations (Panel B) of the CAPM-adjusted premiums' time series across individual decision nodes. For each decision node, we compare time-series pairs that differ only in the specific node. Then, we take the mean for each node-sorting variable combination. The two panels show means for all categories together (Overall) and individual categories separately. Moreover, the nodes are arranged by impact. By construction, some entries do not produce variation and are left empty.

Panel A: Mean absolute differences

Node	Overall	Int.	Inv.	Mom.	Pro.	Siz.	Tra.	Val.
BP: Quantiles (main)	1.03	1.08	0.99	1.17	0.96	0.76	1.21	1.00
Weighting scheme	0.98	1.08	0.96	1.05	0.99	0.61	0.87	1.05
Positive earnings	0.91	0.87	0.85	0.87	1.08	0.91	1.02	0.88
Size restriction	0.82	0.82	0.73	0.84	0.75	1.47	1.08	0.78
BP: Exchanges	0.81	0.81	0.73	0.76	0.74	1.05	1.07	0.82
Financials	0.74	0.83	0.54	0.63	1.41	0.59	0.67	0.71
BP: Quantiles (second)	0.64	0.66	0.59	0.60	0.56		0.98	0.59
Rebalancing	0.63	0.53	0.72		0.51			0.62
Double sort	0.62	0.60	0.55	0.51	0.44		1.26	0.50
Utilities	0.43	0.18	0.38	0.43	0.62	0.42	0.52	0.54
Sorting variable lag	0.43	0.34	0.51		0.32			0.42
Stock-age restriction	0.41	0.33	0.45	0.28	0.41	0.46	0.50	0.39
Price restriction	0.35	0.36	0.33	0.33	0.33	0.53	0.45	0.32
Positive book equity	0.21	0.24	0.20	0.19	0.22	0.21	0.22	0.21

Panel B: Correlations

Node	Overall	Int.	Inv.	Mom.	Pro.	Siz.	Tra.	Val.
Weighting scheme	0.86	0.82	0.82	0.93	0.87	0.97	0.86	0.91
Positive earnings	0.87	0.89	0.84	0.95	0.80	0.85	0.89	0.94
BP: Quantiles (main)	0.89	0.86	0.86	0.96	0.92	0.92	0.87	0.95
Size restriction	0.91	0.90	0.89	0.96	0.92	0.71	0.88	0.95
Rebalancing	0.91	0.94	0.86		0.95			0.95
Financials	0.91	0.87	0.93	0.98	0.75	0.92	0.95	0.96
BP: Exchanges	0.92	0.91	0.91	0.97	0.93	0.80	0.90	0.95
BP: Quantiles (second)	0.94	0.93	0.93	0.98	0.96		0.90	0.97
Sorting variable lag	0.94	0.97	0.91		0.97			0.97
Double sort	0.95	0.95	0.94	0.99	0.97		0.87	0.98
Stock-age restriction	0.97	0.98	0.95	1.00	0.97	0.93	0.97	0.99
Utilities	0.97	0.99	0.97	0.99	0.94	0.92	0.97	0.97
Price restriction	0.97	0.97	0.97	0.99	0.98	0.92	0.96	0.99
Positive book equity	0.99	0.99	0.99	1.00	0.99	0.98	0.99	1.00

Finally, we present an assessment of the variation in CAPM alphas (i.e., non-standard errors) for the branches of the nodes with the highest mean absolute differences. Table 5 shows the non-standard errors averaged across all sorting variables (irrespective of their group). This means that we do not provide insights into some effects specific to sorting variables or sorting variable groups.[6]

In line with results for premiums, an increase in the number of quantiles increases alphas, but also non-standard errors and average standard errors are increased. Choosing to split the sample into more and consequently smaller portfolios increases the variability in alphas induced by other decision nodes. Alphas based on equally weighted returns are again larger than alphas from value-weighted portfolios. Alongside the average alphas, the number of t-statistics larger than 1.96 is also increased at only a slight increase in non-standard errors. Computing portfolio quantiles based on NYSE-listed stocks decreases alphas on average. Using breakpoints computed from the entire stock universe has significantly higher non-standard errors.

For the group on sample construction decision nodes, we find that applying the earnings filter, the size filter, and including financials reduces alphas, non-standard errors, and average standard errors. Differences in non-standard errors are particularly pronounced when using the earnings and size filters. Only using firms above the 20%-NYSE market capitalization threshold leads to significantly fewer t-statistics above the 5%-significance level.

Overall, the main insights from the decision nodes' impact on premiums are not changed when adjusting premiums for their exposure to the market risk factor. Making certain decisions leads to increases in non-standard errors within the respective branches, irrespective of the adjustment of returns, and some branches lead to a higher number of significant results (as judged by a 5%-threshold).

[6] We show the remaining decision nodes' impact on CAPM alphas in Table V.1 in the Internet Appendix. There, we also show results for the impact of decision nodes on FF3-alphas in Table V.2 and Table V.3. The results are in line with the ones discussed in the main part.

Table 5: Impact of decision node on CAPM alphas.
This table shows the mean statistics across sorting variables for several decision nodes in separate panels. Each table contains the mean (Mean, in %), skewness (Skew.), kurtosis (Kurt.), and interquartile range (IQR, in %) of the average premiums. We also show the non-standard error (NSE, in %), the average standard error (mSE, in %), the standard deviation of the standard error (sSE, in %), and the NSE-SE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: BP: Quantiles (main)

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
5	0.40	0.13	0.13	1.10	0.60	3.32	0.95	0.73
10	0.51	0.16	0.15	1.12	0.53	3.35	0.95	0.72

Panel B: Weighting scheme

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
EW	0.48	0.16	0.14	1.23	0.66	3.43	0.96	0.77
VW	0.42	0.15	0.14	1.14	0.68	3.51	0.94	0.68

Panel C: Positive earnings

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.48	0.17	0.15	1.18	0.53	3.34	0.96	0.75
Yes	0.42	0.13	0.13	1.11	0.47	3.18	0.94	0.71

Panel D: Size restriction

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.50	0.18	0.14	1.36	0.45	3.09	0.96	0.78
0.2	0.40	0.13	0.14	0.97	0.37	3.02	0.94	0.67

Panel E: BP: Exchanges

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
All	0.50	0.17	0.14	1.26	0.47	3.17	0.95	0.75
NYSE	0.40	0.13	0.13	1.05	0.51	3.42	0.95	0.70

Panel F: Financials

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.46	0.16	0.14	1.23	0.61	3.56	0.96	0.73
Included	0.44	0.15	0.14	1.19	0.60	3.54	0.94	0.72

6 Conclusion

We analyze non-standard errors (Menkveld et al., 2021) in portfolio sorts. We find a strong impact on estimated premiums depending on what decisions are taken in the sorting process in terms of sample selection and the eventual sorting procedure.

The choice of breakpoint quantiles, weighting schemes, and the restriction to stocks with specific characteristics such as positive earnings or a large market capitalization have the most significant impact on estimated premiums. That said, the effects are heterogeneous across sorting variables. For instance, the exclusion or inclusion of financial or utility firms greatly impacts profitability, whereas it does not matter as much for other sorting variables.

Overall, we find that while the size of premium estimates varies widely, the *sign* is remarkably robust. Almost all sorting variables yield positive premiums regardless of the exact specification of the sort. The majority of specifications also yield statistically significant premiums, although the picture is less homogeneous, with on average 65% of all considered sorting specifications across all considered anomalies yielding a t-statistic above 1.96. Which of these two stylized facts should be valued more is debatable.

We do not consider the specification of sorting variables, time periods, and coding errors as decision nodes. In that sense, our estimates can be understood as lower bounds for non-standard errors.

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A Construction of sorting variables

In this section we describe all details to construct the 41 sorting variables, which we analyze in this paper.

A.1 Momentum

Return momentum. We follow Jegadeesh and Titman (1993) and compute the 6-month return momentum (MOM6) in each month as the cumulative stock return from month $t-2$ to month $t-7$. As it is common in the literature we skip the most recent month. Moreover, we compute the 11-month return momentum (MOM) in each month as the cumulative return from month $t-2$ to month $t-12$ skipping the most recent month (Fama and French (1996)).

Residual momentum. As in Blitz et al. (2011) we define the 6-month residual momentum (E6) in each month as the cumulative residual stock returns from month $t-2$ to month $t-7$, scaled by the standard deviation of residual returns over the same time horizon. Similarly, we follow Blitz et al. (2011) and measure the 11-month residual momentum (E11) in each month as cumulative residual returns from month $t-2$ to month $t-12$, scaled by the standard deviation of residual returns over the same time horizon. Residual returns are obtained in each month from regressing monthly excess stock returns from month $t-1$ to month $t-36$ on the Fama and French (1993) three factor model. Throughout these rolling regressions we always require 36 monthly returns.

A.2 Size

Size. We follow Fama and French (1993) and compute the size of each stock (ME) in each month as the natural logarithm of the market equity. We obtain market equity data from CRSP by multiplying the shares outstanding (SHROUT) with the corresponding share price (PRC).

A.3 Profitability

Asset turnover. We follow Soliman (2008) and compute asset turnover (ATO) from Compustat data as sales (SALE) divided by net operating assets from the previous fiscal year:

$$ATO_t = \frac{SALE_t}{(AT_{t-1} - CHE_{t-1} - IVAO_{t-1}) - (AT_{t-1} - DLC_{t-1} - DLTT_{t-1} - MIB_{t-1} - PSTK_{t-1} - CEQ_{t-1})}$$

where Compustat item AT is total assets, item CHE are cash and short-term investments and IVAO are other investments and advances. Moreover, item DLC represents debt in current liabilities , DLTT long-term debt, MIB minority interests, PSTK preferred stocks and CEQ common equity. We follow Hou et al. (2020) and replace missing values of IVAO, DLC, DLTT, MIB and PSTK as zero.

Cash-based operating profitability. The definition of cash-based operating profitability (CBOP) closely follows Ball et al. (2016) and is based on Compustat data:

$$CBOP_t = \frac{REVT_t - COGS_t - XSGA_t + XRD_t - \Delta RECT_t - \Delta INVT_t - \Delta XPP_t + \Delta DRC_t + \Delta DRLT_t + \Delta AP_t + \Delta XACC_t}{AT_t}$$

where REVT is total revenue, COGS are cost of goods sold, XSGA are selling, general and administrative expenses and XRD are R&D expenses. Moreover, $\Delta RECT_t$ is the change in accounts receivable, $\Delta INVT$ the change in inventory, ΔXPP is the change in prepaid expenses, $\Delta DRC_t + \Delta DRLT$ the change in deferred revenues, ΔAP the change in trade accounts payable and $\Delta XACC$ is the change in accrued expenses. We follow Hou et al. (2020) and set missing values of XRD and all missing changes to zero.

Capital turnover. We measure capital turnover (CTO) from Compustat data as sales (SALE) divided by total assets from the previous fiscal year (Haugen and Baker (1996)).

Gross profits to assets. We follow Novy-Marx (2013) and obtain gross profits to assets (GPA) from Compustat data as total revenues (REVT) minus cost of goods sold (COGS), scaled by current total assets (AT).

Ohlson's O-score. Ohlson (1980) suggests to assess the financial stability of a firm with the following linear relation:

$$O_t = -1.32 - 0.407 \cdot \log(AT_t) + 6.03 \cdot \frac{DLC_t + DLTT_t}{AT_t} - 1.43 \cdot \frac{ACT_t - LCT_t}{AT_t} + 0.076 \cdot \frac{LCT_t}{AT_t} - 1.72 \cdot \mathbb{1}_{LT_t > AT_t} - 2.37 \cdot \frac{NI_t}{AT_t}$$
$$- 1.83 \cdot \frac{PI_t + DP_t}{LT_t} + 0.285 \cdot \mathbb{1}_{NI_t<0 \text{ \& } NI_{t-1}<0} - 0.521 \cdot \frac{NI_t - NI_{t-1}}{|NI_t| + |NI_{t-1}|}$$

All data items are obtained from Compustat: AT corresponds to total assets, DLC to short-term debt, DLTT to long-term debt, ACT to current assets, LCT to current liabilities, LT to total liabilities, PI to pretax income, DP to depreciation and amortization and NI to net income. We follow Hou et al. (2020) and winsorize all variables except for dummy variables at the 1% and 99 % quantile of their respective distribution.

A.4 Valuation

Book to market ratio. This paper follows Davis et al. (2000) and computes the book-to-market ratio (BM) as book equity from Compustat divided by market equity from CRSP. Market equity is measured at the end of each fiscal year. Book equity corresponds to the book equity of shareholders plus balance sheet deferred taxes and investment tax credit (Compustat item TXDITC) minus the book value of preferred stock. Depending on data availability, we measure shareholders' equity by SEQ, or the sum of common equity (CEQ) and the par value of preferred stock (PSTK), or if all previous items are unavailable by total assets (AT) minus total liabilities (LT). The book value of preferred stock corresponds in the following order either to the redemption value (PSTKRV), or the liquidation value (PSTKL), or if all previous items are unavailable to the par value (PSTK).

Cash-flow to price. Lakonishok et al. (1994) suggest to measure the cash-flow to price ratio (CFP) from Compustat data as income before extraordinary items (IB) plus depreciation (DP), both divided by market equity (CRSP) from the end of the fiscal year. We exclude all stocks with negative cash flows.

Debt to market ratio. Following Bhandari (1988) the debt to market ratio (DM) is defined as short-term debt (Compustat item DLC) plus long-term debt (Compustat item DLTT) divided by market equity obtained from CRSP at the end of each fiscal year. We exclude stocks with missing DLC and DLTT observations.

Earnings to price. We follow Basu (1983) and compute the earnings to price ratio (EP) as income before extraordinary items (Compustat item IB) divided by market equity from CRSP. Market equity corresponds to the end of each fiscal year.

Net payout yield. Boudoukh et al. (2007) suggest to measure the net payout yield (NPY) of each stock in the following way:

$$NPY_t = \frac{(DVC_t + PRSTKC_t + \Delta PSTKRV_t \cdot \mathbb{1}_{\Delta PSTKRV<0}) - (SSTK_t - \Delta PSTKRV_t \cdot \mathbb{1}_{\Delta PSTKRV>0})}{ME_t}$$

where DVC are dividends from common stock, PRSTKC is the purchase of common and preferred stock, PSTKRV is the value of the net number of preferred stocks outstanding and SSTK reflects the sale of common and preferred stocks. $\mathbb{1}_{\Delta PSTKRV<0}$ is a dummy variable which has value one if the annual change in PSTKRV is negative and zero otherwise. Market equity (ME) is from CRSP and corresponds to the end of each fiscal year. Moreover, we exclude stocks with negative net payouts.

Operating cash-flow to price. We follow Desai et al. (2004) and compute the ratio of operating cash-flows to price (OCP) as operating cash flows from Compustat divided by the market equity at the end of each fiscal year from CRSP. Before 1988, we measure operating cash flows as funds from operations (FOPT) and as net cash flows from operating activities (OANCF) thereafter. Moreover, we exclude firms with negative operating cash-flows.

Sales to price We compute the sales to price ratio (SP) as sales (Compustat item SALE) divided by the market equity at the end of each fiscal year (Barbee Jr et al. (1996)). Stocks with negative sales are excluded.

A.5 Investments and financing

Asset growth. We follow Cooper et al. (2008) and measure asset growth (AG) in each fiscal year from Compustat data as the change in total assets (AT) from year t to year $t-1$, divided by total assets from year $t-1$.

Composite share issuance. Daniel and Titman (2006) propose to measure composite share issuance (CSI) from CRSP data as the difference between the change in market equity and the cumulative log return of a stock. Both, the change in market equity and cumulative log returns are measured in each month from year t to year $t-5$.

Change in non-current operating assets. We define non-current operating assets (NCA) similar to Richardson et al. (2005) as total assets (AT) minus current assets (ACT) minus long-term investments (IVAO). Missing values of IVAO are set to zero. The change in non-current operating assets (dNCA) corresponds to the change of NCA from fiscal year t to fiscal year $t-1$.

Change in net non-current operating assets. The definition of net non-current operating assets NCO closely follows from Richardson et al. (2005) and is based on Compustat data:

$$NCO_t = (AT_t - ACT_t - IVAO_t) - (LT_t - LCT_t - DLTT_t)$$

where AT is total assets, ACT current assets, IVAO long-term investments, LT total liabilities, LCT current liabilities and DLTT long-term debt. We replace all missing observations of IVAO and DLTT with zero. The change in net non-current operating assets (dNCO) is then the change of NCO from fiscal year t to fiscal year $t-1$.

Change in property, plant, equipment and inventory to assets. We add the annual change in gross property, plant and equipment (PPEGT) to the annual change in inventory (INVT) and scale this sum by 1-year lagged total assets (AT). Thus, we obtain the change in property, plant, equipment and inventories (dPIA) as in Lyandres et al. (2008) from Compustat data.

Change in net non-cash working capital. Following Richardson et al. (2005) we define non-cash working capital from Compustat data as:

$$WC_t = (ACT_t - CHE_t) - (LCT_t - DLC_t)$$

where ACT corresponds to current assets, CHE to cash, LCT to current liabilities and DLC to short-term debt. We set missing values of DLC to zero. The change in net non-cash working capital (dWC) corresponds to the change of WC from fiscal year t to fiscal year $t-1$.

Investment growth. From Compustat data we compute investment growth (IG) as the annual change in capital expenditures (CAPX) from fiscal year t to year $t-1$, scaled by capital expenditures from year $t-1$

Investments to assets. We follow Lyandres et al. (2008) and measure the investments to assets ratio (IVA) from Compustat data as thze annual change in gross property, plant and equipment (PPEGT) plus the annual change in inventories, all divided by by total assets from the previous fiscal year.

Inventory changes. Thomas and Zhang (2002) suggest to measure the change inventory (IVC) from Compustat data as the annual change in inventories (INVT) from fiscal year t to fiscal year $t-1$, divided by average total assets (AT) over the fiscal year t and $t-1$.

Inventory growth. Similar to Belo and Lin (2012), inventory growth (IVG) is obtained from Compustat data as the annual change in inventories (INVT) from fiscal year t to fiscal year $t-1$, scaled by the inventory (INVT) of fiscal year $t-1$.

Net operating assets. The definition of net operating assets (NOA) closely follows Hirshleifer et al. (2004) and is obtained from Compustat data:

$$NOA_t = \frac{(AT_t - CHE_t) - (AT_t - DLC_t - DLTT_t - MIB_t - PSTK_t - CEQ_t)}{AT_{t-1}}$$

where AT is total assets, CHE cash and short-term investments, DLC short-term debt, DLTT long-term debt, MIB minority interest, PSTK preferred stock and CEQ common equity. We replace missing values of DLC, DLTT, MIB and PSTK as zero.

Operating accruals. The definition of operating accruals (OA) before 1988 closely follows Sloan (1996):

$$OA_t = \frac{(\Delta ACT_t - \Delta CHE_t) - (\Delta LCT_t - \Delta DLC_t - \Delta TXP_t) - DP_t}{AT_{t-1}}$$

where ACT is current assets, CHE cash, LCT current liabilities, DLC short-term debt, TXP taxes payable and DP depreciation and amortization. Moreover, we replace missing values of DLC and TXP with zero. Due to data availability we follow Hribar and Collins (2002) and compute operating accruals from 1988 and onward as:

$$OA_t = \frac{NI_t - OANCF_t}{AT_{t-1}}$$

where NI is net income and OANCF corresponds to net cash flow from operations. All items are from Compustat data.

Percent operating accruals. We follow Hafzalla et al. (2011) and compute percent operating accruals (POA) in each fiscal year from Compustat data as operating accruals (OA) divided by the absolute value of net income (NI).

Percent total accruals. Hafzalla et al. (2011) suggest to measure percent total accruals (PTA) from Compustat data as total accruals (TA) divided by the absolute value of net income (NI). Before 1988 we follow Hou et al. (2020) and define PTA as:

$$\begin{aligned} PTA_t = &\big(\Delta(ACT_t - CHE_t - LCT_t + DLC_t) + \Delta(AT_t - LCT_t - IVAO_t - LT_t + LCT_t + DLTT_t) \\ &+ \Delta(IVST_t + IVAO_t - DLTT_t - DLC_t - PSTK_t)\big)/|NI_t| \end{aligned}$$

where ACT is current assets, LCT current liabilities, DLC short-term debt, AT total assets, IVAO investments and advances, LT total liabilities, DLTT long-term debt, IVST short-term investments, PSTK preferred stock and NI net income. Δ refers to the change from fiscal year t to fiscal year $t-1$. Moreover, missing values of

IVAO, DLTT, DLC, IVST and PSTK are set to zero. From 1988 and thereafter we follow Hribar and Collins (2002) and measure PTA from Compustat data as

$$PTA_t = \frac{NI_t - OANCF_t - IVNCF_t - FINCF_t + SSTK_t - PRSTKC_t - DV_t}{|NI_t|}$$

where NI corresponds to net income, OANCF to total operating cash flows, IVNCF to total investing cash flows, FINCF to total financing cash flows, SSTK to the sale of stocks, PRSTKC to stock repurchases and DV to dividends. Moreover, we set missing valus of SSTK and DV to zero.

A.6 Intangibles

Advertisement expenses to market. Chan et al. (2001) suggest to measure the advertising expense to market ratio (ADM) as advertising expenses (Compustat item XAD) divided by market equity, which is obtained from CRSP at the end of each fiscal year. We exclude observations with negative advertising expenses.

Earnings' predictability. Francis et al. (2004) define split adjusted earnings per share (EPSA) from Compustat data as earnings per share (EPSPX) times the adjustment factor (AJEX). We follow Francis et al. (2004) and measure earnings predictability (EPRD) for each stock as the residual volatility (u_t) from the following auto-regressive process:

$$EPSA_t = \alpha + \beta \cdot EPSA_{t-1} + u_t$$

Moreover, we measure this autoregressive process over the last 10 years and always require 10 years of non-missing observations.

Operating leverage. We follow Novy-Marx (2013) and compute operating leverage (OL) from Compustat data as cost of goods sold (COGS) plus selling, general and administrative expenses (XSGA), both scaled by current total assets (AT).

Industry adjusted real-estate ratio. We define the real-estate ratio (RER) similar to Tuzel (2010) with Compustat data. Prior to 1983 it corresponds to the sum of buildings (PPENB) and capital leases (PPENLS) scaled by net property, plant and equipment (PPENT). After the end of 1983 it is measured as the sum of buildings at cost (FATB) and leases at cost (FATL), both divided by gross property, plant and equipment (PPEGT). Subsequently, we winsorize the real estate ratios in each fiscal year at the 1 % and 99 % percentile. The industry adjusted real-estate ratio is obtained by subtracting the industry average real-estate ratio from each stock specific real-estate ratio. We use 2-digit SIC codes to assign stocks into Industries. Note that real esate data starts in 1969 limiting the observation period for this specific sorting variable.

R&D expenses to market. Chan et al. (2001) propose to compute the R&D expense to market ratio (RDM) as R & D expenses (Compustat item XRD) divided by market equity from the end of each fiscal year. We obtain market equity data from CRSP and include only observations with positive R & D expenses.

A.7 Trading frictions

Dollar trading volume. We follow Brennan et al. (1998) and compute dollar trading volume (DTV) from daily CRSP data as the average dollar trading volume from month $t-1$ to month $t-6$. We require at least 50 days of observations when computing this average. Dollar trading volume is defined as share price (PRC) multiplied with the number of shares outstanding (SHROUT). Moreover, we adjust dollar trading volume from NASDAQ according to Gao and Ritter (2010).

Idiosyncratic skewness relative to the CAPM. In each month we regress the daily excess returns of each stock on the market excess return:

$$r_t^e = \alpha + \beta \cdot (MKT_t - R_t^f) + u_t$$

Throughout these regressions we require at least 15 daily observations for each month. Idiosyncratic skewness (ISCC) relative to the CAPM is then measured in each month as the skewness of residuals u_t (Bali et al. (2016)).

Idiosyncratic skewness relative to the Fama and French (1993) model. We regress the daily excess returns of each stock on the Fama and French (1993) factor model:

$$r_t^e = \alpha + \beta_1 \cdot (MKT_t - R_t^f) + \beta_2 \cdot SMB_t + \beta_3 \cdot HML_t + u_t$$

Throughout these regressions we require at least 15 daily observations for each month. Idiosyncratic skewness (ISCFF) relative to the Fama and French (1993) model is then measured in each month as the skewness of residuals u_t (Bali et al. (2016)).

Idiosyncratic volatility relative to the CAPM. We follow Ang et al. (2006) and obtain idiosyncratic volatility relative to the CAPM (IVOLC) as the volatility of residuals from the following regression:

$$r_t^e = \alpha + \beta \cdot (MKT_t - R_t^f) + u_t$$

In detail, we regress in each month the excess return of each stock on the market excess return using daily from CRSP. Moreover, we require at least 15 daily observations for each month.

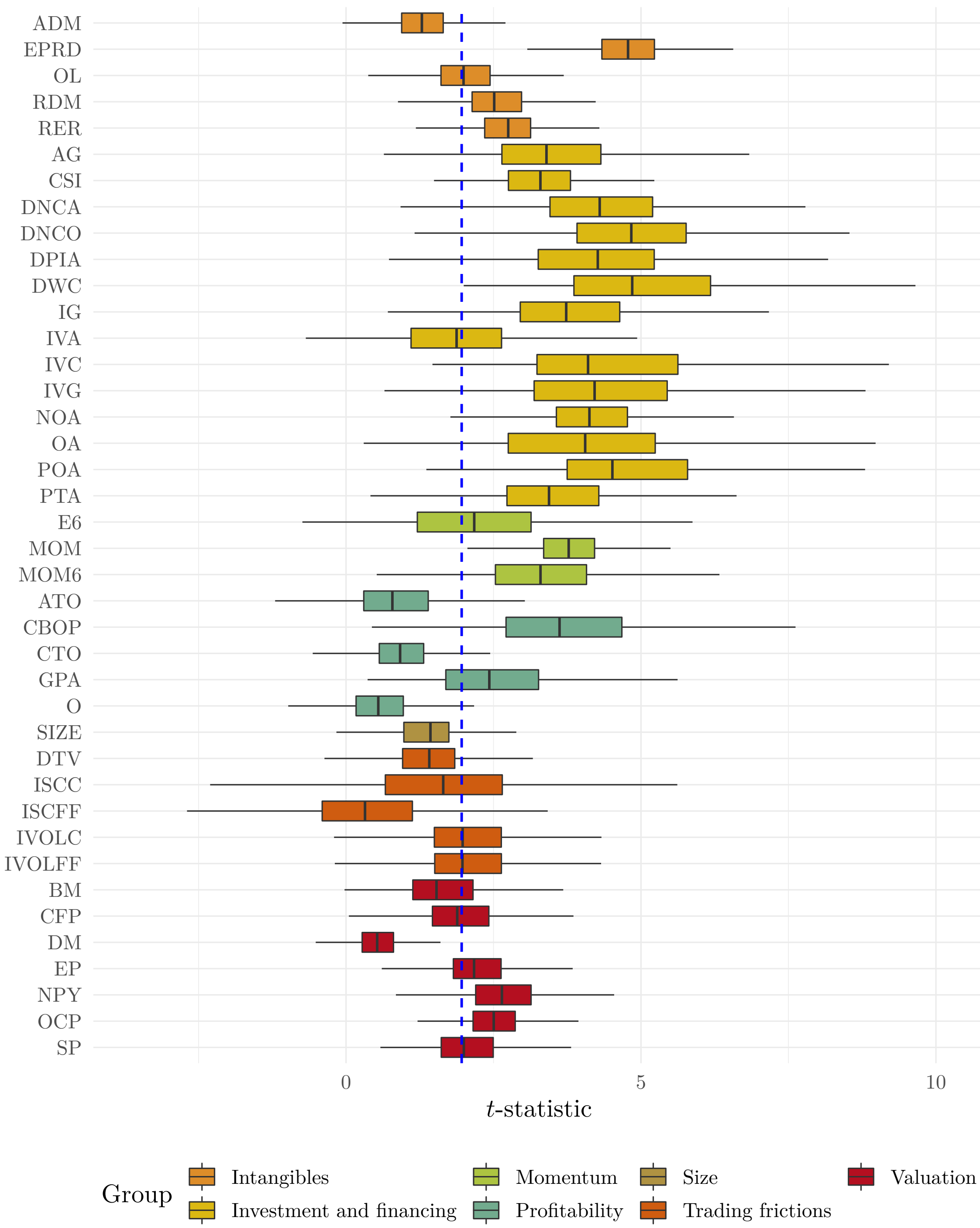
Idiosyncratic volatility relative to the Fama and French (1993) model. We follow Ang et al. (2006) and compute idiosyncratic volatility relative to the Fama and French (1993) factor model (IVOLFF) as the volatility of residuals from the following regression:

$$r_t^e = \alpha + \beta_1 \cdot (MKT_t - R_t^f) + \beta_2 \cdot SMB_t + \beta_3 \cdot HML_t + u_t$$

In detail, we regress in each month the excess return of each stock on the Fama and French (1993) factor model using daily from CRSP and Kenneth French. Moreover, we require at least 15 daily observations for each month.

B Distribution of t-statistics

Figure B.1: Variation in t-statistics across sorting variables.
This figure shows the estimated t-statistics in boxplots for all sorting variables across all decision nodes. The vertical axis shows the associated sorting variable, while the color scheme connects each sorting variable to the respective category. A t-value of 1.96 is indicated by the vertical dashed line.



C Impact of decision nodes

In this section, we present tables documenting the impact of decision nodes on premiums. For each decision node, we show summary statistics for the respective branches.

Table C.1: Impact of decision node: Breakpoint quantiles (main)

For each branch of node: Breakpoint quantiles (main), we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
5	0.32	0.07	0.12	0.60	0.71	3.69	1.00	0.67
10	0.43	0.10	0.16	0.69	0.70	3.58	1.00	0.68

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
5	0.36	0.13	0.09	1.37	0.64	3.14	1.00	0.91
10	0.48	0.16	0.12	1.35	0.58	3.09	1.00	0.95

Panel C: Momentum

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
5	0.48	0.16	0.16	1.02	0.30	2.54	0.98	0.77
10	0.71	0.19	0.20	0.96	0.19	2.88	0.99	0.86

Panel D: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
5	0.20	0.09	0.12	0.75	0.62	3.38	0.97	0.33
10	0.25	0.12	0.15	0.85	0.58	3.19	0.92	0.37

Panel E: Size

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
5	0.24	0.14	0.17	0.83	2.07	11.06	0.98	0.13
10	0.33	0.29	0.20	1.46	2.97	13.83	0.99	0.18

Panel F: Trading frictions

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
5	0.23	0.14	0.14	1.25	0.45	3.81	0.92	0.36
10	0.28	0.17	0.16	1.17	0.35	5.14	0.86	0.34

Panel G: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
5	0.31	0.10	0.16	0.62	0.72	3.53	0.98	0.52
10	0.38	0.13	0.19	0.67	0.65	3.33	0.99	0.52

Table C.2: Impact of decision node: Weighting scheme

For each branch of node: Weighting scheme, we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
EW	0.38	0.11	0.14	0.75	0.65	3.43	1.00	0.70
VW	0.36	0.10	0.14	0.75	0.75	3.60	1.00	0.65

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
EW	0.46	0.15	0.10	1.51	0.69	3.35	1.00	0.97
VW	0.38	0.14	0.11	1.34	0.73	3.29	1.00	0.88

Panel C: Momentum

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
EW	0.62	0.19	0.18	1.08	0.26	2.63	1.00	0.88
VW	0.57	0.22	0.19	1.21	0.48	2.74	0.97	0.74

Panel D: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
EW	0.23	0.11	0.13	0.89	0.67	3.48	0.95	0.38
VW	0.22	0.11	0.14	0.79	0.76	3.84	0.94	0.32

Panel E: Size

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
EW	0.30	0.28	0.17	1.61	3.13	15.59	0.97	0.22
VW	0.26	0.17	0.19	0.85	2.89	15.35	1.00	0.09

Panel F: Trading frictions

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
EW	0.28	0.15	0.15	1.08	0.81	4.28	0.96	0.43
VW	0.23	0.16	0.15	1.22	0.42	3.77	0.82	0.27

Panel G: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
EW	0.39	0.12	0.18	0.70	0.75	3.52	0.99	0.65
VW	0.31	0.11	0.18	0.59	0.86	3.89	0.98	0.40

Table C.3: Impact of decision node: Positive earnings filter

For each branch of node: Positive earnings filter, we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.40	0.11	0.15	0.75	0.65	3.33	1.00	0.71
Yes	0.34	0.09	0.13	0.73	0.59	3.20	1.00	0.63

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.43	0.16	0.11	1.45	0.62	3.08	1.00	0.93
Yes	0.41	0.14	0.10	1.43	0.57	2.95	1.00	0.93

Panel C: Momentum

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.65	0.21	0.19	1.12	0.19	2.60	1.00	0.87
Yes	0.53	0.19	0.17	1.12	0.32	2.60	0.97	0.76

Panel D: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.28	0.11	0.13	0.87	0.52	3.22	0.97	0.43
Yes	0.17	0.08	0.14	0.56	0.36	3.06	0.92	0.27

Panel E: Size

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.25	0.29	0.19	1.48	3.46	16.99	0.97	0.10
Yes	0.32	0.15	0.18	0.85	2.90	12.88	1.00	0.21

Panel F: Trading frictions

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.28	0.18	0.17	1.25	0.41	4.57	0.89	0.34
Yes	0.23	0.14	0.14	1.20	0.21	4.01	0.89	0.36

Panel G: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.38	0.13	0.19	0.65	0.61	3.24	1.00	0.54
Yes	0.31	0.10	0.17	0.60	0.69	3.59	0.98	0.50

Table C.4: Impact of decision node: Size restriction

For each branch of node: Size restriction, we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.40	0.11	0.14	0.81	0.67	3.39	1.00	0.71
0.2	0.33	0.09	0.14	0.69	0.74	3.41	1.00	0.60

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.47	0.17	0.10	1.62	0.53	3.02	1.00	0.95
0.2	0.37	0.13	0.11	1.25	0.53	2.79	1.00	0.91

Panel C: Momentum

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.64	0.22	0.18	1.22	0.16	2.74	0.99	0.88
0.2	0.50	0.17	0.18	0.93	0.32	2.63	0.98	0.69

Panel D: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.23	0.12	0.13	0.90	0.61	3.39	0.95	0.37
0.2	0.19	0.09	0.13	0.69	0.52	3.09	0.93	0.31

Panel E: Size

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.43	0.34	0.21	1.60	2.10	8.29	1.00	0.39
0.2	0.25	0.06	0.16	0.35	−0.24	2.50	1.00	0.07

Panel F: Trading frictions

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.31	0.20	0.15	1.48	0.06	3.80	0.92	0.49
0.2	0.20	0.11	0.15	0.84	−0.35	4.57	0.85	0.18

Panel G: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.39	0.14	0.17	0.77	0.62	3.28	0.99	0.65
0.2	0.29	0.08	0.18	0.46	0.41	3.03	0.98	0.33

Table C.5: Impact of decision node: Breakpoint exchanges

For each branch of node: Breakpoint exchanges, we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
All	0.39	0.11	0.14	0.79	0.76	3.66	1.00	0.67
NYSE	0.36	0.10	0.13	0.76	0.76	3.61	1.00	0.68

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
All	0.47	0.16	0.11	1.49	0.52	2.97	1.00	0.93
NYSE	0.38	0.13	0.10	1.33	0.61	3.21	1.00	0.92

Panel C: Momentum

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
All	0.67	0.22	0.19	1.20	0.07	2.51	0.99	0.87
NYSE	0.52	0.17	0.18	0.97	0.18	2.46	0.98	0.76

Panel D: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
All	0.24	0.12	0.14	0.89	0.68	3.43	0.93	0.36
NYSE	0.21	0.10	0.13	0.75	0.57	3.25	0.96	0.34

Panel E: Size

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
All	0.33	0.31	0.19	1.62	2.55	11.13	0.97	0.22
NYSE	0.23	0.09	0.18	0.53	0.38	3.85	1.00	0.09

Panel F: Trading frictions

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
All	0.32	0.17	0.16	1.29	0.15	4.19	0.92	0.50
NYSE	0.19	0.11	0.14	0.95	−0.19	4.36	0.86	0.20

Panel G: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
All	0.39	0.13	0.19	0.69	0.50	3.17	0.99	0.60
NYSE	0.31	0.10	0.17	0.57	1.05	5.20	0.99	0.44

Table C.6: Impact of decision node: Financials

For each branch of node: Financials, we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.38	0.11	0.14	0.79	0.71	3.54	1.00	0.70
Included	0.36	0.10	0.14	0.73	0.74	3.78	1.00	0.65

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.43	0.16	0.11	1.50	0.66	3.23	1.00	0.92
Included	0.42	0.15	0.10	1.46	0.66	3.27	1.00	0.93

Panel C: Momentum

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.61	0.21	0.18	1.19	0.26	2.66	0.99	0.85
Included	0.57	0.20	0.18	1.14	0.33	2.65	0.98	0.78

Panel D: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.26	0.11	0.13	0.84	0.57	3.41	0.97	0.42
Included	0.19	0.09	0.13	0.69	0.52	3.54	0.92	0.28

Panel E: Size

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.28	0.25	0.19	1.28	3.44	19.31	0.98	0.14
Included	0.28	0.22	0.18	1.22	3.41	19.47	0.99	0.17

Panel F: Trading frictions

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.25	0.17	0.15	1.26	0.34	4.73	0.88	0.33
Included	0.26	0.16	0.15	1.23	0.49	4.28	0.90	0.37

Panel G: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.33	0.13	0.18	0.69	0.81	3.71	0.99	0.44
Included	0.36	0.12	0.17	0.67	0.81	3.68	0.99	0.60

Table C.7: Impact of decision node: Breakpoint quantiles (secondary)
For each branch of node: Breakpoint quantiles (secondary), we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
2	0.37	0.11	0.14	0.79	0.76	3.72	1.00	0.68
5	0.38	0.10	0.14	0.75	0.69	3.42	1.00	0.69

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
2	0.43	0.15	0.10	1.49	0.67	3.25	1.00	0.95
5	0.42	0.15	0.10	1.48	0.66	3.15	1.00	0.95

Panel C: Momentum

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
2	0.60	0.20	0.18	1.10	0.41	2.74	1.00	0.83
5	0.62	0.20	0.18	1.17	0.40	2.64	1.00	0.86

Panel D: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
2	0.22	0.11	0.13	0.85	0.73	3.59	0.95	0.36
5	0.23	0.11	0.13	0.86	0.70	3.63	0.96	0.37

Panel E: Trading frictions

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
2	0.26	0.15	0.15	1.09	0.98	4.12	0.89	0.33
5	0.28	0.14	0.15	1.03	0.99	4.08	0.95	0.40

Panel F: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
2	0.35	0.12	0.18	0.65	0.71	3.35	0.99	0.55
5	0.34	0.11	0.18	0.63	0.73	3.27	0.99	0.53

Table C.8: Impact of decision node: Rebalancing

For each branch of node: Rebalancing, we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
July	0.37	0.11	0.14	0.79	0.81	3.79	1.00	0.66
monthly	0.38	0.11	0.14	0.79	0.79	3.76	1.00	0.68

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
July	0.37	0.13	0.10	1.22	0.74	3.68	1.00	0.91
monthly	0.47	0.16	0.11	1.51	0.38	3.11	1.00	0.94

Panel C: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
July	0.21	0.10	0.13	0.79	0.59	3.36	0.94	0.33
monthly	0.24	0.12	0.13	0.87	0.70	3.53	0.95	0.37

Panel D: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
July	0.34	0.12	0.18	0.65	0.72	3.42	0.99	0.49
monthly	0.36	0.13	0.18	0.71	0.76	3.69	0.98	0.55

Table C.9: Impact of decision node: Double sort

For each branch of node: Double sort, we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Dependent	0.37	0.11	0.14	0.78	0.77	3.84	1.00	0.68
Independent	0.37	0.10	0.14	0.77	0.75	3.63	1.00	0.69
Single	0.37	0.11	0.15	0.78	0.81	3.65	1.00	0.63

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Dependent	0.42	0.15	0.10	1.47	0.64	3.17	1.00	0.95
Independent	0.43	0.15	0.11	1.46	0.62	3.09	1.00	0.95
Single	0.41	0.17	0.12	1.48	0.68	3.15	1.00	0.83

Panel C: Momentum

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Dependent	0.59	0.19	0.18	1.11	0.36	2.62	1.00	0.84
Independent	0.62	0.20	0.18	1.16	0.44	2.71	1.00	0.85
Single	0.54	0.23	0.20	1.20	0.38	2.41	0.93	0.68

Panel D: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Dependent	0.23	0.11	0.13	0.87	0.74	3.62	0.96	0.37
Independent	0.23	0.11	0.13	0.84	0.64	3.47	0.95	0.37
Single	0.21	0.11	0.15	0.77	0.86	4.08	0.91	0.28

Panel E: Trading frictions

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Dependent	0.26	0.13	0.14	1.03	1.29	6.26	0.93	0.39
Independent	0.28	0.16	0.16	1.09	0.80	3.65	0.91	0.35
Single	0.20	0.19	0.16	1.44	0.98	6.23	0.77	0.29

Panel F: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Dependent	0.34	0.12	0.17	0.66	0.70	3.28	0.99	0.55
Independent	0.35	0.11	0.18	0.63	0.74	3.39	0.99	0.53
Single	0.36	0.15	0.19	0.81	0.77	3.38	0.98	0.44

Table C.10: Impact of decision node: Utilities
For each branch of node: Utilities, we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.38	0.11	0.14	0.79	0.81	3.83	1.00	0.67
Included	0.37	0.11	0.14	0.78	0.79	3.76	1.00	0.67

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.43	0.16	0.11	1.47	0.65	3.23	1.00	0.93
Included	0.42	0.16	0.10	1.50	0.67	3.29	1.00	0.93

Panel C: Momentum

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.62	0.21	0.18	1.17	0.28	2.68	0.99	0.85
Included	0.56	0.21	0.18	1.16	0.36	2.69	0.98	0.78

Panel D: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.21	0.11	0.14	0.84	0.77	3.75	0.93	0.33
Included	0.23	0.11	0.13	0.84	0.67	3.58	0.96	0.37

Panel E: Size

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.27	0.24	0.19	1.27	3.43	19.36	0.98	0.13
Included	0.29	0.23	0.18	1.23	3.51	20.23	0.99	0.18

Panel F: Trading frictions

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.27	0.16	0.15	1.25	0.39	4.57	0.90	0.41
Included	0.24	0.16	0.15	1.23	0.43	4.54	0.88	0.30

Panel G: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.35	0.12	0.18	0.68	0.77	3.67	0.99	0.52
Included	0.34	0.12	0.18	0.70	0.80	3.68	0.98	0.52

Table C.11: Impact of decision node: Sorting variable lag

For each branch of node: Sorting variable lag, we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
3m	0.37	0.11	0.14	0.81	0.82	3.84	1.00	0.68
6m	0.37	0.11	0.14	0.81	0.82	3.84	1.00	0.68
FF	0.37	0.10	0.14	0.73	0.72	3.47	1.00	0.67

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
3m	0.46	0.16	0.11	1.48	0.52	3.14	1.00	0.94
6m	0.46	0.16	0.11	1.48	0.52	3.14	1.00	0.94
FF	0.35	0.12	0.10	1.19	0.75	3.59	1.00	0.90

Panel C: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
3m	0.24	0.11	0.13	0.86	0.69	3.57	0.95	0.36
6m	0.24	0.11	0.13	0.86	0.69	3.57	0.95	0.36
FF	0.20	0.10	0.13	0.77	0.61	3.32	0.93	0.32

Panel D: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
3m	0.35	0.13	0.18	0.71	0.82	3.76	0.98	0.50
6m	0.35	0.13	0.18	0.71	0.82	3.76	0.98	0.50
FF	0.35	0.11	0.18	0.63	0.70	3.30	1.00	0.55

Table C.12: Impact of decision node: Stock-age restriction

For each branch of node: Stock-age restriction, we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.38	0.11	0.14	0.79	0.75	3.71	1.00	0.71
2	0.36	0.10	0.14	0.77	0.86	3.97	1.00	0.63

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.45	0.16	0.11	1.47	0.62	3.19	1.00	0.93
2	0.40	0.15	0.10	1.46	0.65	3.20	1.00	0.92

Panel C: Momentum

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.64	0.21	0.18	1.19	0.27	2.58	0.98	0.83
2	0.55	0.19	0.18	1.11	0.29	2.64	0.98	0.80

Panel D: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.23	0.11	0.13	0.86	0.59	3.34	0.93	0.35
2	0.22	0.11	0.13	0.80	0.73	3.54	0.96	0.35

Panel E: Size

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.25	0.23	0.18	1.26	3.43	19.49	0.97	0.11
2	0.32	0.22	0.18	1.22	3.75	21.59	1.00	0.19

Panel F: Trading frictions

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.28	0.17	0.15	1.27	0.41	4.35	0.88	0.39
2	0.23	0.15	0.15	1.20	0.35	4.67	0.90	0.32

Panel G: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.36	0.13	0.18	0.71	0.70	3.46	0.99	0.54
2	0.33	0.11	0.18	0.65	0.82	3.81	0.99	0.50

Table C.13: Impact of decision node: Price restriction

For each branch of node: Price restriction, we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.38	0.11	0.14	0.81	0.79	3.77	1.00	0.67
1	0.38	0.11	0.14	0.80	0.74	3.57	1.00	0.69
5	0.36	0.10	0.14	0.74	0.68	3.44	1.00	0.66

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.43	0.17	0.11	1.56	0.70	3.32	1.00	0.93
1	0.43	0.16	0.11	1.49	0.60	3.06	1.00	0.93
5	0.41	0.14	0.10	1.40	0.57	3.00	1.00	0.92

Panel C: Momentum

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.59	0.21	0.18	1.19	0.31	2.69	0.99	0.82
1	0.61	0.21	0.18	1.20	0.32	2.66	0.98	0.83
5	0.58	0.20	0.18	1.14	0.27	2.60	0.98	0.80

Panel D: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.22	0.11	0.13	0.85	0.71	3.76	0.94	0.35
1	0.23	0.11	0.13	0.84	0.70	3.57	0.95	0.35
5	0.22	0.11	0.13	0.84	0.66	3.37	0.95	0.35

Panel E: Size

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.35	0.32	0.19	1.67	2.75	11.72	0.99	0.23
1	0.29	0.20	0.19	1.04	2.06	8.51	0.99	0.19
5	0.21	0.09	0.17	0.50	−0.47	2.67	0.99	0.04

Panel F: Trading frictions

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.26	0.18	0.15	1.32	0.50	4.66	0.89	0.34
1	0.25	0.16	0.15	1.23	0.39	3.89	0.88	0.34
5	0.26	0.15	0.14	1.17	0.13	4.00	0.90	0.38

Panel G: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.35	0.13	0.18	0.72	0.80	3.68	0.99	0.53
1	0.35	0.13	0.18	0.70	0.73	3.46	0.99	0.53
5	0.33	0.11	0.18	0.62	0.61	3.21	0.99	0.50

Table C.14: Impact of decision node: Positive book equity

For each branch of node: Positive book equity , we show the mean statistics across sorting variables within each group in separate panels. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the premiums. We also show the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: Intangibles

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.37	0.11	0.14	0.78	0.79	3.81	1.00	0.67
Yes	0.37	0.11	0.14	0.79	0.81	3.78	1.00	0.67

Panel B: Investment and financing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.42	0.16	0.11	1.49	0.66	3.27	1.00	0.93
Yes	0.42	0.16	0.11	1.49	0.66	3.24	1.00	0.93

Panel C: Momentum

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.60	0.21	0.18	1.19	0.30	2.67	0.98	0.82
Yes	0.59	0.21	0.18	1.17	0.31	2.67	0.98	0.81

Panel D: Profitability

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.22	0.11	0.13	0.85	0.71	3.67	0.94	0.35
Yes	0.23	0.11	0.13	0.84	0.68	3.52	0.95	0.35

Panel E: Size

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.28	0.24	0.19	1.27	3.51	20.21	0.99	0.15
Yes	0.28	0.23	0.18	1.24	3.39	19.05	0.99	0.15

Panel F: Trading frictions

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.25	0.17	0.15	1.26	0.44	4.57	0.88	0.35
Yes	0.26	0.16	0.15	1.23	0.36	4.51	0.90	0.35

Panel G: Valuation

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.35	0.12	0.18	0.68	0.79	3.70	0.99	0.52
Yes	0.35	0.12	0.18	0.69	0.76	3.62	0.99	0.52

D FF3 alphas and individual decision nodes

In Table D.1, we present the impact of decision nodes on Fama and French (1992)-alphas.

Table D.1: FF3-adjusted returns: Mean absolute differences and correlations.
This table shows mean absolute differences (Panel A, in %) and correlations (Panel B) of the Fama and French (1992)-adjusted premiums' time series across individual decision nodes. For each decision node, we compare time-series pairs that differ only in the specific node. Then, we take the mean for each node-sorting variable combination. The two panels show means for all categories together (Overall) and individual categories separately. Moreover, the nodes are arranged by impact. By construction, some entries do not produce variation and are left empty.

Panel A: Mean absolute differences

Node	Overall	Int.	Inv.	Mom.	Pro.	Siz.	Tra.	Val.
BP: Quantiles (main)	1.01	1.05	0.97	1.16	0.94	0.73	1.18	0.94
Weighting scheme	0.97	1.07	0.95	1.05	0.96	0.56	0.86	1.03
Positive earnings	0.90	0.87	0.84	0.89	1.04	0.91	1.02	0.87
Size restriction	0.81	0.81	0.72	0.82	0.73	1.47	1.07	0.76
BP: Exchanges	0.80	0.80	0.72	0.76	0.73	1.05	1.06	0.80
Financials	0.71	0.78	0.51	0.63	1.31	0.59	0.67	0.70
Rebalancing	0.64	0.54	0.72		0.52			0.63
BP: Quantiles (second)	0.62	0.65	0.58	0.59	0.53		0.92	0.57
Double sort	0.62	0.59	0.55	0.51	0.44		1.24	0.49
Sorting variable lag	0.43	0.34	0.51		0.32			0.41
Utilities	0.43	0.18	0.38	0.43	0.59	0.42	0.51	0.53
Stock-age restriction	0.41	0.33	0.44	0.28	0.41	0.46	0.50	0.38
Price restriction	0.35	0.36	0.33	0.33	0.33	0.54	0.45	0.32
Positive book equity	0.21	0.24	0.20	0.19	0.22	0.21	0.22	0.21

Panel B: Correlations

Node	Overall	Int.	Inv.	Mom.	Pro.	Siz.	Tra.	Val.
Weighting scheme	0.81	0.80	0.78	0.93	0.84	0.92	0.83	0.79
Positive earnings	0.84	0.87	0.82	0.95	0.80	0.71	0.86	0.85
BP: Quantiles (main)	0.87	0.85	0.84	0.96	0.90	0.83	0.85	0.89
Size restriction	0.87	0.89	0.87	0.96	0.91	0.40	0.85	0.89
Rebalancing	0.88	0.93	0.84		0.94			0.89
BP: Exchanges	0.89	0.90	0.89	0.97	0.92	0.64	0.87	0.89
Financials	0.90	0.88	0.93	0.98	0.72	0.86	0.94	0.90
Sorting variable lag	0.93	0.96	0.89		0.97			0.94
BP: Quantiles (second)	0.93	0.92	0.92	0.98	0.95		0.90	0.93
Double sort	0.93	0.94	0.93	0.99	0.96		0.85	0.95
Utilities	0.96	0.99	0.97	0.99	0.93	0.87	0.96	0.94
Stock-age restriction	0.96	0.97	0.95	1.00	0.97	0.88	0.96	0.97
Price restriction	0.96	0.97	0.96	0.99	0.97	0.87	0.96	0.97
Positive book equity	0.99	0.99	0.99	1.00	0.99	0.97	0.99	0.99

Internet Appendix

Non-Standard Errors in Portfolio Sorts

I Sorting Variables

In Table I.1, we present summary statistics for our sorting variables.

Table I.1: Summary statistics for sorting variables

This table provides summary statistics for 40 sorting variables used in the paper. The number of observations (Obs.) is in 1,000s. All variables are winsorized at the 1%-level on either tail for illustrative purposes in this table.

Group	SV	Mean	SD	Minimum	Median	Maximum	Obs.
Int.	ADM	0.06	0.12	0.00	0.02	0.83	90.99
Int.	EPRD	18.91	125.95	0.01	0.51	1152.61	165.55
Int.	OL	1.15	1.28	0.02	0.88	8.52	349.34
Int.	RDM	0.07	0.11	0.00	0.03	0.71	113.35
Int.	RER	−0.00	0.17	−0.36	−0.01	0.51	116.84
Inv.	AG	0.27	0.98	−0.75	0.06	7.33	399.46
Inv.	CSI	0.10	0.46	−0.79	0.00	2.19	1828.21
Inv.	DNCA	0.10	0.39	−0.52	0.02	2.80	338.26
Inv.	DNCO	0.09	0.39	−0.62	0.02	2.75	336.73
Inv.	DPIA	0.09	0.27	−0.62	0.04	1.70	353.81
Inv.	DWC	0.01	0.23	−1.27	0.00	1.03	336.59
Inv.	IG	0.71	2.73	−1.00	0.06	20.02	344.70
Inv.	IVA	73.61	323.02	−486.37	1.75	2411.97	353.81
Inv.	IVC	0.01	0.06	−0.21	0.00	0.26	389.75
Inv.	IVG	0.23	0.95	−1.00	0.06	6.61	282.20
Inv.	NOA	0.58	0.68	−3.45	0.65	3.14	378.31
Inv.	OA	−0.12	0.49	−3.97	−0.05	0.73	369.38
Inv.	POA	−1.41	4.95	−35.00	−0.57	10.01	389.48
Inv.	PTA	0.63	4.40	−14.92	0.30	28.19	389.32
Mom.	E_11	−0.04	0.32	−0.92	−0.02	0.70	2116.38
Mom.	E_6	−0.06	0.48	−1.52	−0.03	1.10	2210.68
Mom.	MOM	0.12	0.55	−0.82	0.05	2.58	2805.76
Mom.	MOM_6	0.06	0.39	−0.72	0.02	1.67	2937.92
Pro.	ATO	1.94	5.71	−25.77	1.43	31.65	396.37
Pro.	CBOP	−0.01	0.67	−5.06	0.11	0.76	246.01
Pro.	CTO	1.10	1.13	0.00	0.82	6.22	398.17
Pro.	GPA	0.27	0.34	−1.02	0.22	1.45	433.03
Pro.	O	−3.40	10.84	−68.06	−2.93	50.98	334.66
Siz.	SIZE	4.67	2.26	0.18	4.49	10.44	3106.39
Tra.	DTV	10.61	37.31	0.00	0.23	270.98	2721.81
Tra.	ISCC	0.22	1.06	−3.37	0.19	3.66	3101.43
Tra.	ISCFF	0.18	0.93	−2.84	0.16	3.10	3101.43
Tra.	IVOLC	0.03	0.02	0.00	0.02	0.14	3071.94
Tra.	IVOLFF	0.03	0.02	0.00	0.02	0.13	3071.94
Val.	BM	0.84	0.73	0.04	0.65	4.24	227.22
Val.	CFP	0.15	0.14	0.00	0.11	0.82	176.33
Val.	DM	0.97	1.84	0.00	0.36	12.51	207.42
Val.	EP	0.09	0.07	0.00	0.07	0.39	167.64
Val.	NPY	−0.03	0.17	−1.05	0.00	0.23	197.18
Val.	OCP	0.18	0.23	0.00	0.11	1.52	157.65
Val.	SP	2.40	3.83	0.00	1.08	24.54	235.20

II t-statistics and standard errors across sorting variables

Below, we show graphs similar to Figure 4 (for premiums), Figure 5 (for CAPM alphas), and Figure 6. We show boxplots for t-statistics and standard errors for all three models.

II.1 Distribution of t-statistics

In Figures B.1-II.3 we show boxplots for t-statistics for unadjusted, CAPM-adjusted, and Fama and French (1992)-adjusted premiums.

II.2 Distribution of standard errors

In Figures II.4-II.6 we show boxplots for standard errors for unadjusted, CAPM-adjusted, and Fama and French (1992)-adjusted premiums.

Figure II.1: Variation in t-statistics across sorting variables.
This figure shows the estimated t-statistics in boxplots for all sorting variables across all decision nodes. The vertical axis shows the associated sorting variable, while the color scheme connects each sorting variable to the respective category. A t-value of 1.96 is indicated by the vertical dashed line.

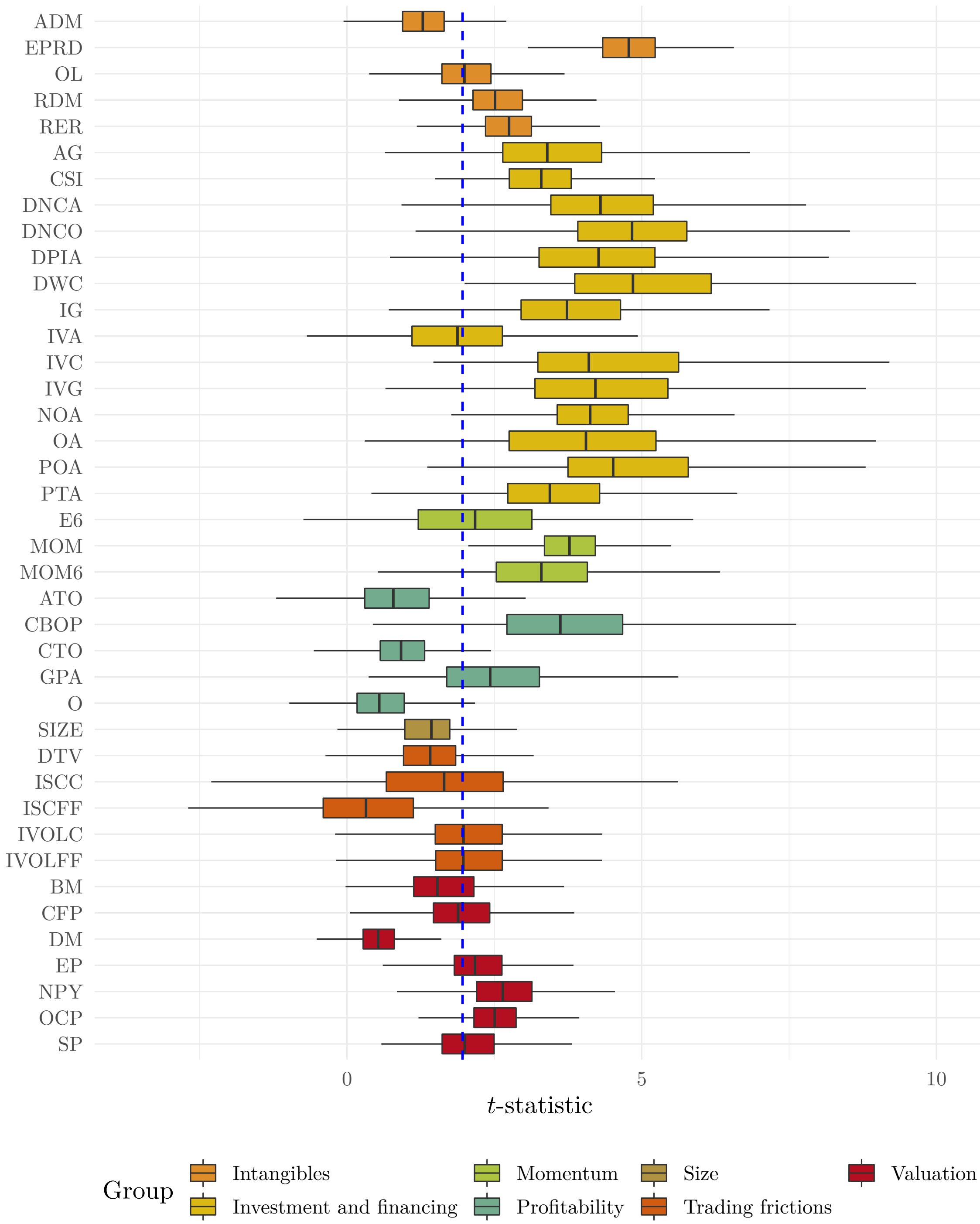


Figure II.2: Variation in CAPM-adjusted t-statistics across sorting variables.
This figure shows the estimated t-statistics for CAPM-adjusted returns in boxplots for all sorting variables across all decision nodes. The vertical axis shows the associated sorting variable, while the color scheme connects each sorting variable to the respective category. A t-value of 1.96 is indicated by the vertical dashed line.

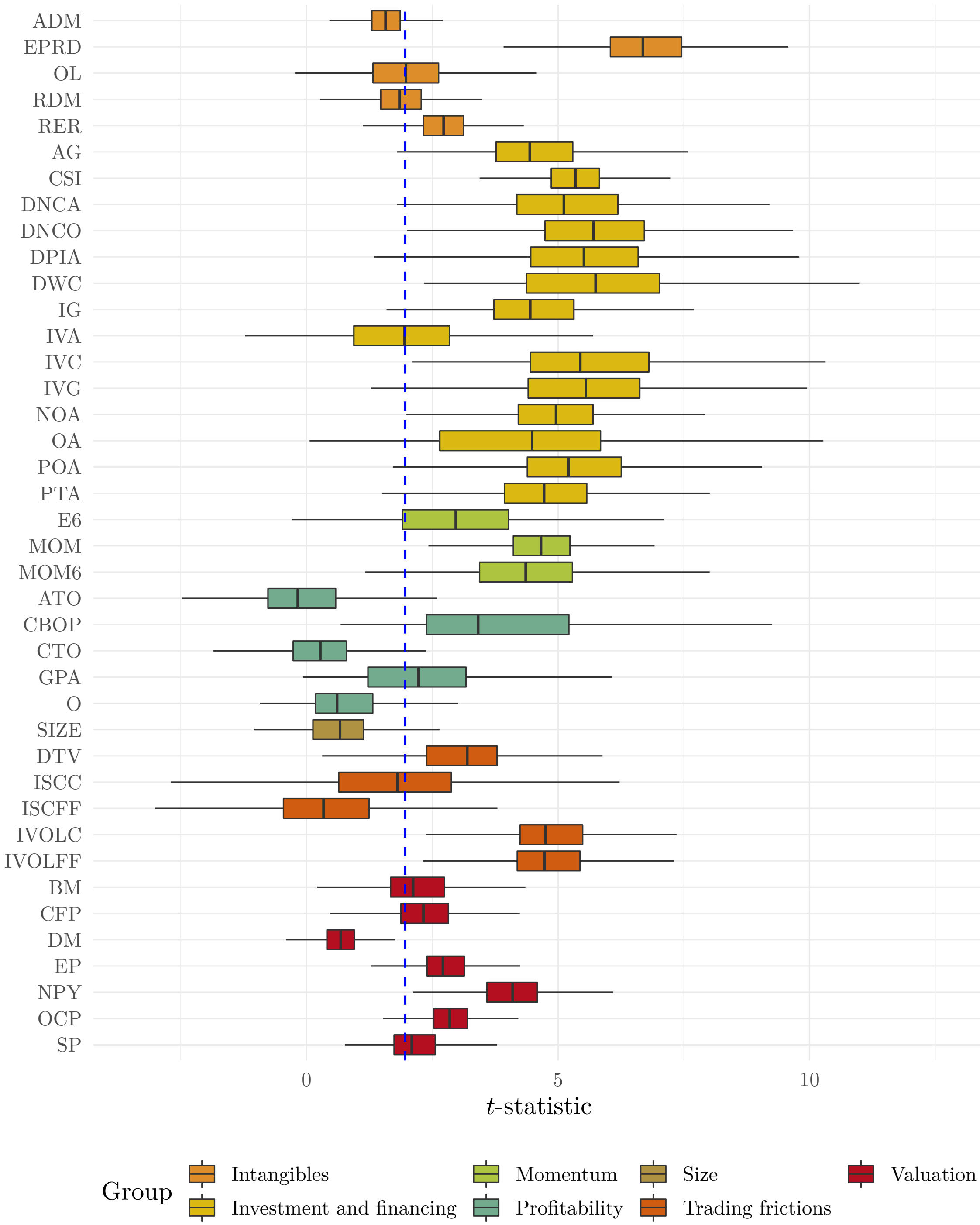


Figure II.3: Variation in FF3-adjusted t-statistics across sorting variables.
This figure shows the estimated t-statistics for Fama and French (1992)-adjusted returns in boxplots for all sorting variables across all decision nodes. The vertical axis shows the associated sorting variable, while the color scheme connects each sorting variable to the respective category. A t-value of 1.96 is indicated by the vertical dashed line.

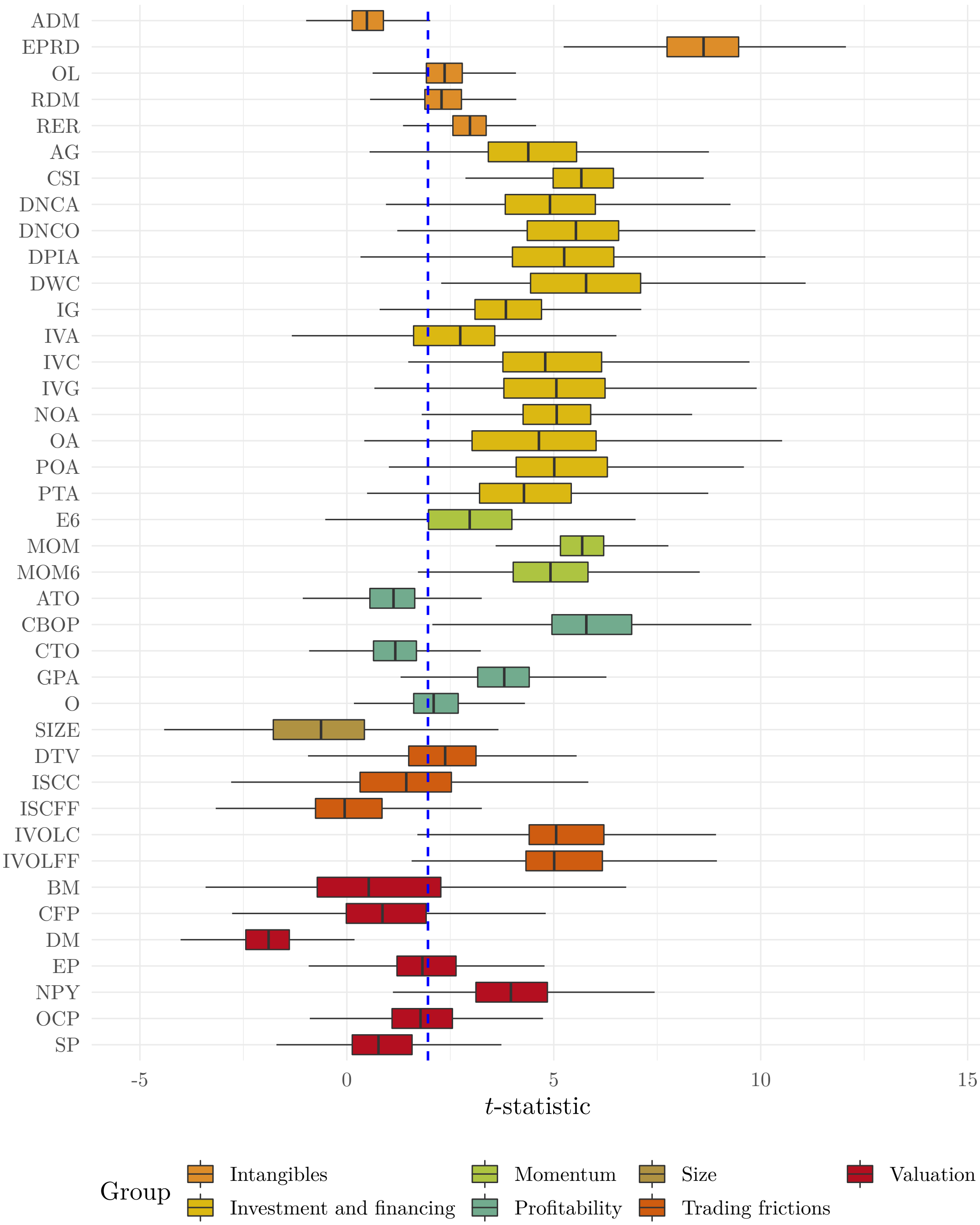


Figure II.4: Variation in standard errors across sorting variables.
This figure shows the estimated standard errors in boxplots for all sorting variables across all decision nodes. The vertical axis shows the associated sorting variable, while the color scheme connects each sorting variable to the respective category.

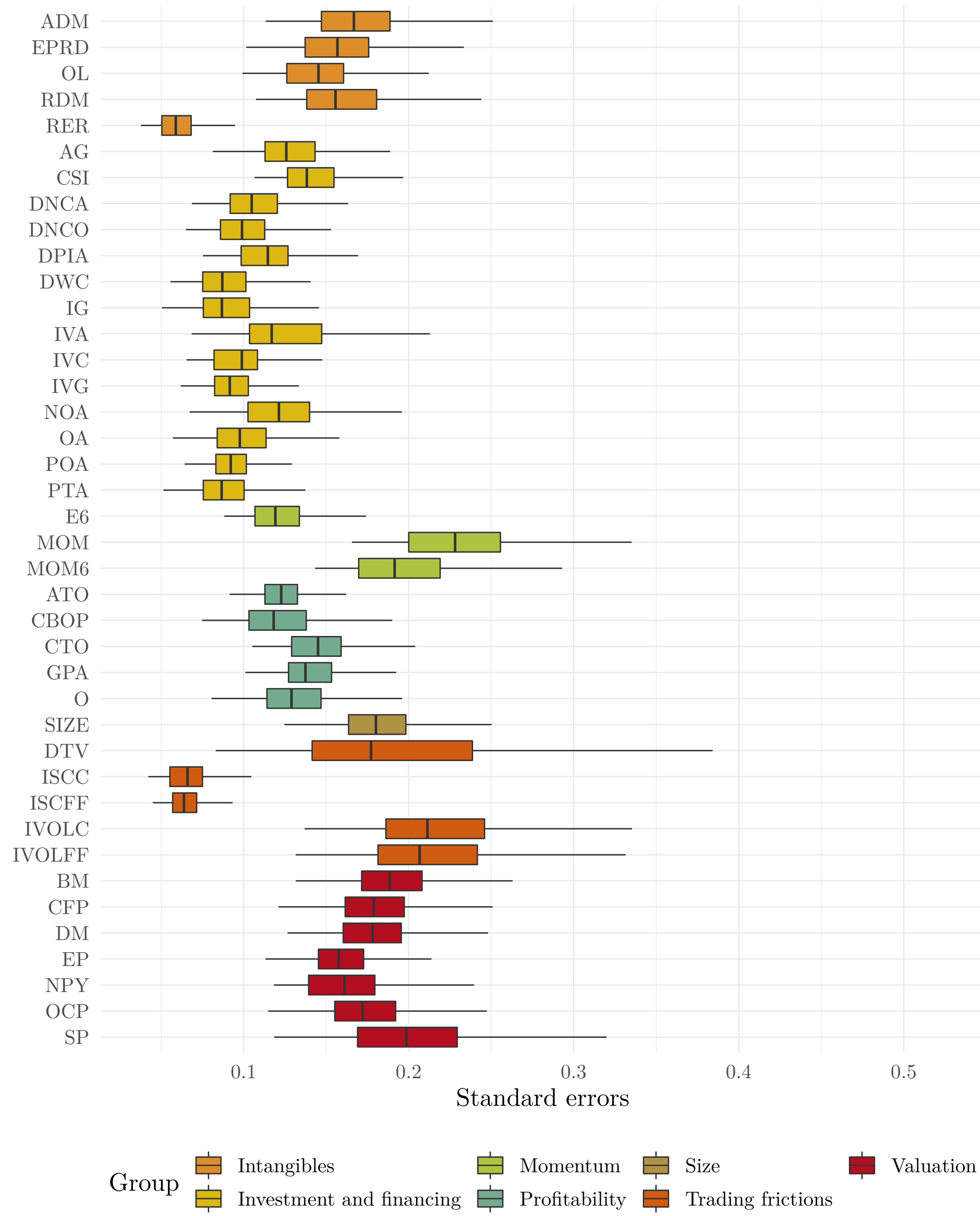


Figure II.5: Variation in CAPM-adjusted standard errors across sorting variables. This figure shows the estimated standard errors for CAPM-adjusted returns in boxplots for all sorting variables across all decision nodes. The vertical axis shows the associated sorting variable, while the color scheme connects each sorting variable to the respective category.

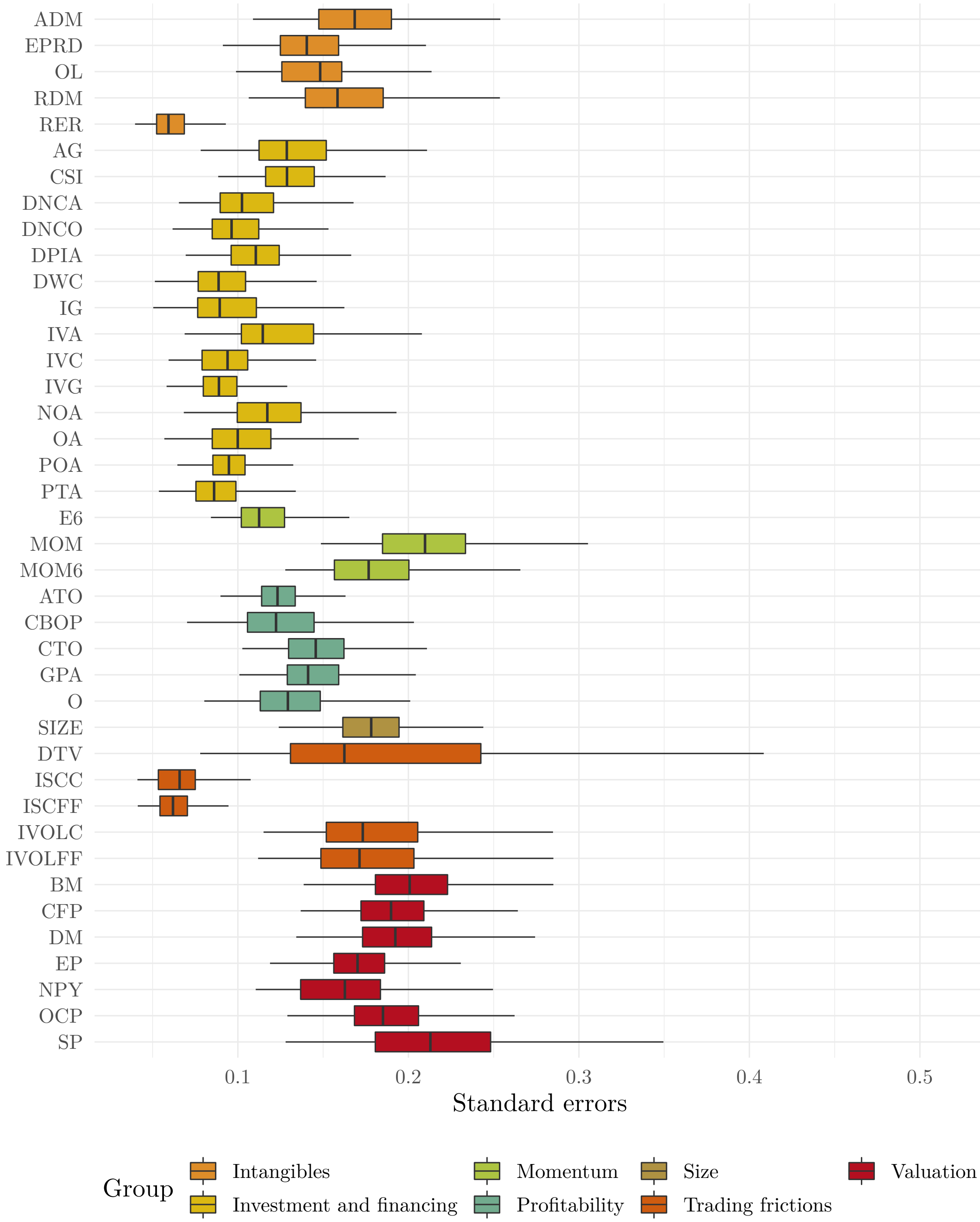
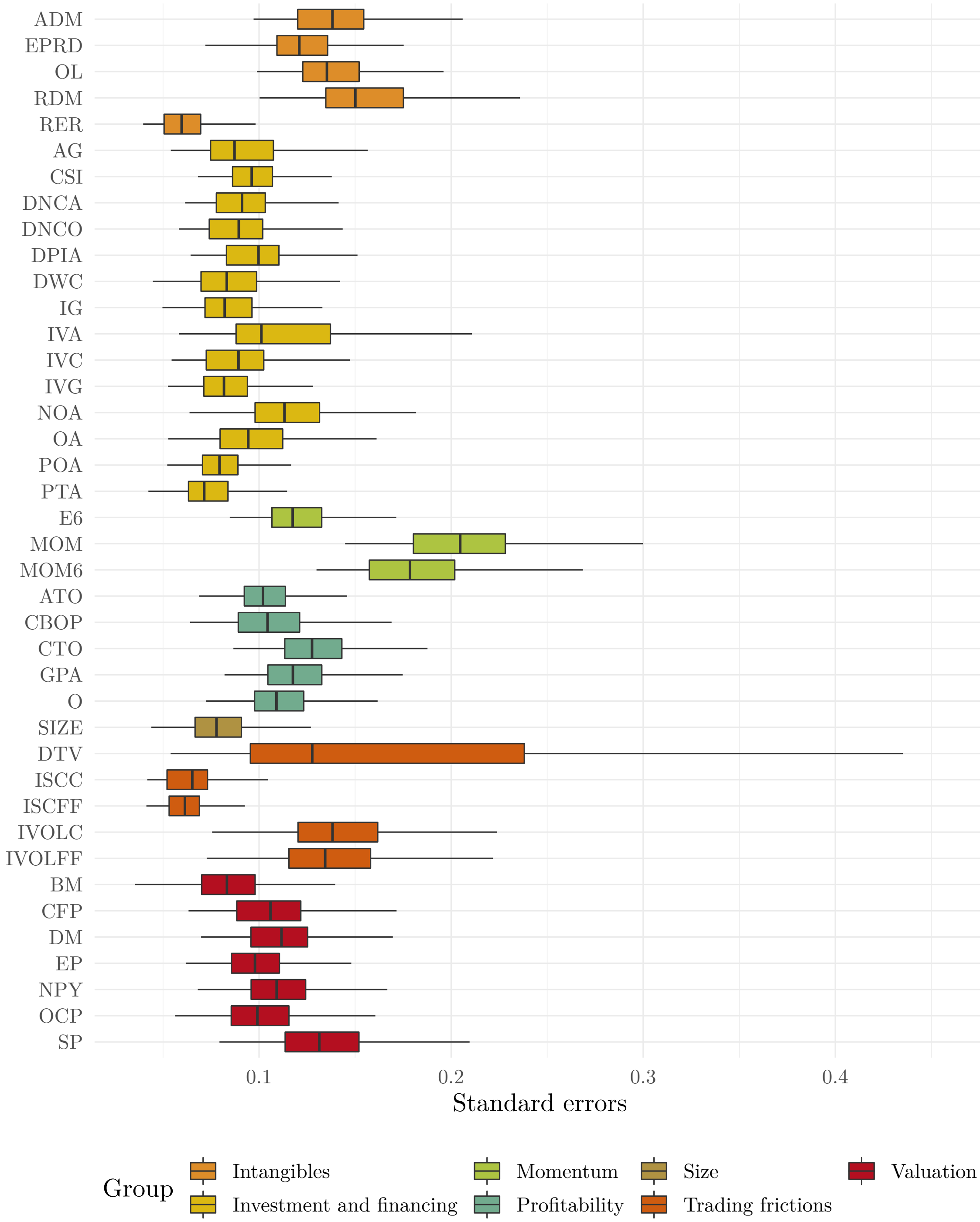


Figure II.6: Variation in FF3-adjusted standard errors across sorting variables. This figure shows the estimated standard errors for Fama and French (1992)-adjusted returns in boxplots for all sorting variables across all decision nodes. The vertical axis shows the associated sorting variable, while the color scheme connects each sorting variable to the respective category.



III Non-standard errors for CAPM- and FF3-adjusted returns

In this section, we present non-standard error summary statistics for returns adjusted for CAPM (see Table III.1) and for the Fama and French (1992)-model (see Table III.2), respectively.

Table III.1: Non-standard errors in CAPM-adjusted premiums across sorting variables. This table shows summary statistics for all sorting variables grouped by the respective category. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the CAPM-adjusted premiums across all decision nodes for each sorting variable. Furthermore, it contains the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and t-statistics larger than 1.96 (Sig.) scaled by the number of premiums, respectively.

Group	SV	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Int.	ADM	0.27	0.09	0.17	0.53	0.74	3.40	1.00	0.19
Int.	EPRD	0.95	0.20	0.14	1.39	0.44	2.46	1.00	1.00
Int.	OL	0.29	0.14	0.15	0.98	0.62	2.85	1.00	0.51
Int.	RDM	0.31	0.12	0.17	0.70	0.86	4.79	1.00	0.43
Int.	RER	0.17	0.05	0.06	0.80	0.97	4.35	1.00	0.90
Inv.	AG	0.62	0.19	0.14	1.41	0.83	3.63	1.00	1.00
Inv.	CSI	0.70	0.15	0.13	1.16	0.60	3.02	1.00	1.00
Inv.	DNCA	0.56	0.18	0.11	1.67	0.68	3.34	1.00	1.00
Inv.	DNCO	0.58	0.17	0.10	1.73	0.66	3.36	1.00	1.00
Inv.	DPIA	0.62	0.20	0.11	1.77	0.70	3.57	1.00	0.99
Inv.	DWC	0.53	0.17	0.09	1.86	0.54	2.95	1.00	1.00
Inv.	IG	0.42	0.11	0.10	1.18	0.74	3.58	1.00	1.00
Inv.	IVA	0.26	0.21	0.13	1.68	0.78	3.52	0.88	0.50
Inv.	IVC	0.53	0.16	0.09	1.75	0.54	2.63	1.00	1.00
Inv.	IVG	0.50	0.15	0.09	1.62	0.36	2.52	1.00	0.99
Inv.	NOA	0.59	0.17	0.12	1.45	0.51	3.18	1.00	1.00
Inv.	OA	0.43	0.18	0.11	1.67	0.58	2.93	1.00	0.89
Inv.	POA	0.51	0.14	0.10	1.41	0.38	2.64	1.00	1.00
Inv.	PTA	0.42	0.11	0.09	1.27	0.15	2.44	1.00	1.00
Mom.	E6	0.33	0.16	0.12	1.40	0.16	2.51	0.99	0.74
Mom.	MOM	0.99	0.23	0.21	1.10	0.43	2.86	1.00	1.00
Mom.	MOM6	0.79	0.28	0.18	1.56	0.44	2.84	1.00	0.96
Pro.	ATO	−0.00	0.12	0.12	0.97	0.55	2.85	0.43	0.03
Pro.	CBOP	0.46	0.19	0.13	1.50	0.93	3.92	1.00	0.86
Pro.	CTO	0.05	0.13	0.15	0.85	0.61	3.69	0.63	0.02
Pro.	GPA	0.33	0.20	0.15	1.35	0.67	2.93	1.00	0.57
Pro.	O	0.10	0.10	0.13	0.73	0.74	3.74	0.85	0.10
Siz.	SIZE	0.17	0.27	0.18	1.46	2.90	14.72	0.79	0.10
Tra.	DTV	0.55	0.22	0.19	1.16	0.64	3.57	1.00	0.86
Tra.	ISCC	0.11	0.12	0.07	1.78	−0.03	3.62	0.86	0.47
Tra.	ISCFF	0.02	0.11	0.06	1.74	−0.41	4.32	0.61	0.15
Tra.	IVOLC	0.87	0.25	0.18	1.40	0.65	3.34	1.00	0.99
Tra.	IVOLFF	0.85	0.24	0.18	1.38	0.67	3.46	1.00	0.99
Val.	BM	0.46	0.19	0.20	0.95	1.03	4.16	1.00	0.59
Val.	CFP	0.45	0.14	0.19	0.71	0.32	2.80	1.00	0.71
Val.	DM	0.13	0.08	0.19	0.43	0.29	3.22	0.95	0.00
Val.	EP	0.47	0.10	0.17	0.58	0.75	3.60	1.00	0.93
Val.	NPY	0.66	0.13	0.16	0.81	0.81	3.43	1.00	1.00
Val.	OCP	0.54	0.11	0.19	0.59	0.31	2.69	1.00	0.97
Val.	SP	0.48	0.19	0.22	0.86	1.06	3.87	1.00	0.60
Mean		0.45	0.16	0.14	1.23	0.63	3.58	0.95	0.73

Table III.2: Non-standard errors in FF3-adjusted premiums across sorting variables. This table shows summary statistics for all sorting variables grouped by the respective category. The table contains the mean (Mean, in %), skewness (Skew.), and kurtosis (Kurt.) of the Fama and French (1992)-adjusted premiums across all decision nodes for each sorting variable. Furthermore, it contains the non-standard error (NSE, in %), the average standard error (ASE, in %), and the NSE-ASE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and t-statistics larger than 1.96 (Sig.) scaled by the number of premiums, respectively.

Group	SV	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Int.	ADM	0.07	0.08	0.14	0.57	0.50	3.81	0.82	0.01
Int.	EPRD	1.06	0.21	0.12	1.67	0.41	2.33	1.00	1.00
Int.	OL	0.33	0.11	0.14	0.81	0.51	2.96	1.00	0.73
Int.	RDM	0.37	0.13	0.16	0.85	0.76	4.62	1.00	0.71
Int.	RER	0.19	0.06	0.06	0.99	1.05	4.48	1.00	0.95
Inv.	AG	0.42	0.19	0.09	2.00	0.90	3.97	1.00	0.96
Inv.	CSI	0.56	0.15	0.10	1.51	0.62	3.25	1.00	1.00
Inv.	DNCA	0.45	0.17	0.09	1.82	0.65	3.33	1.00	0.98
Inv.	DNCO	0.49	0.16	0.09	1.82	0.63	3.32	1.00	0.99
Inv.	DPIA	0.51	0.20	0.10	2.02	0.57	3.40	1.00	0.96
Inv.	DWC	0.50	0.16	0.09	1.88	0.47	2.84	1.00	1.00
Inv.	IG	0.33	0.10	0.09	1.14	0.83	4.20	1.00	0.95
Inv.	IVA	0.30	0.23	0.12	1.98	0.20	3.17	0.89	0.69
Inv.	IVC	0.45	0.16	0.09	1.73	0.56	2.74	1.00	1.00
Inv.	IVG	0.42	0.15	0.08	1.71	0.36	2.61	1.00	0.97
Inv.	NOA	0.59	0.19	0.12	1.61	0.46	3.25	1.00	0.99
Inv.	OA	0.43	0.16	0.10	1.58	0.53	2.89	1.00	0.93
Inv.	POA	0.42	0.12	0.08	1.49	0.37	2.69	1.00	0.99
Inv.	PTA	0.32	0.10	0.08	1.35	0.27	2.50	1.00	0.96
Mom.	E6	0.35	0.17	0.12	1.42	0.01	2.55	0.98	0.75
Mom.	MOM	1.17	0.25	0.21	1.21	0.38	2.68	1.00	1.00
Mom.	MOM6	0.90	0.29	0.18	1.60	0.39	2.73	1.00	0.99
Pro.	ATO	0.12	0.09	0.10	0.88	0.30	2.91	0.91	0.13
Pro.	CBOP	0.62	0.16	0.11	1.46	0.75	4.24	1.00	1.00
Pro.	CTO	0.16	0.11	0.13	0.87	0.35	3.17	0.93	0.15
Pro.	GPA	0.47	0.15	0.12	1.22	0.38	2.66	1.00	0.98
Pro.	O	0.24	0.09	0.11	0.80	1.01	4.73	1.00	0.57
Siz.	SIZE	0.01	0.27	0.09	3.17	3.02	15.38	0.34	0.12
Tra.	DTV	0.36	0.22	0.16	1.34	0.54	3.67	0.97	0.62
Tra.	ISCC	0.08	0.11	0.06	1.69	0.08	3.55	0.82	0.37
Tra.	ISCFF	−0.00	0.10	0.06	1.63	−0.30	4.22	0.48	0.10
Tra.	IVOLC	0.75	0.24	0.14	1.72	0.86	3.56	1.00	1.00
Tra.	IVOLFF	0.72	0.24	0.14	1.71	0.90	3.69	1.00	0.99
Val.	BM	0.08	0.19	0.08	2.25	0.96	4.05	0.60	0.28
Val.	CFP	0.10	0.15	0.11	1.37	0.18	2.91	0.75	0.24
Val.	DM	−0.21	0.09	0.11	0.83	−0.49	3.52	0.00	0.00
Val.	EP	0.19	0.11	0.10	1.10	0.51	3.53	0.97	0.45
Val.	NPY	0.44	0.13	0.11	1.19	0.75	3.43	1.00	0.98
Val.	OCP	0.18	0.10	0.10	1.02	0.19	2.81	0.97	0.44
Val.	SP	0.13	0.16	0.14	1.15	0.98	3.98	0.80	0.16
Mean		0.38	0.16	0.11	1.45	0.56	3.66	0.91	0.70

IV Impact of decision nodes: Figures

Here, we present figures for the decision nodes' impacts.

Figure IV.1: Impact of decision node: Breakpoint quantiles (main).
This figure shows the non-standard error produced when holding the main breakpoint quantiles constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

Figure IV.2: Impact of decision node: Weighting scheme.
This figure shows the non-standard error produced when holding the weighting scheme constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

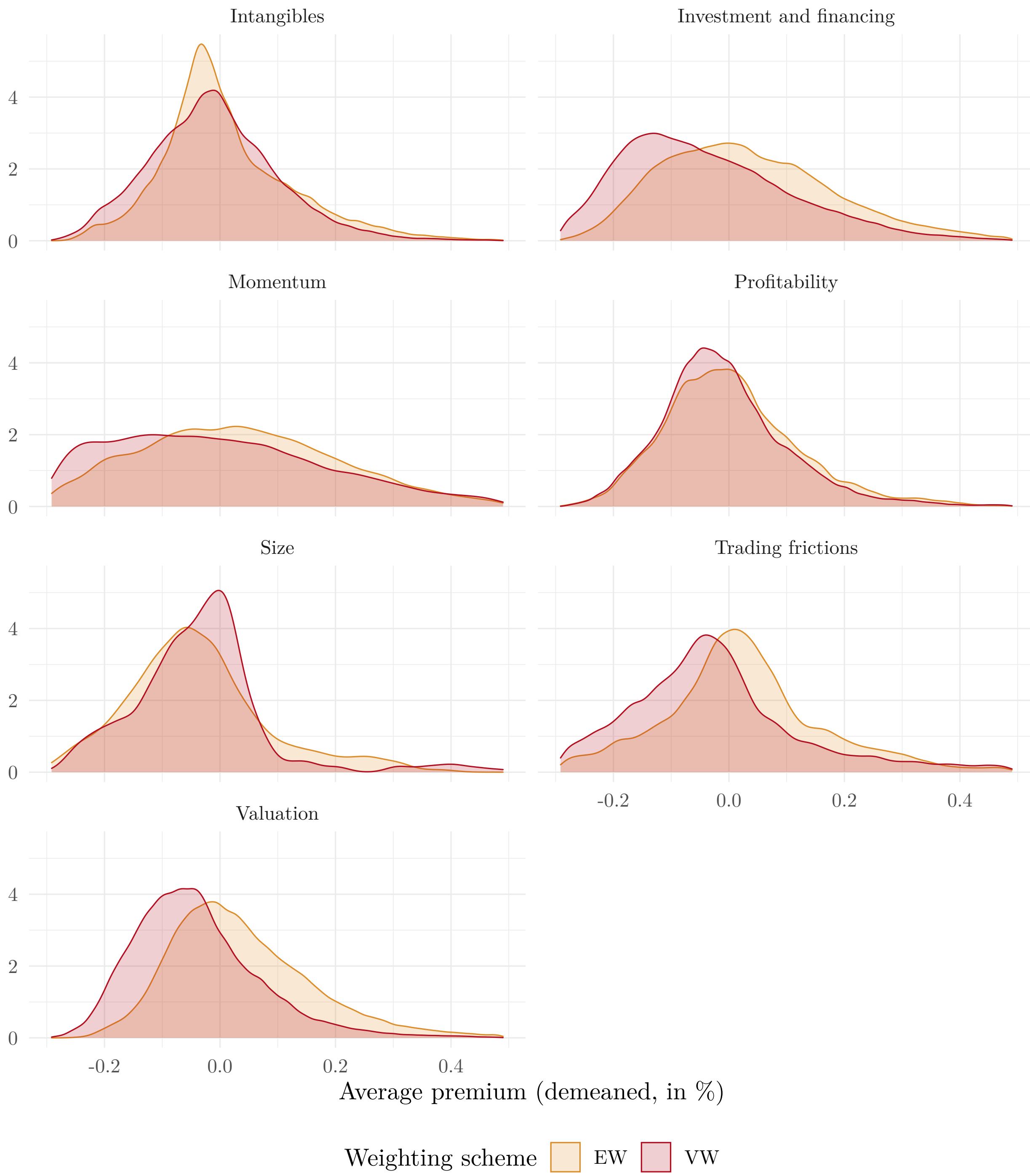


Figure IV.3: Impact of decision node: Positive earnings.
This figure shows the non-standard error produced when holding the positive earnings filter constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

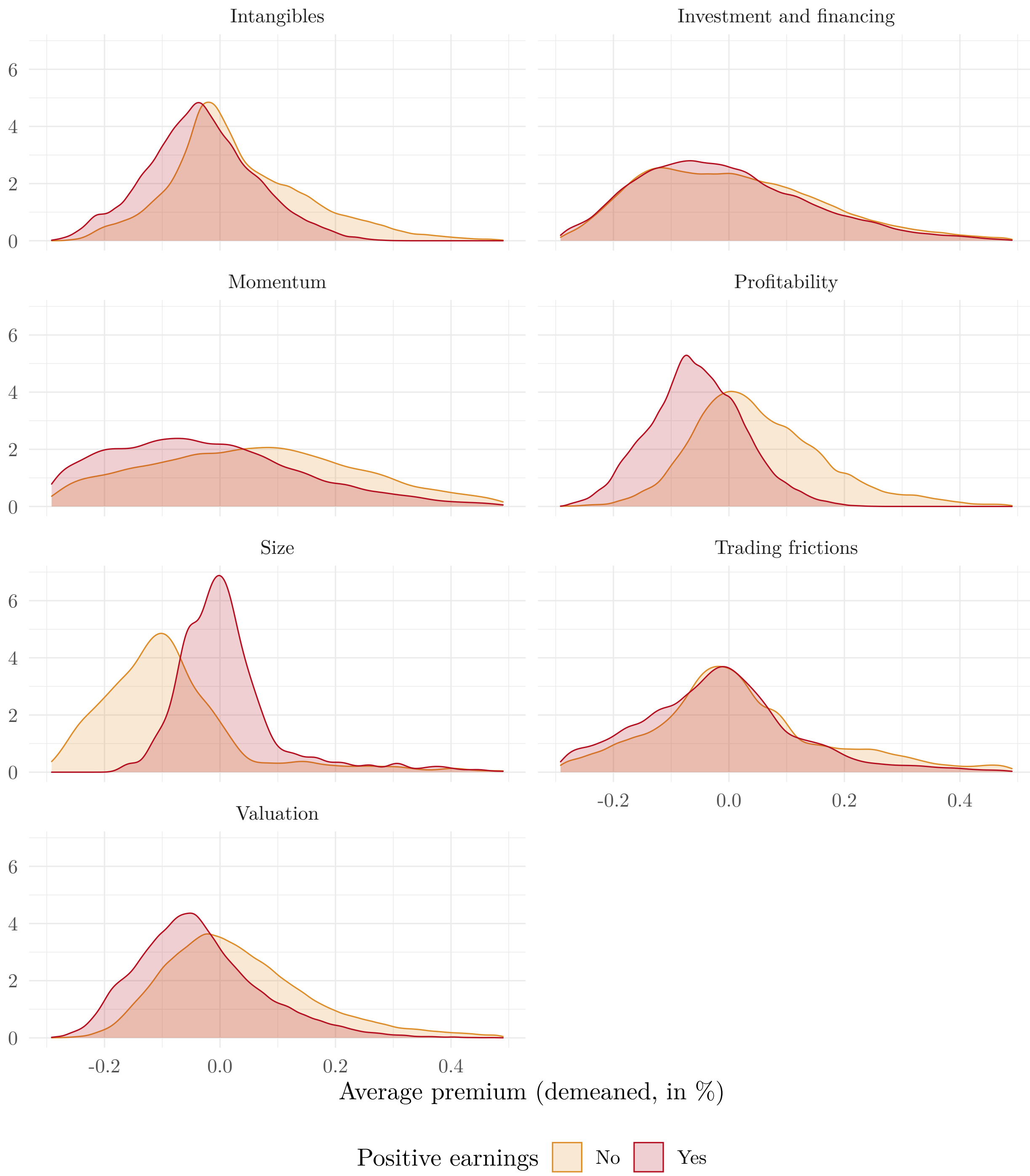


Figure IV.4: Impact of decision node: Size restriction.
This figure shows the non-standard error produced when holding the size restriction constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

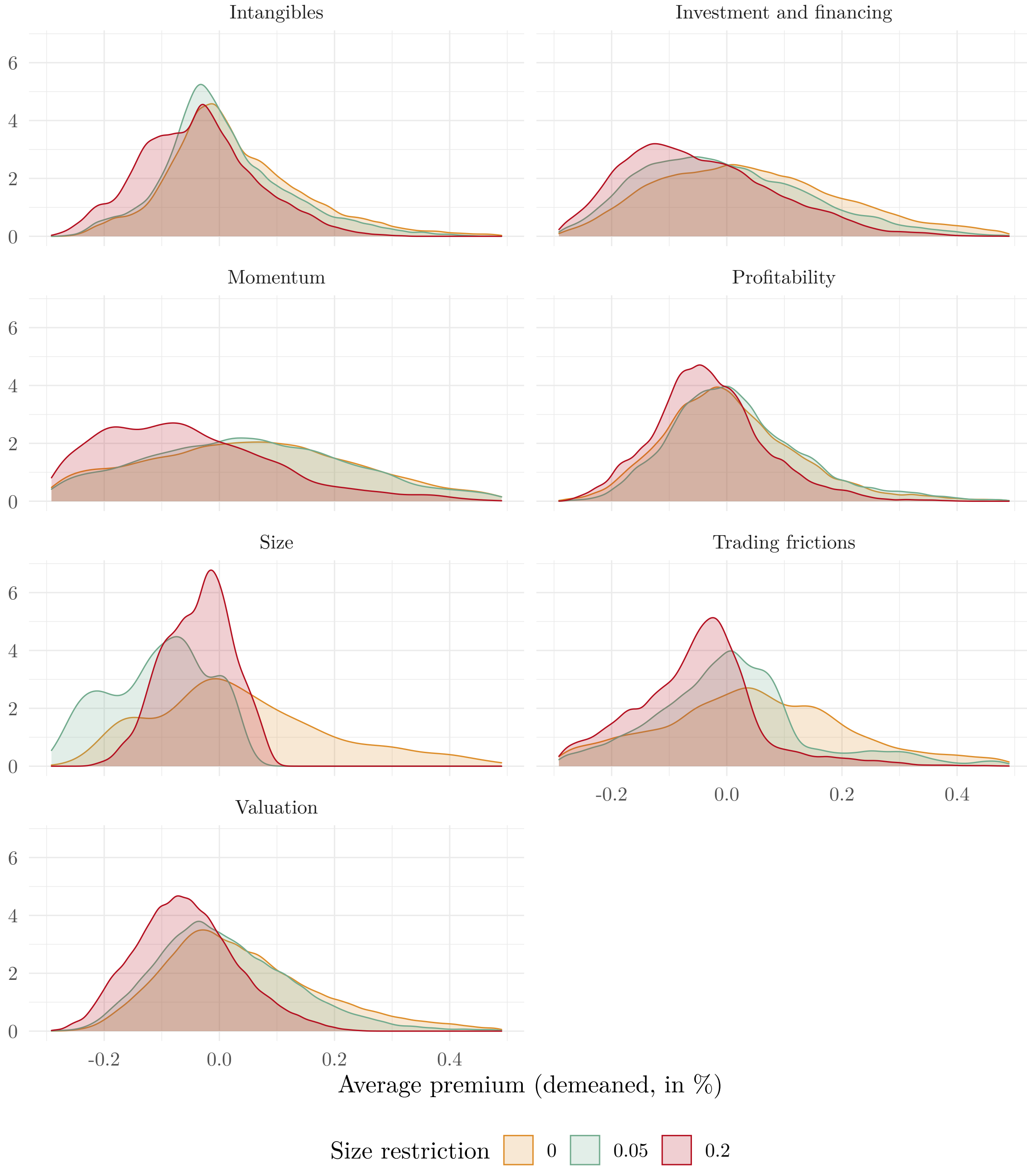


Figure IV.5: Impact of decision node: Breakpoint exchanges.
This figure shows the non-standard error produced when holding the breakpoint exchanges constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

Figure IV.6: Impact of decision node: Financials.
This figure shows the non-standard error produced when holding the decision to include financials constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

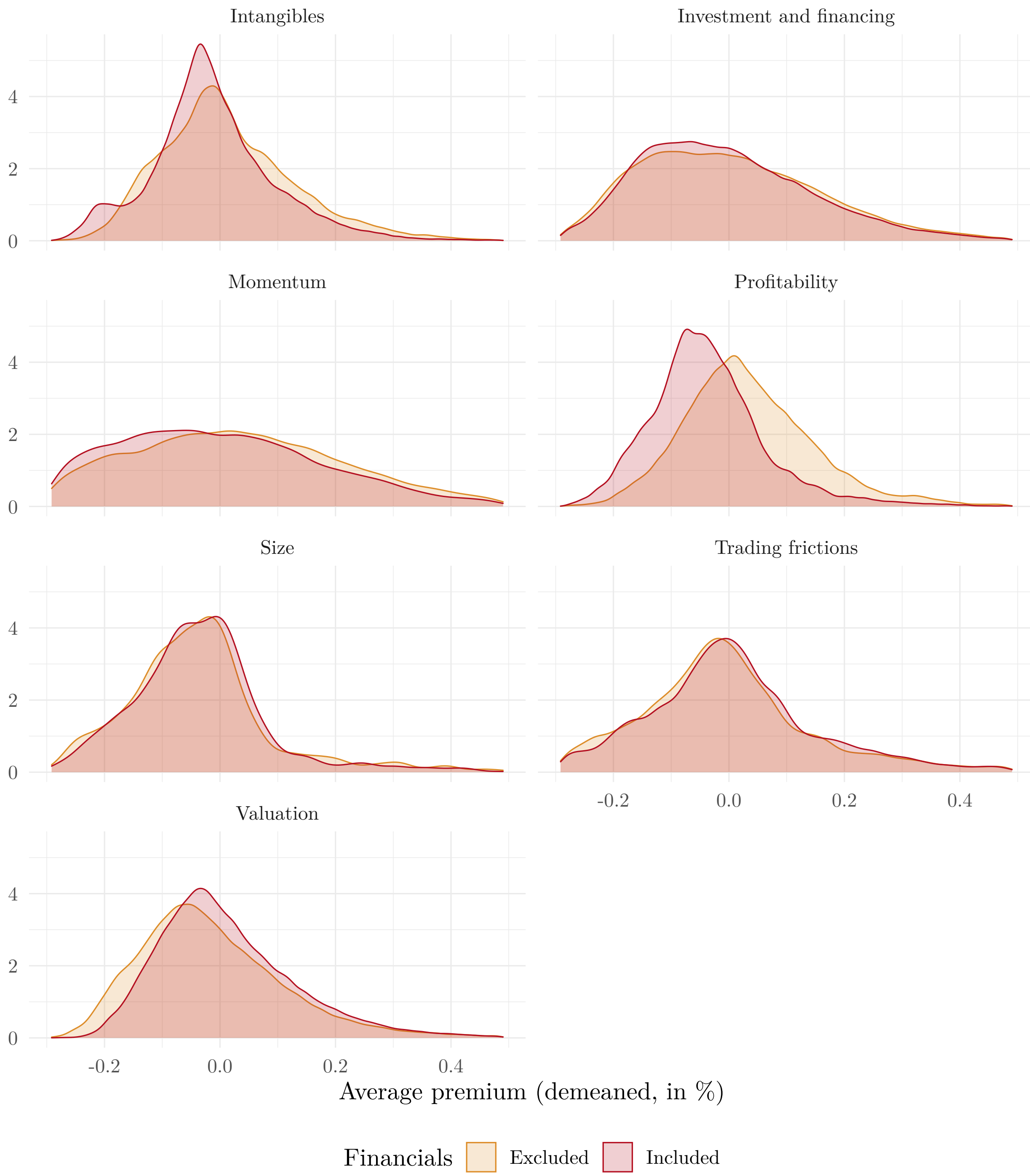


Figure IV.7: Impact of decision node: Breakpoint quantiles (secondary).
This figure shows the non-standard error produced when holding the secondary breakpoint quantiles constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

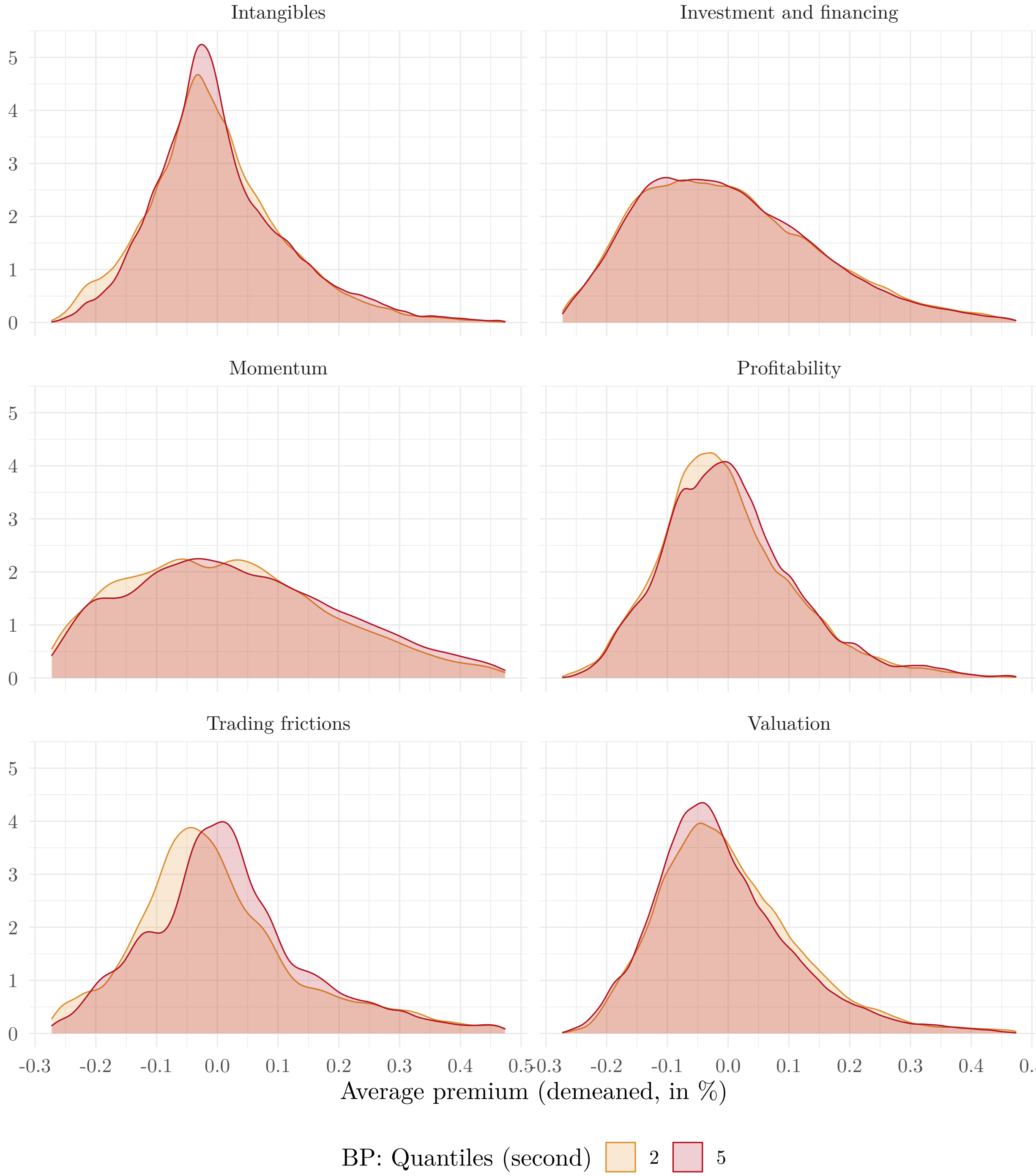


Figure IV.8: Impact of decision node: Rebalancing.
This figure shows the non-standard error produced when holding the rebalancing frequency constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

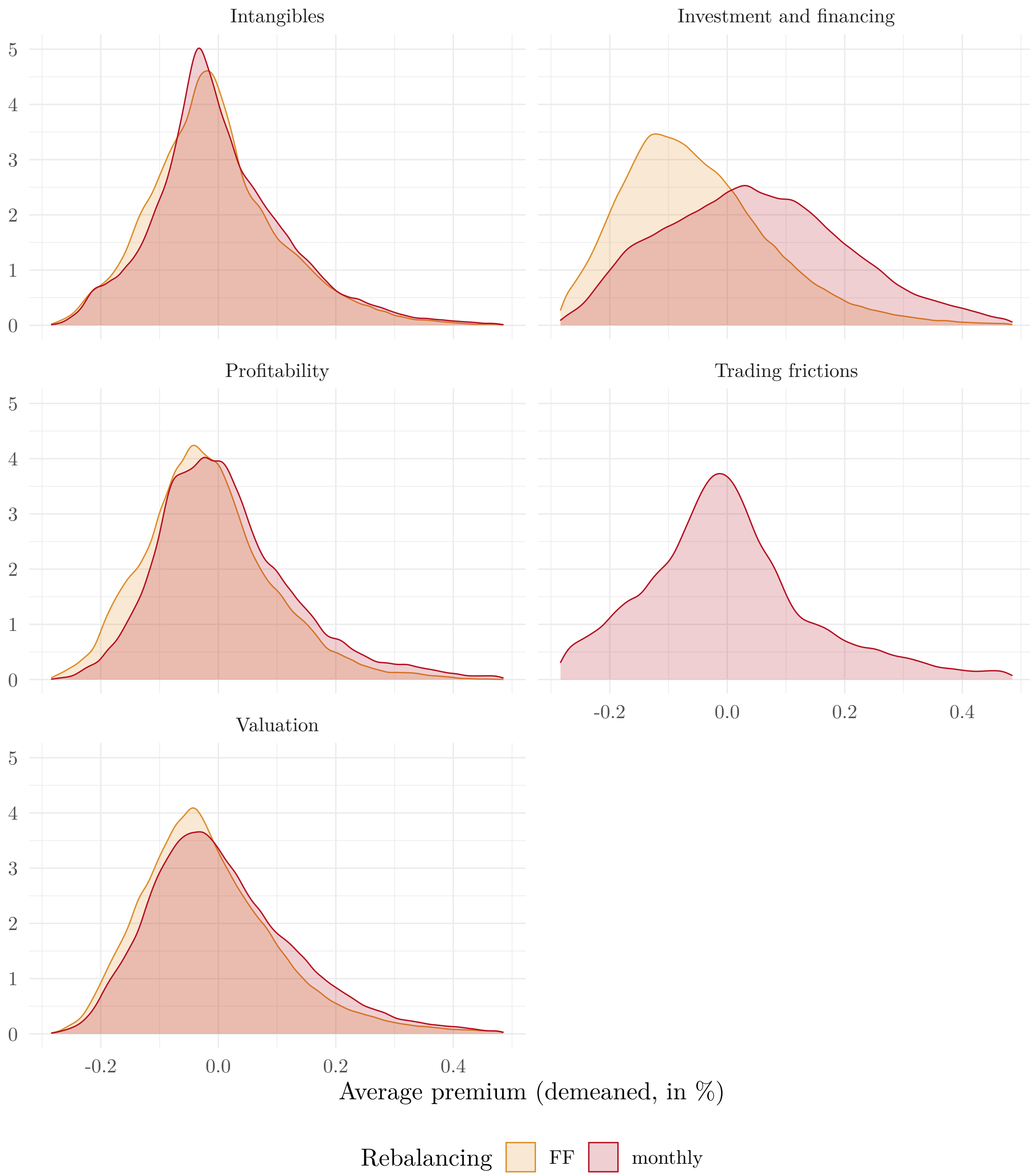


Figure IV.9: Impact of decision node: Double sort.

This figure shows the non-standard error produced when holding double sorting scheme constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

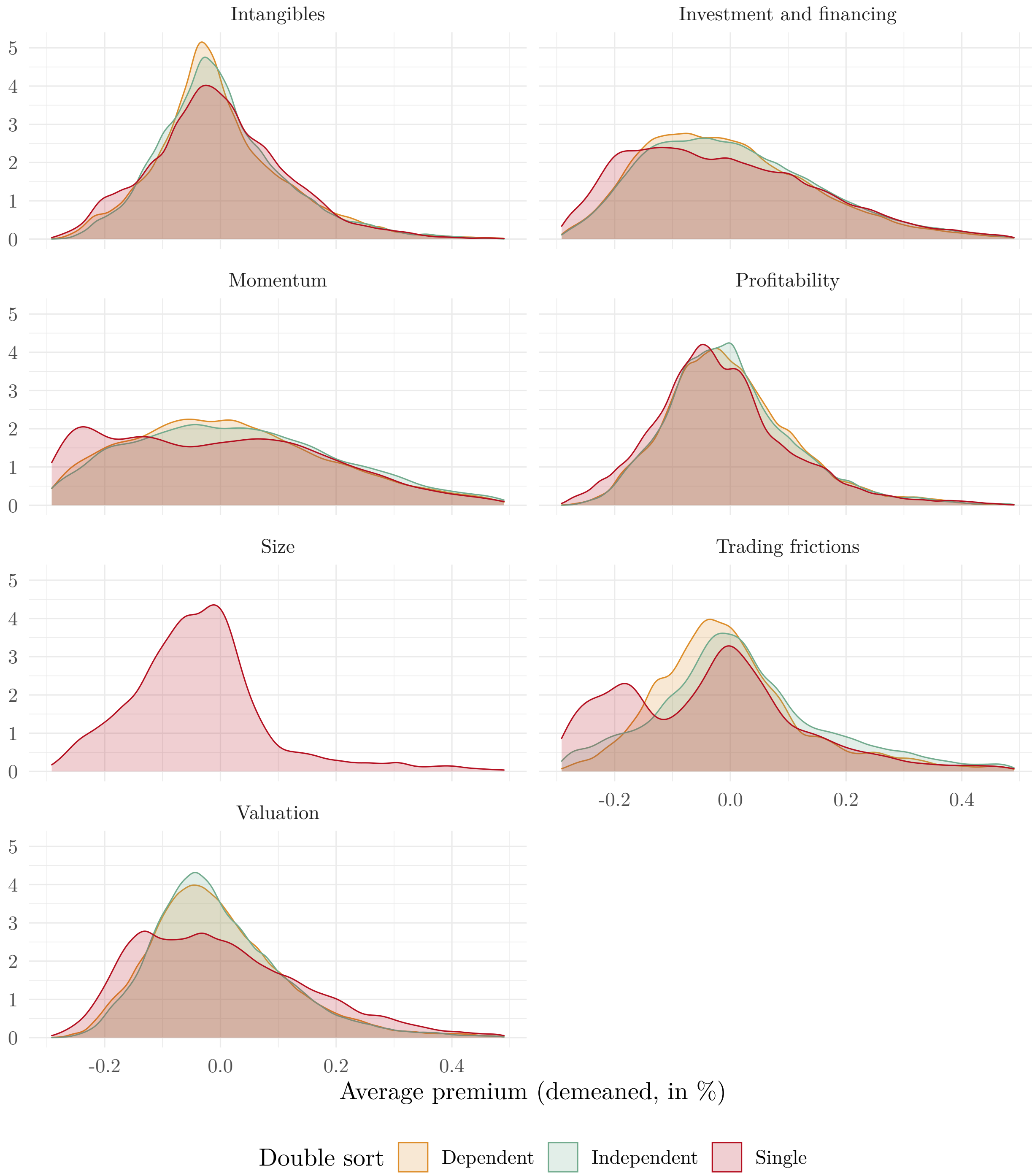


Figure IV.10: Impact of decision node: Utilities.
This figure shows the non-standard error produced when holding the decision to include utilities constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

Figure IV.11: Impact of decision node: Sorting variable lag.
This figure shows the non-standard error produced when holding the sorting variable lag constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

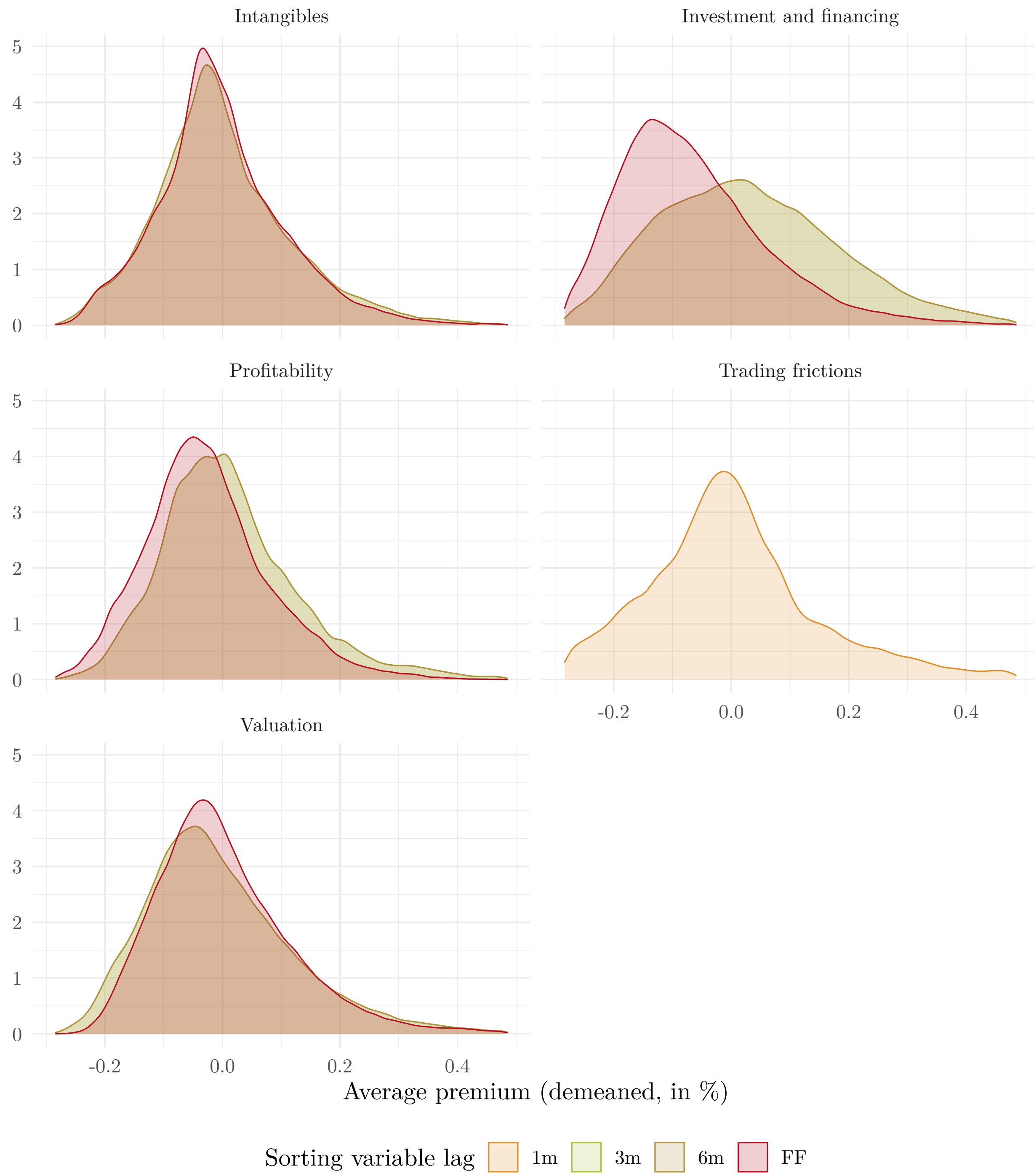


Figure IV.12: Impact of decision node: Stock-age restriction.
This figure shows the non-standard error produced when holding the stock-age restriction constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

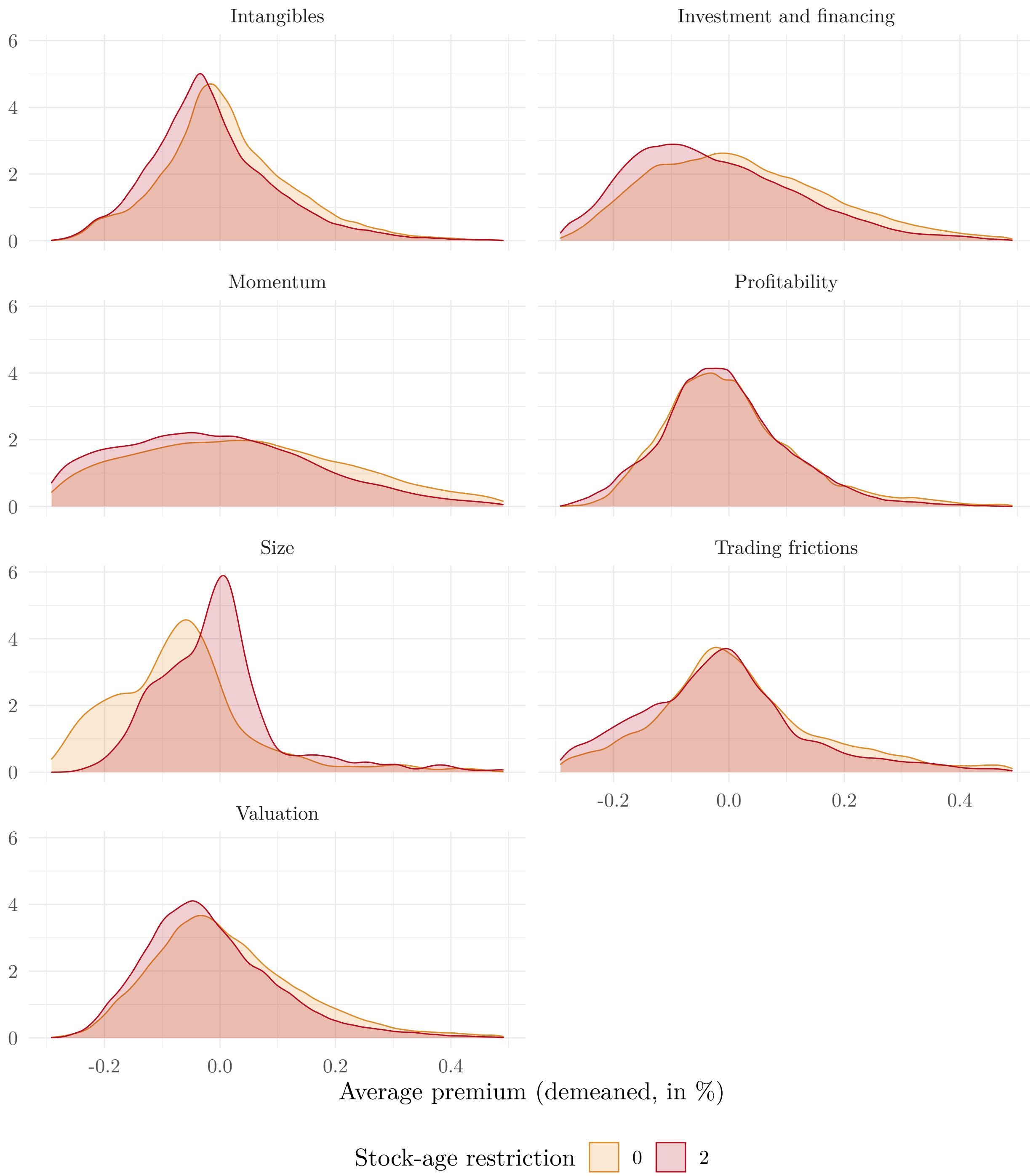


Figure IV.13: Impact of decision node: Price restriction.
This figure shows the non-standard error produced when holding the price restriction constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.

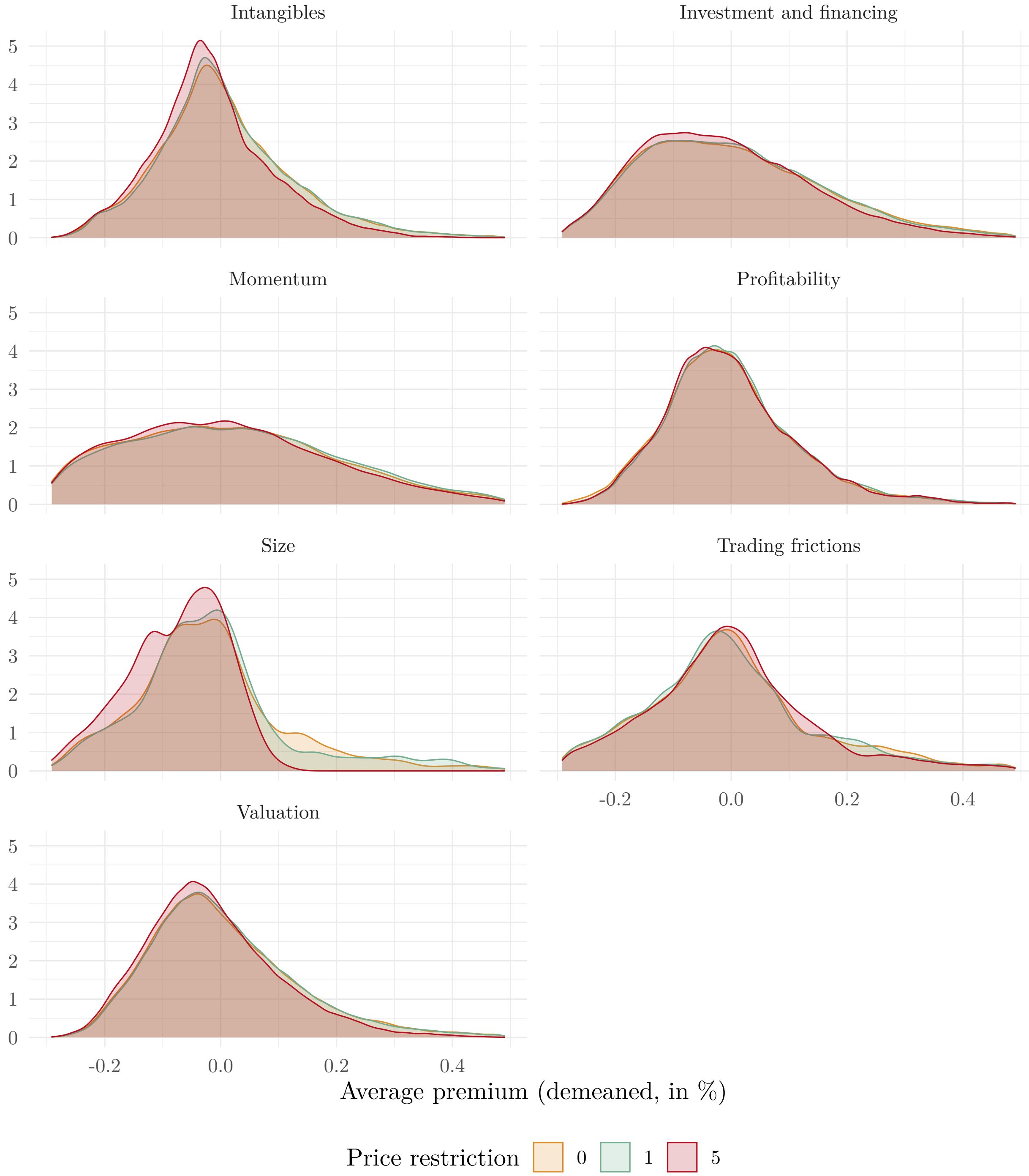
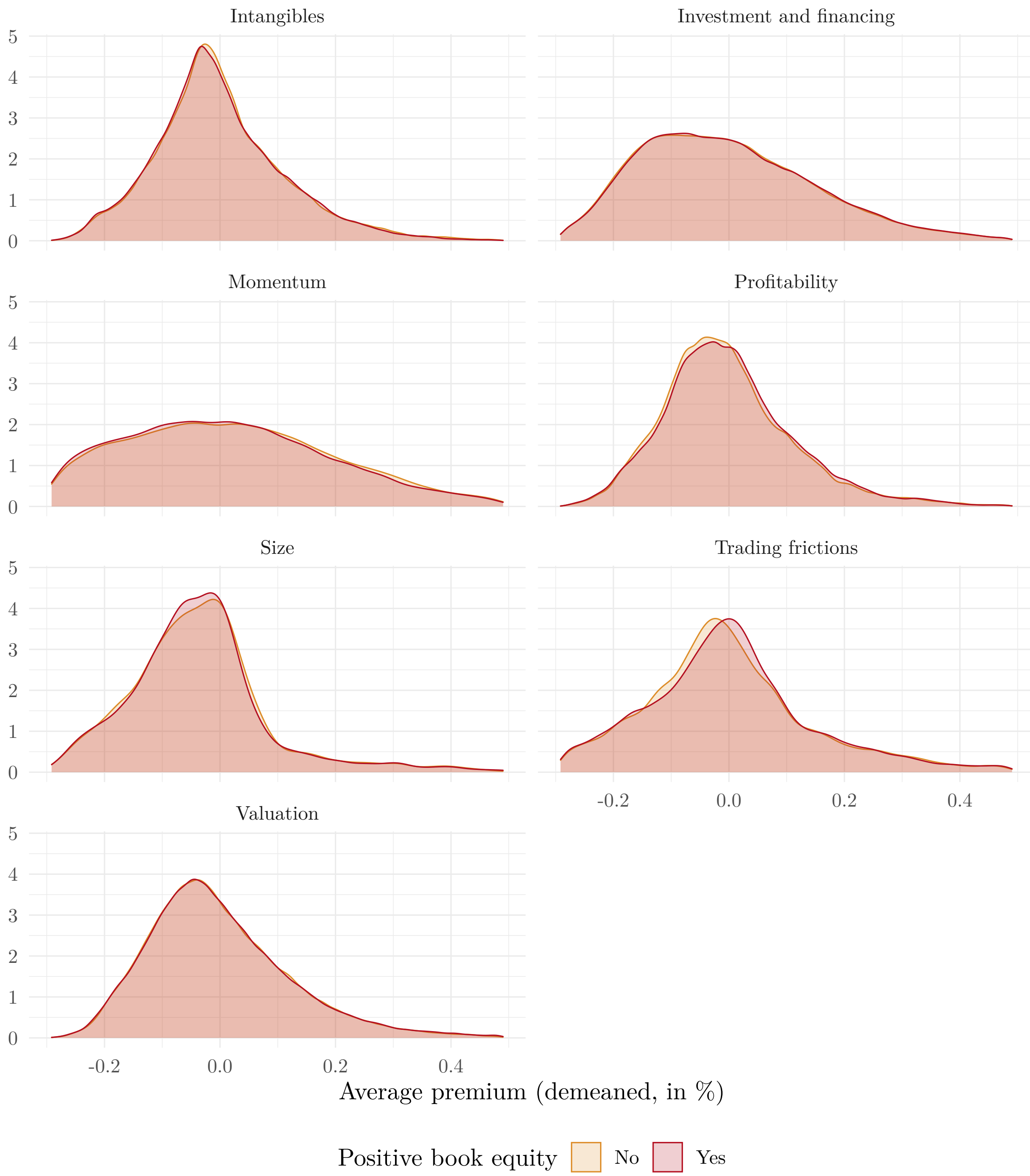


Figure IV.14: Impact of decision node: Positive book equity.
This figure shows the non-standard error produced when holding the book equity filter constant. We demean the average premiums within each sorting variable to make their location comparable. In the separate panels, we show the distribution of demeaned premiums (in %) for the different categories across all remaining decision nodes.



V Alphas and decision nodes

This section shows the impact of decision nodes on alphas for the CAPM and FF3 model, respectively.

Table V.1: Impact of decision node on CAPM alphas.
This table shows the mean statistics across sorting variables for several decision nodes in separate panels. Each table contains the mean (Mean, in %), skewness (Skew.), kurtosis (Kurt.), and interquartile range (IQR, in %) of the average premiums. We also show the non-standard error (NSE, in %), the average standard error (mSE, in %), the standard deviation of the standard error (sSE, in %), and the NSE-SE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: BP: Quantiles (second)

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
2	0.46	0.15	0.14	1.20	0.66	3.29	0.96	0.75
5	0.47	0.15	0.13	1.19	0.65	3.18	0.96	0.76

Panel B: Rebalancing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
FF	0.39	0.13	0.13	1.06	0.66	3.32	0.96	0.71
monthly	0.46	0.16	0.14	1.23	0.50	3.30	0.95	0.73

Panel C: Double sort

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Dependent	0.46	0.15	0.13	1.19	0.66	3.32	0.96	0.75
Independent	0.47	0.15	0.14	1.18	0.61	3.17	0.96	0.76
Single	0.44	0.17	0.15	1.24	0.66	3.39	0.93	0.68

Panel D: Utilities

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.46	0.16	0.14	1.23	0.62	3.57	0.96	0.73
Included	0.44	0.16	0.14	1.23	0.65	3.61	0.94	0.72

Panel E: Sorting variable lag

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
1m	0.48	0.19	0.13	1.49	0.30	3.66	0.89	0.69
3m	0.44	0.15	0.14	1.18	0.60	3.28	0.96	0.73
6m	0.44	0.15	0.14	1.18	0.60	3.28	0.96	0.73
FF	0.39	0.13	0.13	1.04	0.62	3.21	0.95	0.72

Panel F: Stock-age restriction

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.47	0.17	0.14	1.24	0.57	3.44	0.94	0.73
2	0.42	0.15	0.14	1.19	0.65	3.66	0.96	0.71

Panel G: Price restriction

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.46	0.17	0.14	1.28	0.65	3.52	0.95	0.73
1	0.46	0.16	0.14	1.23	0.58	3.26	0.95	0.73
5	0.44	0.15	0.14	1.17	0.47	3.08	0.95	0.72

Table V.2: Impact of decision node on FF3 alphas.
This table shows the mean statistics across sorting variables for several decision nodes in separate panels. Each table contains the mean (Mean, in %), skewness (Skew.), kurtosis (Kurt.), and interquartile range (IQR, in %) of the average premiums. We also show the non-standard error (NSE, in %), the average standard error (mSE, in %), the standard deviation of the standard error (sSE, in %), and the NSE-SE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: BP: Quantiles (main)

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
5	0.33	0.12	0.10	1.34	0.54	3.44	0.91	0.71
10	0.43	0.16	0.12	1.31	0.48	3.49	0.90	0.70

Panel B: Weighting scheme

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
EW	0.41	0.15	0.11	1.41	0.65	3.50	0.93	0.75
VW	0.35	0.15	0.11	1.34	0.59	3.56	0.88	0.66

Panel C: Positive earnings

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
No	0.40	0.16	0.12	1.41	0.52	3.44	0.91	0.72
Yes	0.35	0.14	0.10	1.36	0.44	3.26	0.90	0.69

Panel D: Size restriction

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.43	0.18	0.11	1.61	0.35	3.10	0.93	0.76
0.2	0.32	0.12	0.11	1.07	0.17	2.98	0.88	0.64

Panel E: BP: Exchanges

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
All	0.42	0.17	0.12	1.47	0.38	3.27	0.92	0.73
NYSE	0.33	0.13	0.11	1.22	0.44	3.53	0.89	0.68

Panel F: Financials

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.38	0.16	0.11	1.43	0.57	3.65	0.90	0.69
Included	0.37	0.15	0.11	1.44	0.58	3.67	0.92	0.71

Table V.3: Impact of decision node on FF3 alphas.

This table shows the mean statistics across sorting variables for several decision nodes in separate panels. Each table contains the mean (Mean, in %), skewness (Skew.), kurtosis (Kurt.), and interquartile range (IQR, in %) of the average premiums. We also show the non-standard error (NSE, in %), the average standard error (mSE, in %), the standard deviation of the standard error (sSE, in %), and the NSE-SE ratio (Ratio). The last two columns show the number of positive premiums (Pos.) and fraction of t-statistics larger than 1.96 (Sig.).

Panel A: BP: Quantiles (second)

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
2	0.39	0.15	0.11	1.35	0.60	3.34	0.93	0.73
5	0.39	0.14	0.11	1.32	0.60	3.24	0.94	0.74

Panel B: Rebalancing

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
FF	0.31	0.13	0.10	1.26	0.53	3.35	0.92	0.69
monthly	0.37	0.15	0.11	1.42	0.45	3.39	0.91	0.71

Panel C: Double sort

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Dependent	0.38	0.14	0.11	1.34	0.61	3.37	0.93	0.74
Independent	0.40	0.14	0.11	1.32	0.56	3.20	0.93	0.73
Single	0.36	0.18	0.12	1.53	0.56	3.18	0.87	0.66

Panel D: Utilities

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
Excluded	0.38	0.16	0.11	1.44	0.55	3.65	0.90	0.70
Included	0.37	0.15	0.11	1.45	0.58	3.70	0.91	0.70

Panel E: Sorting variable lag

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
1m	0.38	0.18	0.11	1.62	0.42	3.74	0.85	0.62
3m	0.35	0.14	0.11	1.38	0.51	3.39	0.92	0.71
6m	0.35	0.14	0.11	1.38	0.51	3.39	0.92	0.71
FF	0.31	0.13	0.10	1.24	0.52	3.27	0.93	0.70

Panel F: Stock-age restriction

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.39	0.16	0.11	1.47	0.52	3.58	0.90	0.70
2	0.35	0.15	0.11	1.40	0.57	3.71	0.90	0.69

Panel G: Price restriction

Branch	Mean	NSE	ASE	Ratio	Skew.	Kurt.	Pos.	Sig.
0	0.38	0.17	0.11	1.52	0.60	3.60	0.91	0.71
1	0.38	0.16	0.11	1.45	0.52	3.33	0.91	0.71
5	0.37	0.14	0.11	1.35	0.36	3.05	0.90	0.70