Active Investing

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Proefschrift

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Contents

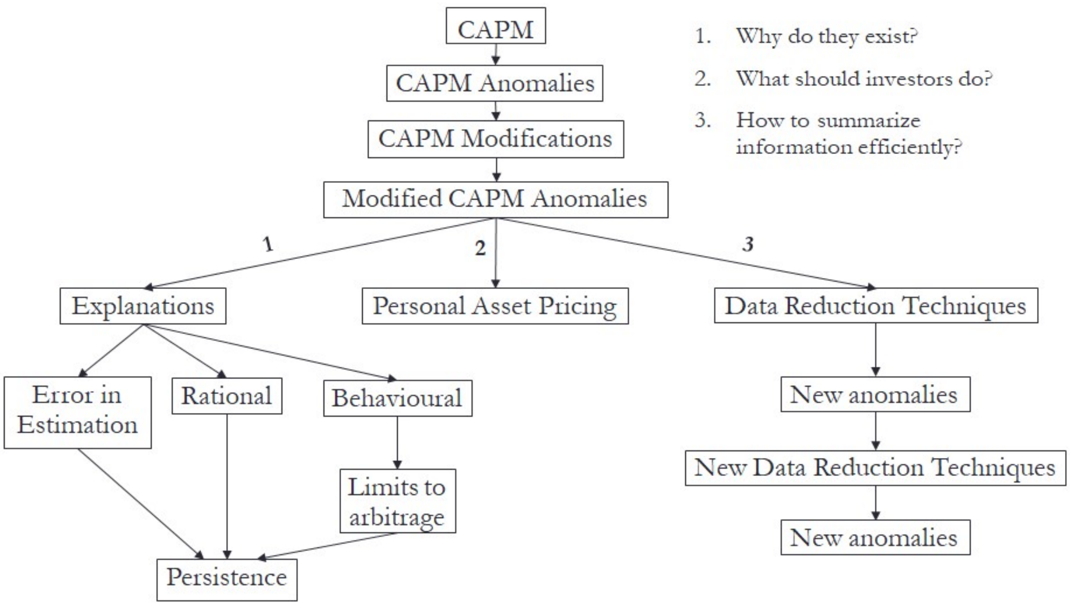
Introduction

The three chapters in this thesis explore different parts of the active investing debate. I would like to start by summarizing the historical development of the area in order to put the research findings in context.

It all started with the capital asset pricing model (CAPM); whenever a security would offer positive expected returns it would also be accompanied by a proportional rise in market beta. However, not long after the initial development of the model, researchers discovered the first generation of asset pricing anomalies; that is, portfolios sorted on certain characteristics, such as a companies' book to market ratio, had realized returns that cannot be explained by the model.

Researchers initially attempted to adjust the CAPM to subsume the anomalies. However, these early modifications were largely unsuccessful. All the while, the set of discovered characteristics that generate "abnormal" performance continued to expand.

Figure 1: Anomaly research. This figure summarizes the historical development of active investing and the strands of anomaly research.



Failure to resuscitate the CAPM has split the literature into three directions. On the left of Figure 1, we have stories regarding the existence of anomalies. They are grouped into error in estimation stories, rational stories, and behavioral stories. Error in estimation stories claim that anomalies are the result of "research errors" (such as data mining) and do not in fact exist. Rational stories claim that portfolios that offer higher returns are risky as they offer poor performance in high marginal utility states. In **Chapter 1**, I delve further into this issue. The literature has proposed a plethora of alternative rational asset pricing models to account for the anomalies, but these models seem to be (over)fit to explaining the performance of a single anomaly. Just like the CAPM, alternative models need to explain or reduce the pricing errors across assets. Consequently, Chapter 1 argues for testing rational asset pricing models on alternative anomalies or portfolios of premiums as an out-of-sample test and shows how popular anomaly explanations fail this test.

The behavioral stories claim that investors are irrational, constrained, or have non-standard preferences. Resultantly, asset prices can deviate from fundamental values. Behavioral explanations are often combined with "a limits to arbitrage" story. For example, if a certain subset of investors is irrational, why is it not the case that rational arbitrageurs exploit the "mispricing" and correct prices in the process. Limits to arbitrage explanations suggest that arbitrageurs face obstacles and prohibitive costs in executing price correcting trades.

In **Chapter 2**, I explore short selling costs and restrictions as a potential limit to arbitrage explanation for anomalies. I find that investors can profitably exploit anomalies without short selling. Moreover, investors can further enhance performance with a market short which is cheap to execute. Finally, I show that the cost associated with borrowing stocks is small relative to the alpha associated with short anomaly positions. Summarized briefly, short selling costs cannot fully explain stock anomalies.

Moving to the middle of Figure 1, we have personal asset pricing. This encompasses methodologies such as spanning tests on a personal predefined benchmark and portfolio theory. These approaches try to prescribe investment recommendations to a specific investor.

Finally, on the right-hand side of Figure 1, we have the data reduction techniques. Data reduction techniques try to reduce the number of predictive signals. Their goal is to reduce dimensionally and improve out-of-sample prediction.

In **Chapter 3**, I test two new signals, shareholder meetings and shareholder support and find that they are associated with positive alphas relative to both the CAPM model with an equity proxy and popular data reduction techniques. In other words, voting data can be used for the creation of new asset pricing anomalies. Moreover, the chapter tests and discusses the viability of the rational, behavioral, and error in estimation explanations for the voting anomalies.

The chapters that follow delve further into the details. Readers interested more in the development of the literature can find a more extensive summary in Chapter 1.

Chapter 1: Testing rational asset pricing models

Abstract

New rational explanations are often developed and tested only on a single asset pricing anomaly. This approach of "testing in isolation" can lead to idiosyncratic findings as rational pricing should hold across assets. The paper empirically demonstrates the problem by showing how recession and crash risk can be relevant for a specific subset of stand-alone anomalies while at the same time being diversifiable in portfolios of premiums. Resultantly, the paper argues for raising the hurdle when assessing new rational models.

1. Introduction

Our inability to explain the returns of 'anomalous' portfolios via CAPM modifications has motivated a widespread search for a better rational model. One of the basic rules of the search is that the new rational model should explain the returns of all valid assets. Or at the very least, the new rational model should extensively reduce overall model-mispricing of anomalous portfolios before being widely accepted as the best available option.

While this approach has become standard practice when testing data reduction techniques, the same hurdle is seldom applied to the development of new rational models. On the contrary, researchers often develop rational models to explain the returns of a single anomaly. One of the testing methods associated with this approach is to regress the performance of a single anomaly on the new rational benchmark. The new model is considered successful if it reduces alpha. An analogous approach is to suggest that an anomaly has significant alphas but that it performs poorly across alternative assessment metrics (such crash risk) or that it underperforms in specific high marginal utility states of the world (such as recessions). These forms of 'testing in isolation' (testing on a single anomaly) have produced an 'overabundance' of rational explanations, whereby multiple risks can explain the same anomaly.

The problem can be traced back to isolated testing. Researchers can explain the performance of an anomaly using the new model. However, the same model needs to also explain alternative anomalies or portfolios of premiums to be considered a rational model. Reasoning more intuitively, a priced risk should not be diversifiable. Anomalies can have crash risk but if crashes occur in different states of the world, then the portfolio of premiums will diversify the risk. In the extreme case, a new rational model may make things worse if it prescribes returns for alternative anomalies that are further from observation. Therefore, for existing 'rational' explanations, a valid out-of-sample test is their ability to explain alternative anomalies or portfolios of premiums.

The paper uses two examples to empirically illustrate the point: (1) recession risk, and (2) crash risk. More specifically, when it comes to cross-sectional stock momentum, it is often argued that it is subject to extreme crashes (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016) or that it performs poorly in recession states (Chordia & Shivakumar, 2002). Multi-premium portfolios that contain both passive and active bets manage to curtail crash risk to passive investing levels and to significantly *improve* recession performance. In other words, crash risk is diversifiable while recession risk makes anomalies even more anomalous. The empirical investigation demonstrates the effectiveness of portfolios as a simple universal tool for reducing idiosyncratic premium risks. More importantly, it shows the importance of out-of-sample testing for assessing new rational explanations. While testing on out-of-sample anomalies is common when assessing new data reduction techniques, we should put the same hurdle when assessing rational asset pricing models.

The most closely related paper is Asness, Moskowitz, and Pedersen (2013); they argue that the combination of value and momentum can diversify a set of risks (such as liquidity risk). In this paper, it is argued that the combination of active and passive premiums (premium investing) can diversify recession and crash risk and should be routinely used as one of the first steps for the assessment of rational anomaly explanations.

2. Understanding anomalies

2.1. Anomalous in relation to what?

Over the past four decades, researchers have uncovered a variety of profitable rule-based active investment strategies. These strategies have been given a multitude of names depending on the setting in which they appear; anomalies, return predicting signals, factors, active bets, and, smart beta are just a few well suited and widely used names that this paper will also interchangeably adopt. And when it comes to academic work, these anomalies are truly widespread (Green, Hand & Zhang, 2013; Harvey, Liu & Zhu, 2015).

The historical development of anomalies is inexorably intertwined with the empirical testing of the conditional CAPM. The returns to portfolios created by sorting assets on some specific characteristic were considered anomalous because they were not associated with a commensurate rise in risk. In the CAMP, the beta of a security with respect to aggregate wealth is synonymous for risk. Consequently, the absence of beta was considered anomalous (Cochrane, 2011). In this respect, the first generation of anomalies was initially developed as CAPM (with equity proxy) anomalies. Whenever researchers 'test' the CAPM with a proxy, they are testing if adding anomalies to the equity premium improves performance. Intuitively, time-series alphas imply that the inclusion of anomalies will increase the risk-adjusted performance of a portfolio consisting of the right-hand side assets in a regression (Ferson, & Lin, 2014).

2.1. CAPM failures and the rising acceptance of data reduction techniques

Early tests of the CAPM discovered a wide variety of characteristic-sorted portfolios that provide significant equity beta-adjusted returns (Ball, 1978; Stattman, 1980; Banz, 1981; Basu, 1983; Rosenberg, Reid, & Lanstein, 1985; Chan, Hamao, & Lakonishok, 1991). This collection of first-generation anomalies was eventually subsumed by two characteristics: (1) book to market (value) and (2) market capitalization (size) (Fama & French, 1992). Not long after, momentum joined center stage (Jegadeesh & Titman, 1993; Grundy & Martin, 2001) to form the Fama-French (FF)-Carhart model (Carhart, 1997).

Regardless of Roll's critique (Roll, 1977) and the inherent non-testability of the CAPM, over the years, researchers have used a variety of approaches in the hope that they will resurrect the underlying logic and intuition of the CAPM. Their hope was to obtain a positive coefficient on market betas and insignificant coefficients (alphas) for all the other factors (anomalies) in cross-sectional (time-series) tests. This strand of work has mainly centered on better Bayesian estimates of betta (Vasicek, 1973; Karolyi, 1992), better proxies for the portfolio of aggregate wealth (Stambaugh, 1982; Jagannathan & Wang, 1996) and beta conditioning (Ferson & Harvey, 1999; Avramov & Chordia, 2006; Lewellen & Nagel, 2006).

Even when successful at resurrecting the significance of beta, most studies failed to account for the anomalous alphas associated with core anomalies. For example, Avramov and Chordia (2006) find that the conditional CAPM cannot explain size, book to market, and momentum. Similarly, Lewellen and Nagel (2006) show that if the conditional CAPM truly holds, then deviations from the unconditional CAPM should be smaller than the ones observed empirically.

2.2. Data reduction techniques

Since early tests of the conditional CAPM failed to convincingly account for the main factors (size, value, and momentum), they became accepted in the literature and formed a new benchmark. Later studies had to face a higher hurdle; they needed to remain significant after controlling for the FF+ Carhart factors.

The resulting empirically motivated FF+ Carhart model did not last long. An extensive second generation of anomalies soon followed (Sloan, 1996; Pontiff & Woodgate, 2008; Ang, Hodrick, Xing & Zhang, 2006; Asness, Frazzini, & Pedersen, 2015) and their excess returns could not be explained by a proportional rise in value, size, market or momentum betas. Consequently, they were considered anomalous also in relation to the benchmark anomalies. And the ink was not yet dry on the five-factor model (Fama & French, 2015), when a third generation of anomalies started to appear and gain in prominence. Even more disturbingly, the ability of the five-factor model to subsume or even dominate the existing multitude of anomalies remains highly questionable (Green, Hand, & Zhang 2014).

Empirically motivated models often do a reasonable job at data reduction, but they do not explain the underlying causes of anomalies. Resultantly, failure to resuscitate the CAPM has separated investigations into data reduction techniques that summarize signal information in a concise format useful for out-of-sample prediction and assessing new anomalies but devoid of economic content (such as the Fama-French models or models based on principal component analysis); and investigations that try to explain anomalies. The next section summarizes the later strand of work which is of more interest in this paper (Figure 1).

2.3. Revisiting anomaly explanations

Our inability to subsume anomalies via CAPM modifications has driven the emergence of four strands of anomaly explanations. They are broadly grouped into (1) errors in estimation stories, (2), rational stories (3) behavioral stories and (4) implementation stories.

Error in estimation stories focus on faults with the data or construction process. In effect, errors in estimation stories do not explain anomalies but question their existence. Consequently, the validity of error in estimation concerns can eliminate the predictive significance of anomalies and cast doubt on their true historical population relevance. To deal with error in estimation, out-of-sample tests in other markets (Fama & French, 2012), asset classes (Asness, Moskowitz, & Pedersen, 2013) or time frames (Davis, 1994; Chabot, Ghysels, & Jagannathan, 2014) are often employed. Alternatively, to account for extensive data-mining, it is also possible to adopt the complementary multiple hypothesis testing approach which requires profitable strategies to pass a higher t-statistic hurdle (Harvey, Liu, & Zhu, 2015). Assuming the evidence is strong enough to pass the existence hurdle, a key issue that needs to be examined is why the average investor prefers a particular side of a bet. Behavioral and rational stories are competing explanations for anomaly existence.

Rational stories rely on the key concept of high marginal utility states. Investors prefer a particular side of an active bet because it has positive realizations in periods of high marginal utility. In a sense, the CAPM is the ultimate rational story and it designates periods of low aggregate wealth as high marginal utility states.

Behavioral stories on the other hand, claim that the average investor chooses a particular side of the bet because: (1) he derives non-monetary utility from his bet (non-standard preferences), (2) is subject to some bias that leads him to wrongfully assess the probabilities of the bet (errors in expectations) (Daniel, Hirshleifer, & Subrahmanyam, 1998; Barberis, Shleifer, & Vishny, 1998) or (3) prefers a particular side of the bet due to constraints (rational but constrained; segmented markets) (Frazzini & Pedersen, 2013; Blitz & Vilet, 2007). Behavioral stories suggest that mispricing is a source of excess income for unconstrained investors that do not share the same non-standard preferences.

When it comes to non-standard preferences, the distinction between rational and behavioral becomes blurred. Is a preference for 'moral dividends' irrational? In a sense, all preferences are behavioral; people prefer safer cash flows over riskier cash flows. Having mentioned this caveat, it is useful to keep the accepted terminology 'rational' to refer to a commonly accepted set of normative preferences. The distinction between rational and behavioral is particularly relevant when normative preferences are 'tested' against behavioral explanations in which investors make errors.

Assuming we have established that an anomaly exists, and we have a good story to justify its existence, an important question to consider is anomaly implementation. Even if anomalies exist and have a behavioral explanation, can they still be traded profitably? Implementation stories examine if executing an anomaly bet is impossible due to (1) transaction costs (Frazzini, Israel & Moskowitz, 2012; Novy-Marx & Velikov, 2016), (2) shorting and leverage constraints (Bekjarovski, 2018), or (3) an inability to execute in real time (Lewellen, 2015). In this respect, implementation stories do not explain why anomalies arise, which is what the rational-behavioral debate tackles. Rather implementation stories can motivate why anomalies persist. For example, following a price distorting demand shock induced by irrational investor behavior, market prices do no adjust as shrewd investors face difficulty placing offsetting bets.

When trying to explain anomalies we can take one of two routes. We either claim a rational explanation and test if it can explain a multitude of anomalies; or alternatively, we test a behavioral explanation which we combine with limits to arbitrage. The behavioral explanation, unlike the rational explanation, need not be common across anomalies. The next section lays out some general concerns about existing rational and behavioral theories.

2.4. *Common problems with rational and behavioral theories*

A commonly expressed concern with behavioral theories is that they have difficulty explaining the comovement *between* stocks in portfolios sorted on anomalous characteristics (Cochrane, 2011).

Comovement and behavioral explanations are not inconsistent. Nevertheless, as Cochrane (2011) points out, theoretical behavioral models that motivate both alpha and the comovement pattern are rare.

Rational models, on the other hand, have difficulty accounting for the lack of comovement *across* anomalies. The various active bets seem unrelated (or even negatively correlated) which makes fitting a single rational model difficult. To understand the intuition of this statement, consider the extreme case whereby two tradable portfolios with positive excess returns are perfectly negatively correlated. Such a setting would lead to an arbitrage opportunity which cannot be explained by any rational asset pricing model. More generally, the more independent anomalies researchers discover the closer we are moving from model mispricing to violations of the law of one price; that is, developing a rational model becomes more difficult as we move from a single anomaly with extensive idiosyncratic risk to uncorrelated multi-premium combinations.

This reasoning is well understood through the Hansen-Jagganathan bound which places a high hurdle on rational theories (Appendix A develops the argument formally). If we find the magnitude of the equity premium puzzling (Mehra & Prescott, 1985), consider fitting something four times as large, which is what the passive-active combination in this paper implies. Yet, the literature is filled with papers claiming they can rationally explain anomalies; usually by matching individual anomalies with specific environment mapping variables. The next section turns to pitfalls in reasoning and testing which can cause this overabundance of rational explanations.

2.5. Pitfalls in the empirical testing of rational models

Empirical investigations of rational models can have two issues: (1) risk model mining and (2) isolated risk model testing. Risk model mining occurs when a researcher looks at anomaly performance to identify loss periods and then proceeds to test environment mapping variables that would define them as high marginal utility states. The anomalies aren't arbitrage opportunities. Inevitably there will be periods in which losses are made. What is needed is a clear normative a priori argumentation as to why a variable is used. We want to *test* explanations rather than forming them ex-post for each premium by conveniently splitting the sample. Analogous to the standard arguments against data mining (Harvey, Liu & Zhu, 2015), testing for an array of rational anomaly explanations will inevitably lead to a significant finding by chance.

The problem of model mining is exacerbated by the second issue which is the tendency to test risk explanations in isolation. In the absence of market segmentation, pricing needs to hold for all valid assets ('for all assets i' in asset pricing models). We do not have one model to price stock A and another to price stock B. Consequently, rational explanations ought to explain all valid anomalies and portfolios of anomalies (as the HJ bound also implies). At the very least, new rational models should not make other anomalies even more anomalous; that is, they should not prescribe expected returns for other anomalies that are even further from observation.

Resultantly, a valid out-of-sample test for existing premium specific rational explanations is their ability to explain alternative anomalies. To demonstrate the relevance of the approach, the paper empirically shows that recessions and crashes are anomaly specific which invalidates their use as risk stories (Chordia & Shivakumar, 2002; Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016).

3. Methodological issues and methods to assess performance

3.1. Benchmark choice and bond-anomaly independence

The performance of anomalies will be assessed relative to a passive benchmark consisting of the equity, term structure, and default premium. The choice to use the term structure and default premium is grounded in the work of Fama and French (1993) who find that they capture, along with the equity premium, most of the bonds return variation[1]. Bond premiums were included to raise the hurdle and show the diversification potential of anomalies above and beyond the impact of simple bond-stock combinations.

3.2. The Sharpe and Sortino Ratio

Sharpe ratios are the most well-known metric for assessing portfolio performance and they take center stage. The statistical significance of Sharpe ratio differences is estimated using the Ledoit & Wolf (2008) bootstrap test[2]. The paper also shows the annualized Modigliani & Modigliani (M2) performance measure which volatility matches strategies to a benchmark[3]. M2 has intuitive appeal, which is why it accompanies the results; however, it cannot qualify as a new measure as it is simply a restatement of the Sharpe ratio.

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[1] Investors can get exposure to these premiums by buying (long term) corporate (and government) bonds.

[2] Previous drafts arrived at equivalent conclusions using the Jobson & Korki's (1981) statistic augmented with Memmel's (2003) adjustment as well as Opdyke's tests (2007). Ledoit & Wolf's bootstrap test is preferred as it better accounts for non-normality and serial correlation in Sharpe ratios. Memmel (2003) does not account for either non-normal returns or serial correlation while Opdyke (2007) does not account for serial correlation. Serial correlation can be an issue for the denominator in the Sharpe ratio due to volatility clustering (Ledoit & Wolf, 2008).

[3] M2 is defined as: $\mathrm{M2} = \mathrm{R_p}\frac{\sigma_b}{\sigma_p}$ .Where $\mathrm{R_p}$ and σ_p are the annualized return and volatility of the portfolio and σ_b is the annualized volatility of the benchmark.

Anomalies are notorious for having highly asymmetric distributions (Figure 2) (for performance evaluation under asymmetric returns see Eling & Schuhmacher, 2007). To corroborate conclusions in the presence of non-normally distributed returns, the paper also uses higher moments as well as the Sortino ratio which is an alteration of the Sharpe ratio that uses downside deviation as the denominator. It is defined as:

$$S = \frac{R - T}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\min(0, R_t - T))^2}}$$

Where R is the average period return, T is the 'target' return, and R_t is the return in period t. With downside deviation, only returns falling below a certain threshold are considered risky. Since the paper investigates the performance of zero-cost portfolios, the natural target for downside deviation is zero. Sortino ratios also indicate how close investment strategies are to an arbitrage opportunity. Intuitively, a zero-cost portfolio that provides positive returns without downside deviation is the definition of arbitrage. Moreover, large Sortino ratios also indicate the absence of large losses which is especially relevant for compounded performance. These characteristics make Sortino ratios particularly well suited to the assessment of anomalies.

3.3. Recession Performance

Finally, the paper investigates anomalies' recession performance. The choice is intuitive as recessions lead to a drop in labor income which is a noteworthy risk for most investors. Moreover, consumption falls in recessions (closer to habit; Campbell and Cochrane, 1995), which makes good returns particularly valuable (Cohrane, 2017). Consequently, recessions have a reasonably strong prior. It is therefore interesting to examine if they are a valid out-of-sample explanation or a premium specific risk.

3.4. Anomaly construction method

The most common methods for constructing and examining anomalies are (1) portfolio sorts and (2) Fama-MacBeth regressions. Fama-MacBeth regressions produce a time-series of cross-sectional estimates (Fama & MacBeth, 1973) which have an interpretation of mean long-short hedge portfolios returns (Fama 1976, Chapter 9; Campbell 2014). The sorting approach on the other hand, places securities in portfolios based on the value of a specific characteristic. An anomaly is then constructed by going long the 'undervalued' portfolio and short the 'overvalued' portfolio.

Fama-MacBeth regressions and portfolio sorts have subtle differences, such as the effect of small stocks on the estimates (Fama & French 2008), nevertheless, they are conceptually equivalent given that portfolio sorts are the same as nonparametric cross-sectional regressions (see Cochrane (2011) for a visual illustration). It is common practice to apply both approaches when developing new anomalies and they generally provide equivalent conclusions (see the consistency of results across approaches in Fama & French, 2008). There is a very simple way to think about anomaly construction. All approaches make use of a panel data set containing an array of forecasting signal (Cochrane, 2011). These signals can be used to select securities and construct active portfolios.

The paper will use value-weighted decile sorts, where applicable, as the focus is placed on the performance of tradable portfolios. On average, equally weighted sorts provide stronger results (Green, Hand & Zhang, 2013) given that anomalies are often more pronounced in microcaps (Fama & French 2008). However, equally weighted (EW) portfolios are costlier to execute as they require rebalancing back to equal weights following monthly return realizations. Moreover, EW portfolios require a disproportionately high trading volume in small stocks. In fact, empirical studies show that EW portfolios have two to three times the transaction costs of VW portfolios (Novy-Marx & Velikov, 2015). Fama-MacBeth estimates have similar issues. They can be influenced extensively by microcaps, which are plentiful in the population and tend to take more extreme values in the characteristics (Fama & French 2008). Furthermore, the approach would also be inappropriate for anomalies such as betting against beta (Frazzini & Pedersen, 2014) which require further transformations before application.

The use of quintile rather than decile portfolios is another modeling alternative. Quintile portfolios have lower average idiosyncratic volatility due to the larger number of stocks per portfolio. However, quintile sorts have higher anomaly correlations due to the presence of a larger number of overlapping stocks. It is worth noting that overlapping stocks do not negatively influence the results above and beyond their impact on correlations. In fact, they can reduce the transaction costs of the overall portfolio when they give opposite trading recommendations.

3.5. Data Description

The main investigation uses US monthly return series for 13 zero-cost long-short decile portfolios constructed from 07/1963 until 12/2014. The paper gives all zero-cost long-short portfolios the general designation 'premiums', given that they all have positive average realized returns. The shorthand notation for the premiums used throughout the paper is as follows, MKT is the equity premium, GOV is the term structure premium (Asvanunt & Richardson, 2016), CORP is the default premium (Asvanunt & Richardson, 2016), SMB is the size (Banz, 1981; Fama

& French, 1992, 2008, 2015), BTM is value (Rosenberg, Reid, & Lanstein, 1985; Chan, Hamao, & Lakonishok, 1991, Fama & French, 1992, 2008, 2015), RWM is profitability (Cohen, Gompers, & Vuolteenaho, 2002; Fama & French, 2008, 2015), CMA is investment (Fairfield, Whisenant, & Yohn 2003; Titman, Wei, & Xie, 2004; Fama & French, 2015), WML is momentum (Jegadeesh & Titman, 1993; Carhart, 1997; Fama & French, 2008), IVOL is idiosyncratic volatility (Ang, Hodrick, Xing & Zhang, 2006), QUAL is quality (Asness, Frazzini & Pedersen, 2015), BAB is betting against beta (Frazzini & Pedersen, 2014), AC is accruals (Sloan, 1996; Fama & French, 2008) and NI is net share issuance (Daniel & Titman, 2006; Pontiff & Woodgate, 2008; Fama & French, 2008). Return series were taken as given from previous work to enable ease of result replicability[4]. The construction procedure for each premium follows the specifics determined by the last paper cited. Interested readers can see the original papers for the details on anomaly construction. For ease of communication, the paper refers to MKT, GOV and CORP as the traditional premiums or passive bets. Remaining premiums are referred to as anomalies or active bets. All the anomalies, except betting against beta, are value-weighted; betting against beta is constructed using the methodology of Frazzini & Pedersen (2013) whereby weights are assigned based on beta ranks. In later sections, the paper demonstrates that the conclusions are not sensitive to the choice of anomalies. Recession data was obtained from the US national bureau of economic research (NBER). Recessions are defined as periods between peak and trough.

4. Results

4.1. Understanding the data: the premiums as stand-alone investments

Table 1 summarizes premium information and reveals several interesting patterns. First and foremost, the results show that premiums have highly asymmetric return distributions consistent with claims in the literature (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2016). Skewness and kurtosis tend to be quite large and the Jarque-Bera test rejects all the normality hypothesis.

However, skewness does not seem to have a universal sign deviation as five of the examined premiums have negative skewness while eight of them have positive skewness. Consequently, if skewness was a valid anomaly explanation, more than half of the active bets would become even more anomalous. Similarly, when it comes to kurtosis, it is difficult to explain why a premium goes in a particular direction as the opposite short-long bet can crash as well. Finally, and perhaps most importantly, higher moment explanations also assume that higher moment risks are not diversifiable. In the case of kurtosis, they assume that the multitude of premiums experience

[4] Special thanks to Fama, French, Frazzini, Pedersen, Asness, Asvanunt and Richardson for providing public access to their data.

crashes simultaneously. This paper argues that the reduction of crash and skewness risk resulting from multi-premium combinations, along with the absence of a singular sign deviation of individual anomalies when it comes to skewness, are strong indications of the irrelevance of higher moment explanations for anomalies.

Second, except for the equity premium, all remaining portfolios have positive average returns in recessions. In fact, value, quality, idiosyncratic volatility, investments and net issuance, have higher than average returns during recessions (Table 1). This finding is in fact intuitive. In a crisis, most stocks will lose in value. But highly volatile junk stocks can be expected to have an above average plunge. Since these stocks form the short positions in the respective anomaly portfolios, it is only natural that the accompanying anomalies do well in recessions. However, recessions are also accompanied by an increase in volatility (see SD recessions in Table 1). Therefore, with investment being the exception, recession performance is not statistically significant.

Table 2 shows that average correlations among the various strategies are remarkably low which implies significant diversification potential. The choice of Pearson or Spearman correlations does not meaningfully alter the results. Among the strategies, the equity premium has the lowest average correlation. Bond premiums are also uncorrelated with each other and on average with the rest of the anomalies. In fact, relative to the equity premium, the correlation matrix suggests that anomalies show greater diversification potential than the bond premiums.

Concerning recession performance, plotting the data illustrates a noteworthy preliminary pattern (Figure 3). The equity premium has contrasting performance relative to anomalies such as idiosyncratic volatility and quality specifically during recession periods.

5. Premium Portfolios

5.1. Portfolio choice

The investigation turns to multi-premium portfolios. The main objective is to investigate performance improvement across alternative performance dimensions such as recessions and crashes. The analysis makes use of five equally weighted portfolios. The traditional portfolio (TP) is a combination of the equity, term structure and default premiums. It proxies for investors' long-short version of a passive bond-stock investment. Size-value-momentum (SVM) represents a basic anomaly portfolio. The factor portfolio (FP) is an EW portfolio of all anomalies. It represents factor investing with an expanded anomaly universe. The mixed portfolio (MP) is a per premium EW portfolio. It represents a passive-active portfolio benchmark tilted towards active premiums. Finally, the balanced portfolio (BP) is a classification EW portfolio. It represents a balanced investment in active and passive investments.

An alternative to equal weights is the use of dynamic weights as prescribed by optimization techniques. However, past research indicates that alternative optimization methods underperform a naïve equally weighted benchmark out-of-sample due to estimation error (De Miguel, Garlappi & Uppal, 2009). Moreover, using equal weights is conservative as optimization techniques (especially in-sample) can further enhance the performance of an expanded universe and therefore even further corroborate the conclusions.

5.2. The risk-adjusted performance of passive-active combinations

The multi-premium portfolio investigation suggests that passive-active combinations work well across all performance measures (Table 3). Both the premium portfolio (PP) and the balanced portfolio (BP) offer an economically sizable improvement in Sharpe ratios relative to the traditional portfolio (TP). M2 intuitively captures the magnitude of this improvement. The M2 of the balanced portfolio is 20.08% compared to only 7.83% for the traditional portfolio. The improvement in Sharpe ratios is statistically significant at the 1% level for the balanced portfolio and at 2% level for the premium portfolio. Transitioning from a factor portfolio to a balanced portfolio also results in an economically large and statistically significant improvement in Sharpe ratios.

5.3. Higher moments and the Sortino ratio

When it comes to skewness, we can see that multi-asset portfolios do not significantly deviate from normality. Excess kurtosis is an issue for the factor portfolio. However, in relative terms, the balanced portfolio has the smallest kurtosis. As figure 4 illustrates, and as the downside deviation statistic corroborates, the balanced portfolio does not have any large losses. The crash risk of individual premiums seems to be idiosyncratic.

The Sortino ratio provides an equivalent performance ordering as the Sharpe Ratio (Table 4). In fact, the Sortino ratio for passive-active portfolios is exceptionally high (0.69 for the balanced portfolio relative to 0.22 for the traditional portfolio). The improvement can be attributed to both an increase in returns and a decrease in downside deviations. In fact, as we move from the traditional to the balanced portfolio, downside deviations fall by more than a half.

The results show that the momentum crashes considered in Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) are in fact premium specific. Complicated methods are not required to deal with crashes. Multi-premium portfolios are a simple universal tool that can be applied to deal with the crash risk of any anomaly.

5.4. *Recession performance*

The high recession returns of the factor portfolio suggest that active premiums have a role to play in improving recession performance. The factor portfolio itself does not have significant recession returns. However, the premium and balanced portfolios have positive and statistically significant raw recession returns (t-statistics above 2). This suggests that passive-active combinations are specifically well suited to reducing recession volatility (and volatility in general) (Table 3). Overall, the result suggests that investors that hold passive-active portfolios can improve recession performance and even diversify recession risk.

5.5. *Rolling betas and performance persistence*

The strong performance of the balanced portfolio can be attributed to the strong negative relation between active and passive strategies. The unconditional lambda of the factor portfolio, with respect to the traditional portfolio, stands at surprising -0.41 (see Figure 5). There is a valid concern that correlations among asset classes and markets can increase over time (Bekaert, Hodrick, & Zhang, 2009) and rise sharply in recessions. However, rolling least squares estimates suggest that this is not the case when it comes to active and passive bets. The beta of the factor portfolio on the traditional portfolio does not rise during crisis; in fact, it takes a favorable turn and sharply falls during the dot-com bubble before bouncing back close to unconditional levels. Despite the use of a limited set of observations for estimation, all the rolling beta estimates are reliably smaller than zero at a 99% confidence level; this implies a strong persistence to the negative relationship between active and passive bets. When it comes to outperformance persistence, Figure 6 illustrates that the outperformance of the balanced portfolio does not come from a sub-period.

6. Robustness Check: Performance ordering with anomaly exclusion

6.1. *Performance as a function of the number of anomalies*

The previous section showed that anomalies, as a group, can improve upon passive portfolio performance across an array of performance measures. To investigate the sensitivity of the results to the specific choice of anomalies, Table 5 shows simulation results whereby all possible equally weighted sets of balanced portfolios are progressively constructed. The simulation has two goals: (1) to discover the cut-off point, in terms of the number of anomalies utilized, where the worst performing balanced portfolio still outperforms the traditional portfolio and (2) to investigate the sensitivity of the results to the anomaly choice.

The results reveal that the average Sharpe ratio of the balanced portfolios is always economically larger than that of the traditional portfolio (Table 5). For example, a balanced portfolio constructed using four anomalies has an average Sharpe ratio that is twice as large as the Sharpe ratio of the traditional portfolio. As the number of anomalies increases, the improvement in performance becomes stronger (Figure 7). As expected, the use of more anomaly assets improves the distribution of achievable performance by removing premium specific risk.

The inclusion of any set of three anomalies to the traditional portfolio *always* offers a better Sharpe ratio relative to the traditional portfolio. This means that even if seven of the most performance enhancing anomalies were excluded from the analysis, the balanced portfolio would have still outperformed in terms of Sharpe ratios.

Sortino ratios provide equivalent conclusions (Table 5). The maximum, average and minimum Sortino ratio, are monotonically increasing with the set of invested anomalies. Adding the three worst performing anomalies to the balanced portfolio provides a better Sortino Ratio relative to the traditional portfolio.

Given that time is fixed across portfolios, t-statistics represent scaled Sharpe ratios. Consequently, focus can be shifted from recession raw returns and Sharpe ratios to recession t-statistics. The goal is to investigate the proportion of balanced portfolios that offer statistically significant recession performance.

The results reveal that recession return t-statistics display an even stronger pattern than Sharpe and Sortino ratios (Table 5). The inclusion of any anomaly would improve the recession Sharpe ratio of the balanced portfolio above the level achieved by the traditional portfolio. Above and beyond that, recession return t-statistics larger than 2 are quite common. More than 30% of portfolios containing at least six anomalies exhibit robustness to recession performance (t-statistics larger than 2). The average t-statistics of recession performance is monotonically increasing from 1.16 for one anomaly, to 1.85 for six anomalies. The improvement can be considered sizable given that the recession return t-statistic of the traditional portfolio is only 0.37. Again, the improvement in recession performance is on top of the favorable recession effect of bond premiums. Overall, the simulation results show that the conclusions are not dependent on the anomaly choice.

6.2. Compounded performance

Passive-active combinations perform significantly better than passive portfolios across all three dimensions: (1) Sharpe Ratio, (2) crash metrics and (3) recession performance. The results do not seem to suggest that this outperformance is limited to a sub-period or that it depends strongly on the choice of anomalies. As Figure 8 shows, the magnitude of risk-adjusted performance improvement is substantial. This improvement comes in addition to the fact that passive-active portfolios do specifically well in recessions. Figure 8 also shows the performance of the counterparty portfolio and the high hurdle that rational explanations face. Equilibrium rational risk theories would have to explain the huge spread between the balanced portfolio (M2 = 20%) and the counterparty portfolio (M2 = -3.7%) whilst taking also into account the fact that the balanced portfolio does better in recessions and does not experience large crashes. For future work, it would be interesting to examine if variants of models based on long-run risk (Bansal, & Yaron 2004), consumption growth, and alternative preference structures (Barberis, Huang, & Santos, 2001) are better suited for explaining the cross-section of premiums. This paper showed why in general, raising the hurdle on rational tests is important.

7. Conclusion

The facts are simple. Adding anomalies to your passive portfolio diversifies recession risk and helps control crash risk. The reduction of these risks suggests that they cannot account for anomalies and are not valid risk explanations. In short, not only are anomalies profitable but they also hedge. Robustness checks reveal that the conclusions are not sensitive to the choice of anomalies.

The empirical findings show why rational anomaly explanations should be tested out-of-sample. Trying to rationally explain the performance of a single anomaly is likely to lead to idiosyncratic findings. Consequently, one of the first steps for assessing rational asset pricing models should be to test their "out-of-sample" explanatory power on portfolios of premiums.

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FIGURES

Figure 1: Anomaly research. This figure summarizes the historical development of active investing and the strands of anomaly research.

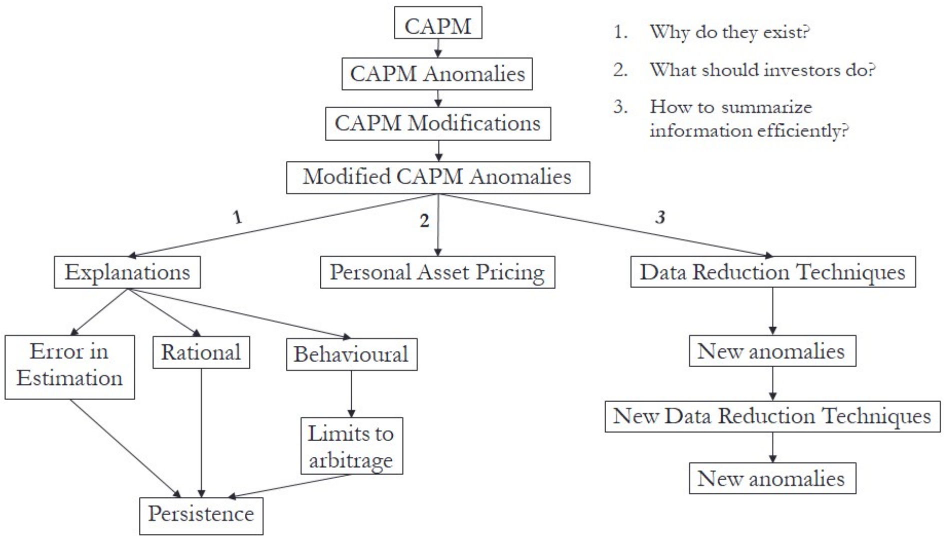


Figure 2: Momentum returns. This figure displays the frequency of monthly realized returns for momentum. Momentum has an asymmetric return distribution with negative skewness and high kurtosis.

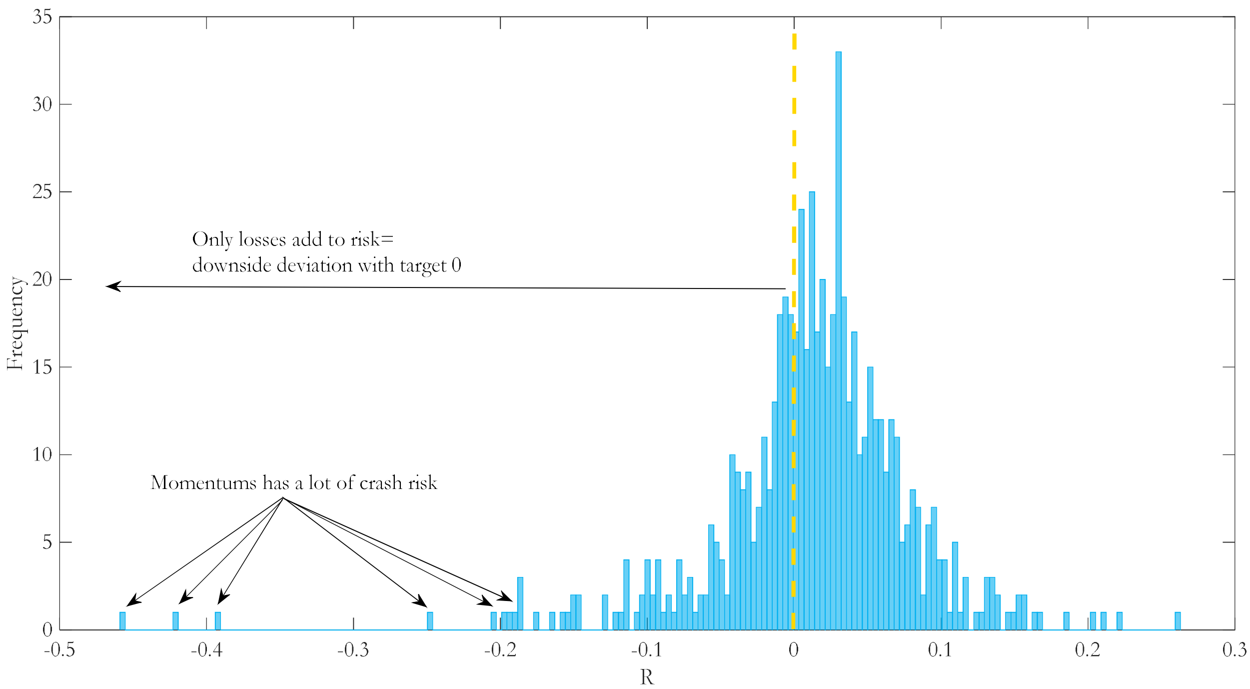


Figure 3: Panel A: Performance of Demeaned Characteristic Bets. This figure displays the average demeaned 12-month rolling performance of the equity premium (MKT) and quality (QUAL). **Panel B: Rolling Sharpe Ratios.** This figure displays the 12-month rolling Sharpe ratio for the equity premium (MKT) and idiosyncratic volatility (IVOL). Gray rectangles indicate economic recessions as defined by NBER.

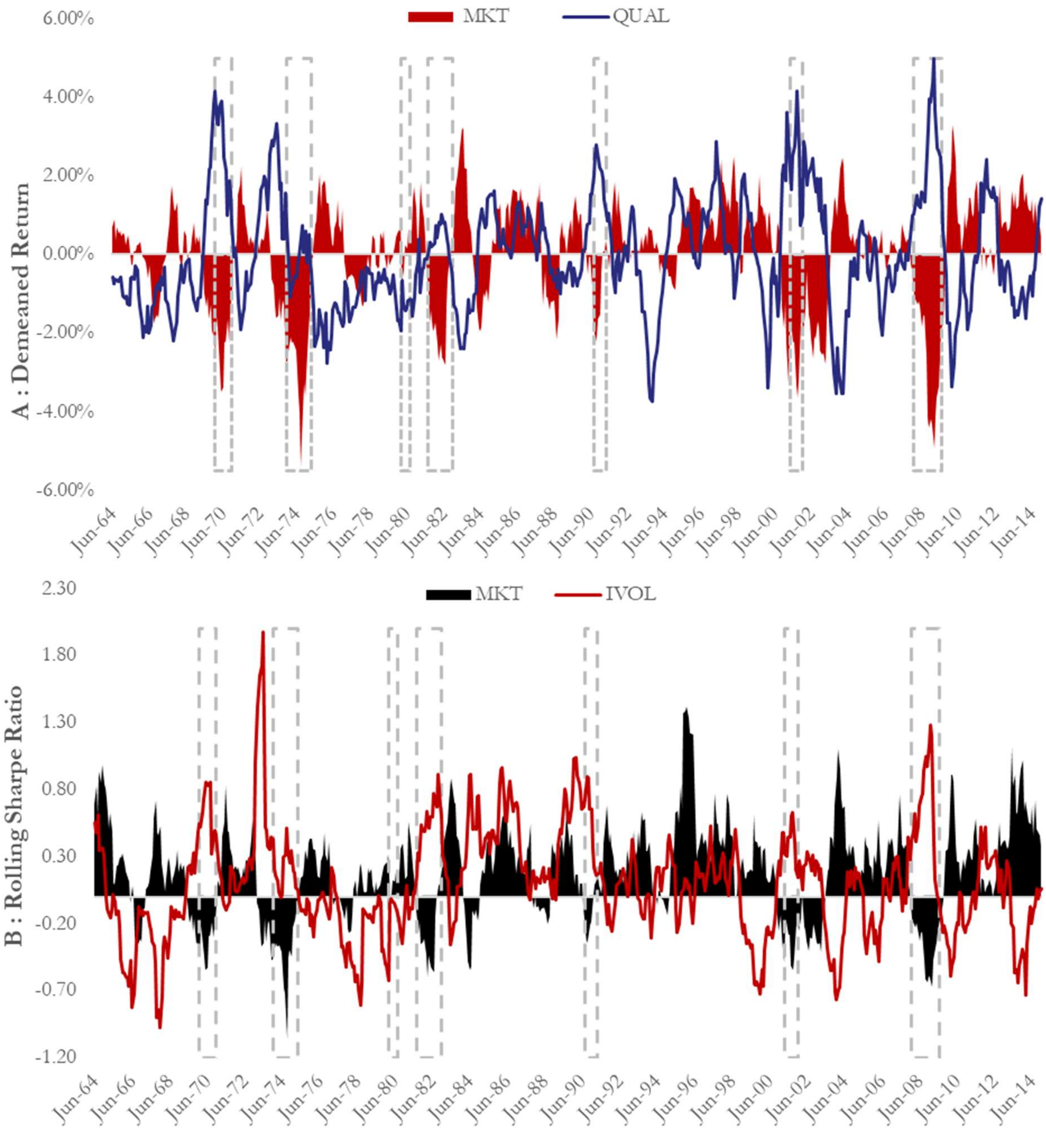


Figure 4: Balanced portfolio returns. This figure displays the frequency of monthly realized returns for the balanced portfolio which is constructed as an EW combination of the passive and active portfolio.

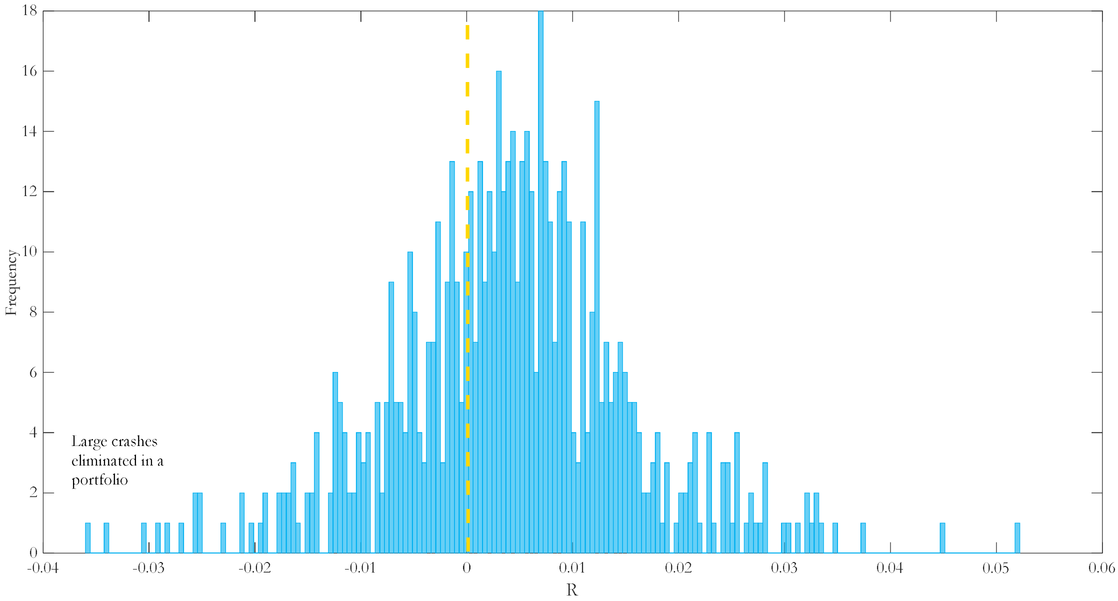


Figure 5: Rolling betas. This figure shows the 10-year rolling beta of the factor portfolio on the traditional portfolio with the corresponding 99% confidence intervals. The full sample unconditional estimate is shown in red. (TP) is constructed as an EW portfolio of equity (MKT), term structure (GOV) and default (CORP) premiums. The factor portfolio (FP) is constructed as an equally weighted portfolio of size, value, profitability, investment, momentum, idiosyncratic volatility, quality, betting against beta, accruals and net issuance.

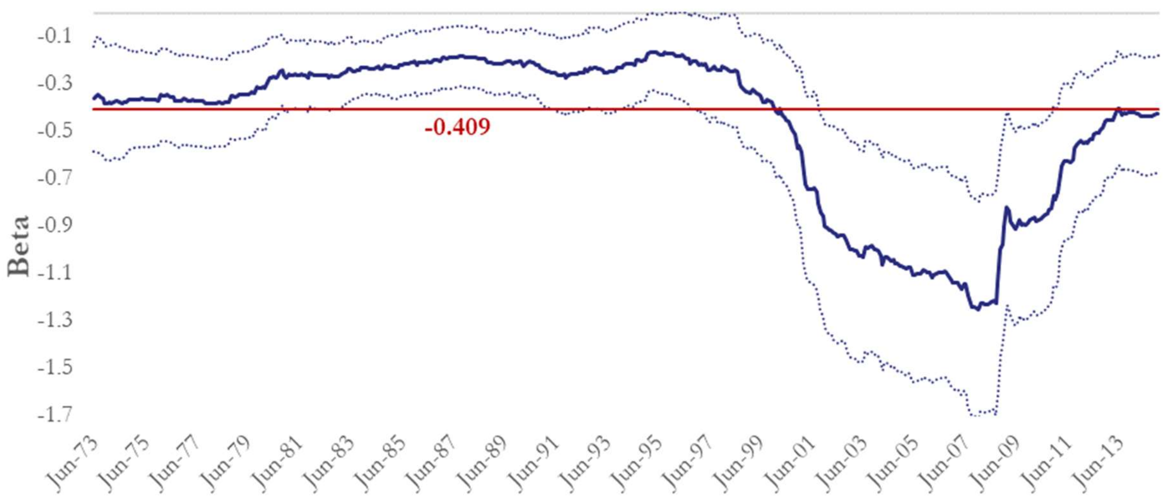


Figure 6: Outperformance persistence. This figure displays the 12-month rolling Sharpe ratio for the traditional portfolio (TP) and the balanced portfolio (BP). The traditional portfolio (TP) is constructed as an EW portfolio of equity (MKT), term structure (GOV) and default (CORP) premiums. The balanced portfolio is constructed as an EW combination of the traditional (TP) and factor portfolio (FP).

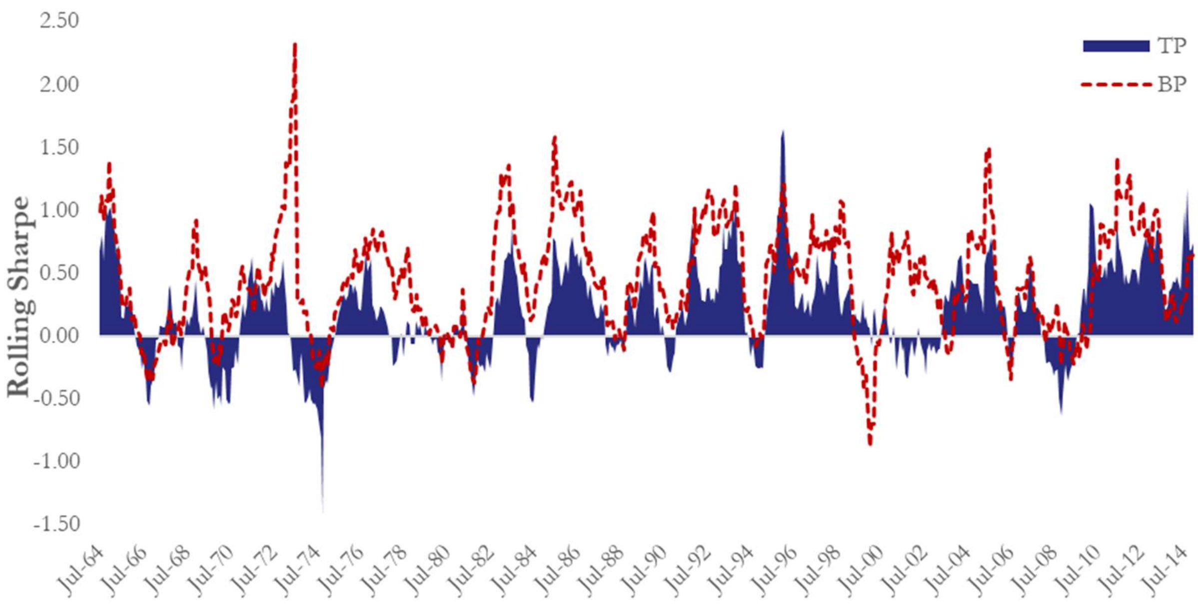


Figure 7: The distribution of Sharpe ratios as a function of the number of anomalies. This figure displays the distribution of balanced portfolios' Sharpe ratios as the number of anomalies included in the factor portfolio increases. The Sharpe ratio of the traditional portfolio is 0.14 and is displayed with a red dotted line. The Sharpe ratios of portfolios constructed with a lower (higher) number of anomaly assets are displayed in blue (orange).

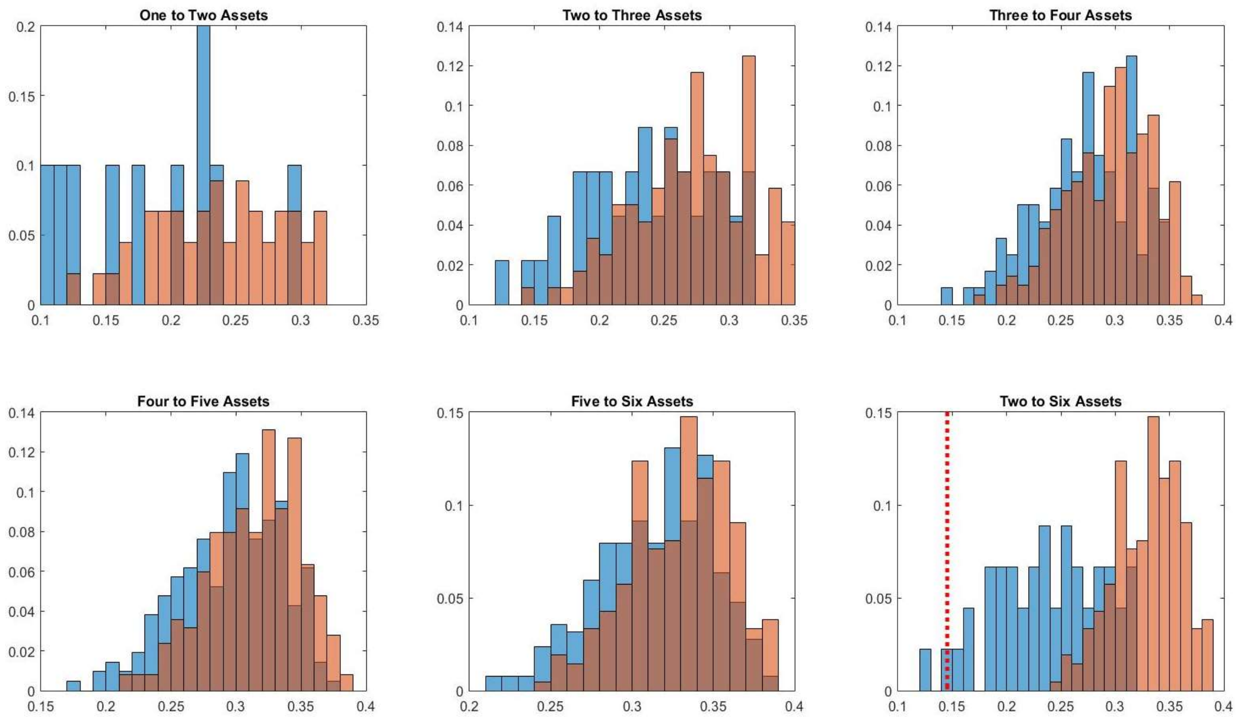
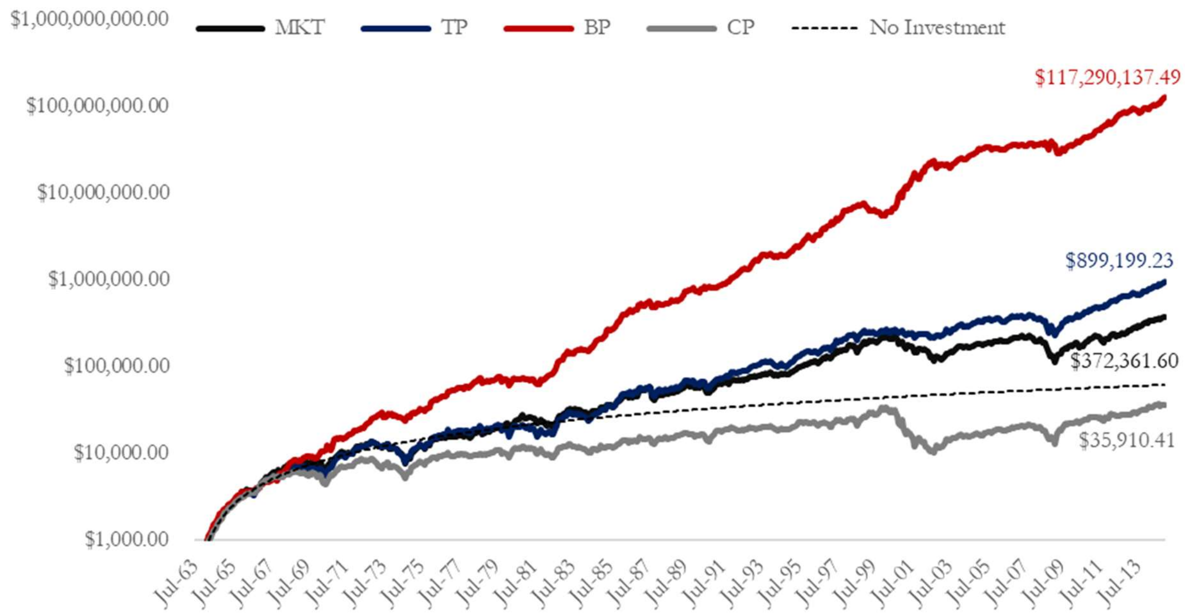


Figure 8: Compounded performance: dollar cost averaging the volatility matched portfolios. This figure displays end of sample compounded performance of volatility-matched dollar-cost-averaged portfolios that invest 100$ monthly and reinvests the proceeds. Dollar cost averaging reduces the impact of early investing months. Portfolios are leveraged to have an equivalent full sample annual volatility as the equity premium (equivalent logic as M2). The dotted line represents the 'no investment' portfolio, which in the case of zero-cost investing is the size of the position. MKT is the equity premium. TP is the traditional portfolio which is an equally weighted combination of the equity (MKT), terms structure (GOV) and default premiums (CORP). The balanced portfolio (BP) is an EW combination of the traditional (TP) and factor portfolio (FP) (comprised of SMB, BTM, RMW, CMA, WML, IVOL, QUAL, BAB, ACC and NI). The counterparty portfolio (CP) takes the opposite bet by buying the traditional portfolio and selling the factor portfolio.



TABLES

Table 1: Data summary. This table shows summary statistics for anomalies constructed using monthly US data from 07/1963 until 12/2014. MKT is the equity premium, GOV is the term structure premium, CORP is the default premium, SMB is the size, BTM is value, RWM is profitability, CMA is investment, WML is momentum, IVOL is idiosyncratic volatility, QUAL is quality, BAB is betting against beta, AC is accruals, NI is net share issuance and μ is the average value. The target for the Sortino ratio and downside deviation is zero. 'M2' is the annualized Modigliani & Modigliani measure which volatility matches strategies to the equity premium. 'JB' is the Jarque-Bera test for normality. The critical values for the test are 4.38 (10%), 5.88 (5%), 10.53 (1%). Maximum drawdown ('Max DR') is the maximum percentage drop from a peak. T-statistics for the mean are computed using the heteroskedasticity consistent standard errors of White (1980). Statistical significance of differences in Sharpe ratios is calculated using the Ledoit-Wolf bootstrap test (with equity premium as benchmark).

	MKT	GOV	CORP	SMB	BTM	RMW	CMA
R	0.51%	0.24%	0.13%	0.33%	0.51%	0.21%	0.46%
t-stat	*2.83*	*2.01*	*2.49*	*1.68*	*2.72*	*1.29*	*3.57*
R recession	-0.35%	0.45%	0.28%	0.15%	0.67%	0.19%	0.89%
t-stat	*-0.51*	*0.98*	*1.09*	*0.27*	*1.04*	*0.43*	*2.30*
SD	4.46%	2.99%	1.34%	4.83%	4.63%	3.97%	3.23%
SD recessions	6.43%	4.38%	2.44%	5.31%	6.11%	4.32%	3.69%
M2	6.26%	4.39%	5.39%	3.68%	6.02%	2.80%	7.87%
Sharpe Ratio	0.11	0.08	0.10	0.07	0.11	0.05	0.14
p-val Bootstrap		*0.58*	*0.78*	*0.37*	*0.94*	*0.43*	*0.67*
Skew	-0.54	0.34	-0.13	0.74	0.55	0.22	0.34
t-stat	*-5.5*	*3.5*	*-1.3*	*7.5*	*5.6*	*2.3*	*3.4*
Ex. Kurtosis	1.94	2.29	9.16	4.22	2.41	2.81	2.06
t-stat	*9.9*	*11.6*	*46.5*	*21.4*	*12.2*	*14.2*	*10.5*
JB test	127	147	2162	515	181	208	131
Max DR	56%	56%	21%	83%	52%	60%	32%
Target DD	3.08%	1.92%	0.90%	2.99%	2.82%	2.66%	1.96%
Sortino Ratio	0.16	0.13	0.15	0.11	0.18	0.08	0.24

Continued	WML	IVOL	QUAL	BAB	AC	NI	M
R	1.32%	0.47%	0.42%	0.83%	0.40%	0.43%	0.48%
t-stat	*4.73*	*1.49*	*2.37*	*6.36*	*3.50*	*3.34*	2.95
R recession	0.40%	1.30%	0.88%	0.18%	0.11%	0.69%	0.45%
t-stat	*0.35*	*1.27*	*1.50*	*0.40*	*0.29*	*1.58*	0.84
SD	6.92%	7.85%	4.44%	3.24%	2.88%	3.18%	4.15%
SD recessions	10.9%	9.8%	5.6%	4.3%	3.5%	4.2%	5.45%
M2	10.9%	3.3%	5.2%	14.3%	7.7%	7.4%	6.56%
Sharpe Ratio	0.19	0.06	0.10	0.26	0.14	0.13	0.12
p-val Bootstrap	*0.34*	*0.53*	*0.83*	*0.03*	*0.69*	*0.79*	0.58
Skew	-1.51	-0.32	0.02	-0.61	0.55	0.22	-0.01
t-stat	*-15.3*	*-3.3*	*0.2*	*-6.2*	*5.6*	*2.2*	-0.10
Ex. Kurtosis	8.30	3.00	1.38	3.61	2.36	0.93	3.42
t-stat	*42.1*	*15.2*	*7.0*	*18.3*	*12.0*	*4.7*	17.4
JB test	2006	242	49	374	175	27	488
Max DR	80%	84%	56%	52%	26%	36%	53%
Target DD	4.94%	5.53%	2.91%	2.08%	1.71%	1.95%	2.73%
Sortino Ratio	0.27	0.09	0.15	0.40	0.24	0.22	0.18

Table 2: Correlation. This table reports Spearman correlation coefficients. Numbers below (above) the diagonal are the correlations (p-values). MKT is the equity premium, GOV is the term structure premium, CORP is the default premium, SMB is the size, BTM is value, RWM is profitability, CMA is investment, WML is momentum, IVOL is idiosyncratic volatility, QUAL is quality, BAB is betting against beta, AC is accruals and NI is net share issuance.

Rho/Sig.	MKT	GOV	CORP	SMB	BTM	RMW	CMA	WML	IVOL	QUAL	BAB	AC	NI
MKT		0.00	0.00	0.00	0.39	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00
GOV	0.15		0.41	0.00	0.14	0.21	0.52	0.52	0.00	0.31	0.00	0.51	0.27
CORP	0.27	0.03		0.01	0.00	0.00	0.89	0.00	0.00	0.00	0.00	0.72	0.01
SMB	0.16	-0.13	0.11		0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00
BTM	-0.03	-0.06	0.15	0.34		0.00	0.00	0.00	0.89	0.00	0.00	0.14	0.45
RMW	-0.37	0.05	-0.17	-0.54	-0.38		0.00	0.00	0.00	0.00	0.17	0.40	0.00
CMA	-0.22	-0.03	0.01	0.12	0.46	-0.14		0.87	0.00	0.10	0.00	0.00	0.00
WML	-0.12	0.03	-0.14	-0.07	-0.16	0.15	-0.01		0.04	0.00	0.83	0.00	0.07
IVOL	-0.61	0.17	-0.15	-0.57	-0.01	0.58	0.20	0.08		0.00	0.00	0.00	0.00
QUAL	-0.46	0.04	-0.18	-0.61	-0.42	0.78	-0.07	0.15	0.66		0.70	0.01	0.00
BAB	-0.08	0.12	0.12	0.17	0.27	0.06	0.25	0.01	0.27	0.02		0.22	0.00
AC	-0.14	0.03	0.01	-0.15	0.06	0.03	0.17	0.17	0.18	0.10	0.05		0.01
NI	-0.38	0.04	-0.10	-0.45	-0.03	0.44	0.30	0.07	0.60	0.56	0.15	0.10	
Average	-0.15	0.04	0.00	-0.14	0.02	0.04	0.09	0.01	0.12	0.05	0.12	0.11	0.11

Table 3: Portfolios. The traditional portfolio (TP) is an EW combination of the equity, term structure and default premiums. The size-value-momentum portfolio (SVM) is an EW portfolio of size, value and momentum. The factor portfolio (FP) is an EW portfolio of the size, value, profitability, investments, momentum, idiosyncratic volatility, quality, betting against beta, accruals and net issuance. The mixed portfolio (MP) is a per premium equally weighted portfolio containing all active and passive premiums. The balanced portfolio (BP) assigns an EW weight to the traditional and factor portfolio (per classification EW). The target for the Sortino ratio and downside deviation is zero. 'M2' is the annualized Modigliani & Modigliani measure which volatility matches strategies to a benchmark (the equity premium). 'JB' is the Jarque-Bera test for normality. The critical values for the test are 10% (4.38), 5% (5.88), 1% (10.53). Maximum drawdown ('Max DR') is the maximum percentage drop from a peak. T-statistics for the mean are computed using the heteroskedasticity consistent standard errors of White (1980). Statistical significance of differences in Sharpe ratios is calculated using the Ledoit-Wolf bootstrap test (LW Bootstrap p-val). The p-value for the Ledoit-Wolf Bootstrap TP and BP test is calculated with respect to the traditional portfolio (TP) and the balanced portfolio (BP) respectively (and the equity premium for the traditional portfolio).

	Traditional	Factor Investing		Premium Investing	
	Passive	Active		Passive-Active	
	TP	SVM	FP	MP	BP
R	0.29%	0.72%	0.54%	0.48%	0.42%
t-stat	*3.58*	*5.65*	*6.38*	*8.05*	*9.12*
R recession	0.13%	0.41%	0.55%	0.45%	0.34%
t-stat	*0.37*	*1.03*	*1.74*	*2.10*	***2.01***
SD	2.05%	3.15%	2.09%	1.49%	1.13%
SD recessions	3.29%	3.76%	2.99%	2.04%	1.59%
M2	7.83%	12.64%	14.14%	17.79%	**20.08%**
Skew	-0.11	0.19	0.10	0.13	**0.04**
t-stat	*-1.07*	*1.95*	*1.04*	*1.36*	***0.38***
Excess Kurtosis	1.32	3.36	6.40	6.40	1.31
t-stat	*6.71*	*17.06*	*32.47*	*32.48*	*6.67*
JB test	44.8	288.4	1035.4	1036.8	43.3
Max DR	28.3%	25.0%	21.8%	14.9%	**8.3%**
Target DD	1.32%	1.84%	1.27%	0.85%	**0.60%**
Sortino Ratio	0.22	0.39	0.42	0.56	0.69
Sharpe Ratio	0.14	0.23	0.26	0.32	0.37
LW Bootstrap p-val (with TP)	0.225	0.173	0.149	**0.016**	**0.000**
LW Bootstrap p-val (with BP)	**0.000**	**0.000**	**0.014**	0.222	/
TP Beta	/	-0.08	-0.41	-0.08	0.30

Table 4: Expanding anomaly universe. This table displays the results for a simulation which calculates the Sharpe Ratio, Sortino Ratio and recession return t-statistics for all possible balanced portfolio combinations. The balanced portfolio contains an equal weight in the traditional portfolio (MKT+GOV+CORP), which is fixed, and an equal weight in the factor portfolio, which contains a varying number of anomalies. The number of included anomalies in the factor portfolio is increased at every step without replacement and every possible combination of the investigated measure is calculated. The table displays the maximum, minimum and average of the distribution of the investigated measure. '% (<Base)' shows the percent of balanced portfolios that fall under the traditional portfolio. '% (<2)' shows the percent of recession return t-statistics that are larger than 2. # 'Portfolios' is the number of possible portfolio combinations without replacement ($\frac{n!}{k!(n-k)!}$) given a universe of anomaly assets.

	Number of Included Anomalies					
	1	2	3	4	5	6
Max Sharpe	0.29	0.32	0.35	0.38	0.38	0.39
Average Sharpe	0.19	0.24	0.27	0.30	0.31	0.33
Min Sharpe	0.11	0.13	**0.15**	0.18	0.21	0.24
TP Sharpe	0.14	0.14	**0.14**	0.14	0.14	0.14
% (<Base)	30.0%	4.4%	**0.0%**	0.0%	0.0%	0.0%
Max Sortino	0.48	0.55	0.64	0.66	0.68	0.69
Average Sortino	0.30	0.40	0.46	0.51	0.55	0.59
Min Sortino	0.15	0.19	**0.23**	0.28	0.35	0.43
TP Sortino	0.22	0.22	**0.22**	0.22	0.22	0.22
% (<Base)	30.0%	4.4%	**0.0%**	0.0%	0.0%	0.0%
Max Recession Return	2.56	3.20	2.80	2.91	2.89	**2.84**
Average Recession Return	1.16	1.43	1.59	1.70	1.78	**1.85**
Min Recession Return	**0.39**	0.53	0.61	0.74	0.86	**1.08**
TP Recession Return	**0.37**	0.37	0.37	0.37	0.37	0.37
% (<Base)	**0%**	0%	0%	0%	0%	0%
% (<2)	20%	16%	24%	25%	28%	**30%**
# Portfolios	10	45	120	210	252	210

Appendix A – Hansen-Jagganathan bound

This section derives the Hansen-Jagganathan bound formally and discusses its intuition for rational testing:

$$\frac{\sigma_t(M_{t+1})}{E_t(M_{t+1})} \geq \frac{E_t(R_{i,t+1}^{ex})}{\sigma_t(R_{i,t+1}^{ex})}$$

Where E_t is conditional expectation on today's information σ_t is the standard deviation, M_{t+1} is the stochastic discount factor and $R_{i,t+1}^{ex}$ is excess returns over the risk-free rate for asset i. The Hansen-Jagganathan (HJ) bound states that the portfolio of assets with the highest Sharpe ratio puts a lower bound on the volatility of the SDF (Shiller, 1982; Hansen & Jagannathan, 1991; Campbell, 2000). Decomposing a portfolio's standard deviation gives further insights.

$$\frac{\sigma_t(M_{t+1})}{E_t(M_{t+1})} \geq \frac{E_t(R_{i,t+1}^{ex})}{\sqrt{\sum_{k=1}^{N}\sum_{j=1}^{N} w_k\, w_j \sigma_k \sigma_j p_{kj}}}$$

Where σ_k and σ_j is the standard deviation of comprising assets and p_{kj} is their correlation. Holding all else constant, as the correlation among premiums falls, the maximum Sharpe ratio of the combined strategy rises, which increases the difficulty of fitting a discount factor in the HJ bounds. Furthermore, if we assume absence of correlation between assets in an equally weighted portfolio, the bound reduces to:

$$\frac{\sigma_t(M_{t+1})}{E_t(M_{t+1})} \geq \frac{E_t(R_{i,t+1}^{ex})}{\sqrt{\frac{1}{N}\,[\sigma_j']}}$$

Where σ_j' is the average standard deviation of comprising portfolio assets. As N goes to infinity the variance of the portfolio goes to zero. The HJ bound gives a good intuition as to why the existence of many uncorrelated positive excess return bets makes rational pricing more difficult.

Appendix B- Time-series regressions

In this section, the paper examines if the term structure and default loadings are economically relevant and statistically significant and if anomalies have alphas in recessions controlling for their co-movement with bond premiums. The results and specifications are shown in Table 5.

The first specification (Table 5) contains the traditional premiums as benchmark assets. The loadings on these assets represent a portfolio replicating anomaly performance. Exact replicability would imply the absence of alpha and the mean-variance efficiency of a portfolio constructed with the passive benchmark assets (Gibbons, Ross & Shanken, 1989). Insignificant alphas would imply substitutability between the passive and active bets.

The first specification provides several noteworthy results. Looking at anomalies as a group, average loadings on all benchmark assets are very small. The average loading is -0.27 for the equity premium, 0.1 for the term structure premium and 0.03 for the default premium. Surprisingly, the average loading on the market is lower than the average loading on bond premiums. In other words, stock anomalies comove more with bond premiums than the equity premium.

As a group, anomalies are highly statistically significant as suggested by the high average alpha t-statistic of 3.86. This implies that loadings are not sufficiently large to annul anomaly significance. In fact, negative average loadings make average alphas (0.64%) larger than average anomaly excess returns (0.54%).

Looking at the individual regressions, we can see that between anomaly variation in loadings is considerable. The average loading for the equity premium is negative; in fact, except for size, all anomalies have negative equity loadings. For seven of the ten examined anomalies, equity loadings are statistically smaller than zero.

Anomalies based on characteristics associated with safety should comove more strongly with bonds. This hypothesis is supported by the data. As expected, IVOL has the strongest loading on the term structure premium. Similarly, quality, profitability and big (the reverse of size) have a statistically significant term structure loading. The result is in line with Baker and Wurgler (2012) who find that safe, large and profitable firms are more bond-like.

Default loadings are on average very small and are only economically and statistically significant for value and momentum (0.63 and -0.84 respectively). However, the sign of the loadings is opposite. Momentum looks more profitable while value looks less like an anomaly when default loadings are considered. For six of the anomalies examined, the term structure and default loadings go in the opposite direction. Overall, the out-of-sample model tests show that the equity, term structure and default premium are irrelevant for explaining anomaly returns.

The second specification expands the benchmark regressions with a dummy variable for recessions. The end goal of this modification is to examine whether anomaly alphas are negative or reliably smaller during recessions after controlling for the term structure and default loadings. Intuitively, positive alpha should be even more important during recessions if they are high marginal utility states. Controlling for bond loadings is relevant as we already know that bond premiums have good recession performance (Table 1). Consequently, it is prudent to rule out the possibility that recession alphas cannot be attributed to anomalies' bond-like features.

Alpha ($\dot{\alpha}$) can be interpreted as benchmark-adjusted expansion returns, while $\dot{\alpha}$ - r represents benchmark-adjusted recession returns (Table 5). The second specification reveals that anomaly alphas on average are not reliably lower in recessions (the average t-statistic on the recession dummy is -0.47). The exception is betting against beta. The recession alpha of BAB is lower than its expansion alpha and the result is marginally significant with a t-stat of -1.97. It seems that all of BAB's alpha is outside recessions. Stated alternatively, during recessions, BAB returns are replicated well by the passive benchmark assets.

The estimated recession dummies, despite being generally insignificant, do suggest that anomaly alphas are meaningfully lower in recessions (approximately 43% lower than outside recession). However, there is no evidence that recession alphas are negative. In other words, anomalies still outperform in recessions but not as much.

Appendix C - Fama-French benchmarks

Benchmarking against anomalies that comprise the three-factor (Fama & French, 1993) or the five-factor model (Fama & French, 2015), also gives economically large and statistically significant alpha estimates that easily pass the new data mining adjusted t-statistics hurdles (Table 6). Even profitability passes the higher t-statistic hurdle of 3 when benchmarked against the FF3 premiums. In fact, the average alpha t-statistic of non-benchmark anomalies *increases* considerably when size and value are used as benchmarks (average alpha t-statistic of 5.35) instead of the term structure and default premiums (average alpha t-statistics of 4.34). This is intuitive as second-generation anomalies were developed as violations of the Fama-French three factor model. Overall, the result suggests that the use of a passive benchmark is not particularly lenient when it comes to assessing anomaly significance. Above and beyond that, it shows that non-benchmark anomalies are not linear combinations of benchmark anomalies. Conducting this specific robustness check has its merits but there are several notable drawbacks specific to this approach. First and foremost, anomaly alpha when benchmarked against other anomalies is meaningless if investors do not already hold the benchmark anomalies to begin with. In other words, if investors do not already hold size, value, investment, and profitability in their portfolio, benchmarking against them does not make much sense. Second, assessment with anomaly benchmarks is highly sensitive to the arbitrary choice of initial anomalies to be included in the benchmark. For example, if quality is first included in the benchmark, then the alpha of size becomes significant (Asness, Frazzini & Pedersen, 2015). Stated alternatively, the order of adding anomalies to the benchmark can matter. Finally, anomaly benchmarking is a data reduction technique and not a rational model. Having mentioned these caveats, the academic tradition of showing anomaly alpha with respect to other anomalies, as a *complement* to the regressions with passive proxies, is a good starting point for assessing between anomaly substitutability.

Appendix D- Alpha decay and the use of excess returns for anomaly assessment

Using equilibrium reasoning, and in the absence of frictions, the performance-enhancing potential of anomalies should be eroded by the price readjustment pressure induced by investors who arrive at equivalent conclusions. If investors have a subset of the benchmark and evaluation criteria proposed in this paper, they will assess anomaly attractiveness in an equivalent manner and commit to premium investing. In the process, they will put price pressure on anomalies and reprice assets until passive-active combinations are no longer attractive. In the context of time-series regressions, anomaly alphas should disappear.

The question of decay has received some attention recently. McLean and Pontiff (2016) find a degree of post-publication *raw return* decay for an extensive array of anomalies[5]. While the significance of raw returns may indeed be relevant for the assessment of anomalies as stand-alone investments, it is not the right approach from an investment perspective. The assumption underlying the use of raw returns is that the evaluated asset is the only one in the investment universe. Alternatively, in the presence of other securities, the procedure assumes that betas with respect to benchmark assets are zero. The argument is best understood looking back at Figure 9. The only setting in which alpha and excess returns are equivalent, is when an asset's beta to passive assets is zero.

Having this reasoning in mind, it is easy to see that anomalies can offer value even in the absence of significant raw returns if they have sufficiently high diversification potential as captured by their low betas to existing invested assets. Stated alternatively, distance to the zero-cost security market line is more relevant than distance from zero. In fact, if return decay is coupled with a strong enough decline in betas, then alphas could theoretically become larger. Alternatively, alpha decay can also come via an increase in benchmark betas (this can also be understood via Figure 3 as a shift in observations to the right). Therefore, raw return decay is only a proxy for the true measure of anomaly profitability decay. As Figure 5 suggests, there has been a significant reduction of the factor to traditional beta in the past two decades (mainly concentrated during the dot com bubble). Consequently, researchers looking at excess return in this period, when betas declined sharply, could have derived erroneous conclusions regarding the profitability enhancing potential of anomalies.

To assess anomaly alpha decay, the paper implements a two-step approach. In the first step, five year rolling anomaly alphas are estimated using the bond-stock benchmark. In the second step, anomaly alphas are regressed on a time trend. Since alphas are the explained variables in the second regression, potential measurement error will not cause bias and inconsistency in the time trend estimates. Results are reported in Panel A of Table 7. The sign for the time trend is negative for six and positive for four of the examined anomalies. However, only two of the positive time trend coefficients are associated with a t-statistic above 2. More specifically, the alphas of quality

[5] Focusing on raw returns (or Sharpe ratios) is not limited to investigations of anomaly persistence. For example, Hou, Xue & Zhang (2014) declare 38 out of 80 anomalies to be insignificant based on the absence of raw returns. Similarly, Bali & Cakici (2008) criticize IVOL, among other issues, on its insufficient raw returns.

and profitability have *increased* over time. Overall, the results do not support the existence of strong alpha decay across anomalies.

Finally, the paper estimates the rate of anomaly decay that would annul the usefulness of passive-active combinations. The procedure subtracts each month a constant from the raw returns of the factor portfolio. Following this modification, two tests are made: (1) an alpha significance test in a time-series regression of the factor portfolio on the passive benchmarks (MKT, GOV, CORP) and (2) a bootstrap test on the difference between the decay adjusted balanced portfolio and the traditional portfolio. Results for both procedures are displayed in panel B of Table 7.

Subtracting a constant from raw returns is equivalent to alpha decay as it holds betas fixed. Intuitively, in the time-series regressions, subtracting a constant from the left-hand side variable has no effect on the slopes but it reduces the intercept by an equivalent amount. Consequently, modeling raw return decay in this manner is equivalent to alpha decay.

The Sharpe ratio significance test reveals that the cutoff point above which anomalies no longer add value is close to a 3.5% percentage point decrease in anomaly returns and alphas. Such a decrease would yield a significant improvement in Sharpe ratios only at the 5% confidence level. The alpha significance test is even less strict. The inclusion of the factor portfolio spans the efficient frontier constructed by the benchmark assets by a statistically significant amount even following a 4.5% decay in alpha and returns. Overall, the results suggest that a 50% drop in alphas is required to lose the statistical significance of the risk-adjusted improvement resulting from passive-active combinations. The results mean that either (1) wrongly assessed historical alphas by 50% or (2) future anomaly alpha decay of 50%, would make the passive-active strategy no longer statistically superior in terms of risk-adjusted performance relative to the passive benchmark.

Appendix F – Supplementary tables and figures

Figure 9: **Anomaly alphas.** This figure displays the alpha of anomalies relative to the traditional portfolio (TP). Lambdas (λ) are calculated using constant coefficient unconditional time-series regressions of anomalies on the traditional portfolio Alpha t-statistics are calculated using the heteroskedasticity-consistent standard errors of White (1980) and are reported in brackets. Asterisk accompany t-statistics higher than 3 (Harvey, Lie & Zhu, 2015).

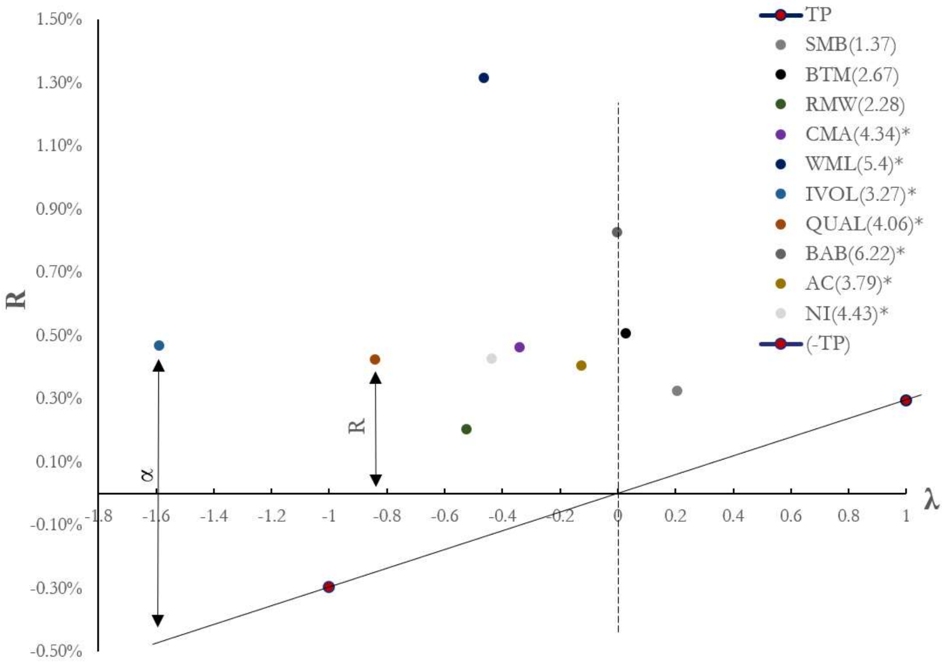


Table 5: Bond-Anomaly independence and recession alphas. This table reports the alphas and loadings from constant coefficient unconditional time-series regressions:

(1) $$R_{i,t} = \alpha_i + \text{ß}_i MKT_t + \gamma_i GOV_t + \eta_i CORP_t + \varepsilon_{i,t}.$$

(2) $$R_{i,t} = \acute{\alpha}_i + b_i MKT_t + \gamma_i GOV_t + \acute{\eta}_i CORP_t + r_i Recession_t + \acute{\varepsilon}_{i,t}.$$

where $R_{i,t}$ is the return of strategy i in month t. MKT is the equity premium, GOV is the term structure premium, CORP is the default premium, SMB is size, BTM is value, RWM is profitability, CMA is investment, WML is momentum, IVOL is idiosyncratic volatility, QUAL is quality, BAB is betting against beta, AC is accruals and NI is net share issuance. Recession is a dummy variable (1 for recession) obtained from NBER. T-statistics are computed using the heteroskedasticity-consistent standard errors of White (1980).

	α	ß	γ	η	ά	R
SMB	0.26%	0.19	**-0.24**	0.20	0.26%	0.01%
BTM	0.46%	-0.05	-0.08	**0.63**	0.46%	0.05%
RMW	0.35%	**-0.34**	**0.16**	-0.11	0.41%	**-0.38%**
CMA	0.55%	-0.20	-0.02	0.16	0.51%	**0.28%**
WML	1.49%	-0.19	0.16	**-0.84**	1.66%	**-1.17%**
IVOL	0.89%	**-1.14**	**0.60**	0.07	0.94%	-0.33%
QUAL	0.66%	**-0.49**	**0.17**	-0.23	0.66%	0.04%
BAB	0.81%	-0.09	0.12	0.24	0.95%	**-0.93%**
AC	0.43%	-0.10	0.04	0.09	0.50%	**-0.49%**
NI	0.54%	-0.30	**0.11**	0.09	0.55%	-0.03%
μ	**0.64%**	**-0.27**	**0.10**	0.03	**0.69%**	**-0.29%**

t-stat (HC se)	*t (a)*	*t (ß)*	*t (γ)*	*t (η)*	*t (ά)*	*t (r)*
SMB	1.37	3.62	**-4.17**	1.32	*1.27*	*0.02*
BTM	2.56	-0.77	-1.08	**3.35**	*2.40*	*0.08*
RMW	2.33	**-7.50**	**3.54**	-0.99	*2.55*	*-0.87*
CMA	**4.23**	-5.25	-0.41	1.42	***3.69***	*0.75*
WML	**5.73**	-2.01	1.56	**-2.07**	***6.38***	*-1.03*
IVOL	**3.71**	**-15.22**	**7.40**	0.29	***3.66***	*-0.42*
QUAL	**4.40**	**-10.69**	**3.00**	-1.56	***4.01***	*0.08*
BAB	**6.23**	-1.67	1.97	1.46	***7.07***	***-1.97***
AC	**3.58**	-3.12	1.08	0.91	***4.17***	*-1.31*
NI	**4.50**	8.72	**2.81**	0.94	***4.57***	*-0.07*
μ	**3.86**	**-3.39**	**1.57**	0.51	**3.98**	**-0.47**

Table 6: Fama-French Benchmark regressions. This table reports alphas and loadings from constant coefficient unconditional time-series regressions on the Fama-French anomalies:

(FF3) $$R_{i,t} = \alpha_i + \beta_i MKT_t + \upsilon_i SBM_t + \iota_i HML_t + \varepsilon_{i,t}$$

(FF5) $$R_{i,t} = \acute{\alpha}_i + ß_i MKT_t + \acute{\upsilon}_i SMB_t + \acute{\iota}_i HML_t + \theta_i RMW_t + \zeta_i CMA_t + \acute{\varepsilon}_{i,t}$$

where $R_{i,t}$ is the return of strategy i in month t. T-statistics are computed using the heteroskedasticity-consistent standard errors of White (1980).

	FF3				FF5					
	α	β	υ	ι	ά	ß	ύ	ί	θ	Z
RMW	0.51%	-0.26	-0.38	-0.10						
CMA	0.38%	-0.19	0.01	0.34						
WML	1.60%	-0.26	0.05	-0.34	1.34%	-0.13	0.12	-0.46	0.19	0.42
IVOL	1.08%	-0.91	-0.88	0.28	0.60%	-0.67	-0.62	0.23	0.69	0.32
QUAL	0.90%	-0.42	-0.43	-0.25	0.56%	-0.24	-0.22	-0.25	0.56	0.15
BAB	0.77%	-0.06	0.00	0.18	0.52%	0.07	0.12	0.14	0.34	0.21
AC	0.44%	-0.07	-0.10	0.06	0.45%	-0.07	-0.14	0.01	-0.10	0.12
NI	0.59%	-0.22	-0.30	0.09	0.35%	-0.10	-0.23	-0.01	0.21	0.36
μ	*0.79%*	*-0.30*	*-0.25*	*0.03*	*0.64%*	*-0.19*	*-0.16*	*-0.06*	*0.31*	*0.26*

	t-stats				*t-stats*					
	t(α)	***t(β)***	***t(υ)***	***t(ι)***	***t(ά)***	***t(ß)***	***t(ύ)***	***t(ί)***	***t(θ)***	***t(ζ)***
RMW	***4.11***	*-6.41*	*-10.25*	*-2.15*						
CMA	***3.56***	*-6.74*	*0.24*	*10.65*						
WML	***6.09***	*-3.08*	*0.48*	*-2.93*	***4.58***	*-1.48*	*1.18*	*-3.32*	*1.62*	*2.57*
IVOL	***5.58***	*-13.3*	*-17.65*	*3.42*	***3.45***	*-11.22*	*-11.45*	*2.47*	*7.87*	*3.61*
QUAL	***8.15***	*-12.37*	*-16.97*	*-8.06*	***6.48***	*-9.82*	*-9.38*	*-10.1*	*16.4*	*3.94*
BAB	***5.91***	*-1.24*	*-0.06*	*3.82*	***4.10***	*1.50*	*3.23*	*2.46*	*7.47*	*3.18*
AC	***3.87***	*-2.34*	*-3.12*	*2.12*	***3.83***	*-2.36*	*-3.64*	*0.26*	*-1.77*	*2.34*
NI	***5.50***	*-7.31*	*-13.06*	*3.04*	***3.44***	*-3.38*	*-8.55*	*-0.43*	*5.75*	*8.45*
μ	***5.35***	*-6.60*	*-7.55*	*1.24*	***4.31***	*-4.46*	*-4.77*	*-1.44*	*6.23*	*4.02*

Table 7: Time trend estimates and alpha decay projections. Panel A shows the sign and significance of the time trend coefficient (λ) on rolling alphas.

$$(1) \qquad R_{i,t} = \hat{a}_{i,t} + ß_{i,t}MKT_t + \gamma_{i,t}GOV_t + \eta_{i,t}CORP_t + \breve{\varepsilon}_{i,t}.$$

$$(2) \qquad \hat{a}_{i,t} = a_i + \lambda_i t + e_{i,t}$$

where i are the active premiums. T-statistics are calculated using Newey-West standard errors.

Panel B shows the rate of alpha decay that would annul the validity of passive-active combinations. Holding beta constant, each month a fixed rate is subtracted from the return of the factor portfolio. Following the adjustment, two tests are executed: (1) the adjusted factor portfolio is EW with a traditional portfolio and the improvement and statistical significance of the combined portfolio relative to the traditional portfolio is calculated, and (2) a time-series regression is executed of the adjusted factor portfolio on the passive benchmarks (MKT, GOV and CORP):

$$(3) \qquad R_{i,t} = \dot{\alpha}_i + ß_iMKT_t + \gamma_iGOV_t + \eta_iCORP_t + \varepsilon_{i,t}.$$

where $\dot{\alpha}$ is the intercept in the regression. Standard errors for the regression estimates are calculated using either heteroskedasticity-consistent (t-stat (HC se)) or Newey-west standard errors (t-stat (NW se)). Δ Sh is the difference between the monthly Sharpe ratios of the balanced portfolio constructed with a decay adjusted factor portfolio and the traditional portfolio. The associated p-value is calculated using the Ledoit-Wolf bootstrap test.

Panel A			Panel B					
	Coef. Sign	t-stat (NW se)	Yearly Alpha Decay	Δ Sh	p-val	$\dot{\alpha}$	t-stat (HC se)	t-stat (NW se)
SMB	-	-0.82	No decay	0.22	***0.00***	7.8%	*9.29*	*8.13*
BTM	-	-1.10	-1.0%	0.19	***0.00***	6.7%	*8.00*	*7.00*
RMW	+	**3.56**	-1.5%	0.17	***0.00***	6.2%	*7.43*	*6.50*
CMA	-	-0.13	-2.0%	0.15	***0.00***	5.8%	*6.86*	*6.00*
WML	-	-1.86	-2.5%	0.13	***0.00***	5.3%	*6.29*	*5.50*
IVOL	+	0.10	-3.0%	0.11	***0.01***	4.8%	*5.71*	*5.00*
QUAL	+	**2.02**	-3.5%	0.09	***0.04***	4.2%	*5.00*	*4.38*
BAB	-	-0.33	-4.0%	0.08	*0.09*	3.7%	*4.43*	*3.88*
AC	-	-0.89	-4.5%	0.06	*0.19*	3.2%	*3.86*	*3.38*
NI	+	1.78	-5.0%	0.04	*0.39*	2.8%	*3.29*	*2.88*

Chapter 2: How do short selling costs and restrictions affect the profitability of stock anomalies?

Abstract

Short selling frictions cannot explain the persistence of seven prominent stock anomalies. Long-only investing is robust and profitable and can be further enhanced by a synthetic short. Moreover, portfolios restricted to stocks that are easy to short sell continue to have large and significant alphas. The paper obtains cost bounds for switching between implementation methods and shows, using a proprietary database of borrowing fees, that the cost of short positions is small relative to their profitability. Overall, the evidence doesn't support the implications of arbitrage asymmetry that mispricing is concentrated in short positions where it is too costly to exploit.

1. Introduction

Historical tests of the CAPM have given rise to an abundance of anomalously priced characteristics in the cross-section of stock returns (Cochrane, 2011). These characteristics can also be used as return predicting signals in the construction of profitable rule-based active investment strategies. Their success in empirical work has drawn the attention of practitioners and motivated a proliferation of anomaly replicating funds and smart beta indexes.

The focus in academic work has been placed on the performance of zero-cost long-short portfolios. In practice, investment vehicles that provide anomaly exposure tend to be long-only. Evidence on the impact of short selling frictions on anomaly profitability is scarce. The goal of this paper is to fill this gap and explore the effect of short selling costs and short selling restrictions on the viability of anomaly investing.

From the point of view of practitioners, the impact of short selling frictions is relevant as it can help determine the optimal approach to anomaly investing. Should strategies be executed long-only or long-short? Alternatively, can shorting the market, rather than short selling individual securities, be used to improve between anomaly fit and the performance of anomaly combinations?

From the point of view of academics, the impact of short selling frictions is relevant because mispricing explanations to anomalies require some form of limits to arbitrage. Intuitively, mispricing can persist if savvy investors are unable to profitably execute offsetting trades following a price distorting demand shock. In the specific case of short-selling, investors may not be able to exploit security *overpricing* because short-selling is prohibited or costly. This results in an asymmetry in arbitrage as buying is easy and short selling can be difficult (Stambaugh, Yu & Yuan, 2015).

An explanation of anomalies grounded on arbitrage asymmetry implies two key hypotheses: (1) anomaly profitability should be concentrated in short positions and (2) capturing this profitability should be too costly to be exploited. The paper finds evidence against both claims for seven prominent stocks anomalies. Extensive model mispricing exists in long positions and short selling costs are avoidable and low relative to short position profitability. In other words, short selling costs explain only a small fraction of anomaly alphas. The evidence is as follows.

Time-series alphas are large and statistically significant for *long-only* anomaly portfolios. Moreover, the inclusion of long-only anomalies improves Sharpe ratios by 32% out-of-sample and 60% in-sample relative to traditional passive investment in the market. The improvement is significant at the 1% level. The significant profitability in long-positions is evidence against the first implication of arbitrage asymmetry that anomaly profitability should be concentrated exclusively in short positions. From the point of view of investors, the large profitability of long positions implies that improvements in performance can be achieved even without short selling.

Is it necessary to short sell individual securities to exploit security overpricing and to capture negative alphas? If short selling individual securities is impossible, how can we further improve upon long-only investing? In the presence of all-encompassing prohibitive shorting frictions on individual securities, the paper proposes the use of a synthetic-short strategy. The synthetic bet goes long the highest alpha decile whilst shorting the market. The synthetic-short approach aims to achieve two objectives. First, it removes overexposure to the equity premium which otherwise dominates long-only investing. Second, the synthetic-short approach exploits negative alphas in overvalued securities. Ideally, investors want to buy positive alpha whilst short selling negative alpha securities. In practice, investors can often only easily short sell the market. In other words, investors can only easily short securities in their value-weighted proportions (via futures for example). A long position in a positive alpha decile combined with a market short implies a net short position on all nine remaining decile portfolios. Taking a short position on the lowest negative alpha decile portfolio is beneficial. This is the standard approach in the unrestricted long-short setting. However, short positions in intermediate portfolios can be suboptimal. The results show that using a synthetic-short improves Sharpe ratios by 40% out-of-sample and 80% in-sample relative to long-only investing. Improvements are statistically significant at the 2% level. The findings suggest that long-only investing can be extensively improved by using only a market short. The evidence goes against the second hypothesis as it suggests that short position profitability can be partly exploited using a cheap execution method such as a market short. From the point of view of practitioners, the results imply that executing with a synthetic short is superior to long-only investing.

Short selling *individual securities* in the short leg of anomalies is profitable in the absence of shorting costs. Short alphas capture 63% of average long-short profitability. In addition, portfolio analysis shows that short selling individual securities improves the Sharpe ratio by 64% out of sample and 24% in-sample relative to the synthetic-short approach. Improvements are statistically significant at the 2% level (4% in-sample). The finding suggests that short selling individual securities is profitable in the absence of short selling costs. Overall the results suggest that short selling restriction, on either individual securities or the market, can severely reduce the profitability of anomalies. However, they do not completely annul their investment potential. But how high are short selling costs and can they be easily reduced?

For investors that do not face regulatory or self-imposed short selling restrictions, it is important to get a sense of the magnitude of short selling costs on individual securities relative to their profitability contribution. Towards this goal, the paper uses a proprietary cross-sectional database of borrowing fees to estimate short selling costs. The value-weighted borrowing cost is 46 basis points (BPS) annually which is close to the general collateral (GC) rate of 35 BPS in the data. In contrast, the equally weighted borrowing fee is 416 BPS. This is nine times larger. Even though 37.3% of stocks in the data are on special (not on GC and expensive to borrow), they account for only 2.9% of market capitalization. The evidence suggests that high borrowing costs are concentrated in small market capitalization firms.

The borrowing costs of anomaly short positions are small relative to their alphas. On average, borrowing costs are only 15.4% of the average short anomaly alpha. The highest borrowing costs are for the unprofitable (116 BPS annually) and loser portfolio (110 BPS annual). However, their short selling cost is only a fraction of their gross short alpha which is 504 BPS for profitability and 1124 BPS for momentum. For the remaining five anomalies, costs are below 65 BPS. In fact, size, value, investments and accruals have a higher shorting cost for stocks that fall in the long position than for stocks that fall in the short position. Overall, the results suggest that short selling costs are small relative to anomaly profitability. This goes against the second hypothesis of arbitrage asymmetry which suggests that exploiting short position profitability is too costly.

The approach to anomaly construction can have a large impact on borrowing cost estimates. Throughout the analysis, the paper relies on value--weighted portfolios with NYSE breakpoints for anomaly construction. This method is common in the literature and aims to reduce the impact of small stocks. However, researchers often use equally weighted sorts without NYSE breakpoints to make statements about the population of equities without placing special emphasis on firms with large market capitalization. Conclusions change extensively with this alternative approach to anomaly construction. The average borrowing cost associated with equally weighted anomaly sorts is 974 BPS which is fourteen times larger than its value-weighted counterpart. The difference arises due to the large cross-sectional differences in borrowing costs between small and large market capitalization stocks.

Equally weighted anomalies also have higher alphas but *only in long* positions; in fact, long positions are even more profitable than short positions in small stocks. More importantly, however, short selling costs can be easily and extensively reduced using value weights and NYSE breakpoints without forgoing any significant short position profitability. Empirical investigations of shorting costs that rely on methods which emphasize small market capitalization stocks can severely overstate the relevance of shorting costs in practice. Moreover, investment strategies that make extensive use of small stocks for short positions can have prohibitive short selling costs. However, costs for strategies that are based on large caps seem to be low relative to profitability.

The analysis relies on cross-sectional differences between borrowing costs. However, costs can also vary considerably over time and more importantly, between lender borrower relationships (Kolasinski, Reed & Ringgenberg, 2013). The market for borrowing securities is decentralized and opaque. Prices are not centrally determined, competitive or publicly observable. Therefore, the conditions available to one borrower may not be applicable to another. Nevertheless, short selling costs can be known in advance. Interested arbitrageurs can estimate their own concurrent shorting costs before committing to an anomaly execution approach. Towards this goal, the paper estimates the bound at which investors should switch between execution methods. Based on their concurrent shorting costs, investors can dynamically decide whether to execute with a synthetic-short or a security-short. The results show that investors can no longer be confident that a security-short approach will outperform synthetic-short execution when additional short selling and transaction costs for a portfolio of anomalies exceed 125 basis points annually. Constructing a synthetic short becomes more profitable than a security-short when costs exceed 300 basis points annually. The bounds for switching to a synthetic-short are an order of magnitude larger than the estimated average value-weighted anomaly borrowing cost of 68 BPS.

To sum up, there is significant profitability in the long leg of anomalies and additional improvements in performance can be achieved through a synthetic-short. Short selling costs on individual equities are small relative to their profitability contribution if investors do not extensively rely on small market capitalization firms in portfolio construction. Overall, the evidence does not support the view that short selling frictions can account for the persistence of anomalies.

The paper has three key contributions: (1) it develops the synthetic-short approach which successfully improves upon long-only investing, (2) it derives cost bounds for different methods of anomaly execution and compares them to cost estimates derived from borrowing cost data, and (3) shows the effect of anomaly construction choices on the magnitude of borrowing costs.

2. Short selling and anomalies

2.1. Understanding the market for short selling

Before a stock can be sold short, it must be borrowed. The US market for lending and borrowing stocks is decentralized and opaque. Deals are often made between brokers and institutions and prices are not centrally determined or publicly observable. Resultantly, proprietary datasets from security lenders are routinely used as sources of information in the literature (D'Avolio, 2002; Jones & Lamont, 2002; Cohen, Diether & Malloy, 2007). Alternatively, various proxies for shorting demand (e.g. short interest) and shorting supply (e.g. institutional ownership) are often employed for analysis (Nagel, 2005).

Short sellers are a diverse group. From market makers and options traders to long-short hedge funds. When it comes to mutual funds, only a third can short sell by their charters and only 2% do so in practice (Almazan, Brown, Carlson, & Chapman, 2004). Practitioners often cite regulatory, cultural and client-imposed constraints as common motivators for an underlying reluctance to short sell. Since short sellers do not obtain the proceeds from a sale, there is little benefits from short selling in terms of liquidity. Rather, short sellers are more likely to be motivated by superior information (Diamond & Verrechia, 1987) and hedging needs (Bohemer, Jones & Zhang, 2008).

Lenders are usually custodian banks that clear and hold positions for large asset owners, such as pension funds and mutual funds. Custodian banks enter into revenue sharing contracts with beneficial owners as compensation for their services (Reed, 2013).

The US market for short selling has become relatively more active recently. The market started slowly, with total short interest as a percent of NYSE shares outstanding period being less than 1% in the 1929-1931 (Meeker, 1932). More recent data (2000-2004) suggests that short selling is up to 13% of NYSE share volume (Bohemer, Jones & Zhang, 2008). Estimates of equity loans from 2010 suggest that 15% of stocks available for lending are utilized (Prado, Saffi & Strugess, 2016). However, not all stocks borrowed are used for short selling; they may also be used for voting or tax-arbitrage (Christoffersen, Getzy, Musto & Reed, 2005).

2.2. The mechanics of the short sale

Loans are often intermediated by brokers in order to reduce search costs and enable ease in collateral management. Upon receiving a request to borrow shares, the broker seeks out a willing lender who agrees (but does not commit) to deliver shares in three days. Large institutions can circumvent the process and negotiate directly.

The obligations of share borrowers are simple. Dividends need to be transferred to back to the lender. However, share borrowers do attain the right to vote on shareholder meetings. Consequently, lending involves a trade-off between obtaining the lending fee and the right to express dissent through voting[6].

Short sellers must post collateral for borrowed shares. For US equities, collateral is set at 102% of the value of the stock. Lenders can use posted collateral to close a position if borrowers fail to deliver shares three days after a recall. Cash is used as collateral for 98% of the cases and T-bills for the rest (D'Avolio, 2002). When collateral takes the form of a security, fees are directly arranged by the parties.

The rebate rate is the interest rate that borrowers receive on their collateral. The difference between the rebate rate and the prevailing market rate is the borrowing cost (also known as the loan fee). Intuitively, the market rate is the opportunity cost; it captures the income that the short seller could have obtained if he used his money to invest in a safe market instrument such as the Federal Funds Rate. Therefore, the borrowing fee, which is the difference between the market and rebate rate, is the cost of short selling.

Stocks that are hard to borrow are on 'special' and have higher borrow fees. In contrast, stocks with a baseline fee are on 'general collateral' (GC). Together, GC and specialness equilibrate supply and demand in the market for stock borrowing. Theoretically, borrowing costs would be zero if every asset owner was willing to lend shares in a perfectly competitive market. For positive short selling costs to arise, some investors must hold (overpriced) stocks that they are not willing to lend (Dufee, 1996; Krishnamurty, 2002).

Retail investors who want to short sell receive zero interest on their collateral which usually accrues to the broker. In addition, stocks on special are usually traded by large proprietary trading desks; brokers tend to deny short sales for stocks on special to small investors (Reed, 2013). Resultantly, retail investors or small players are disadvantaged in this marketplace.

Loans are typically on a continuous basis (open-term); this implies that every day they can be renegotiated or terminated by either party. The variability of costs adds some dynamic risk to short selling as investors need to be mindful of fee variance (Engelberg, Reed & Ringgenberg, 2016). The value of the collateral is marked to market daily which ameliorates counterparty risk. In case

[6] In practice, institutional investors often restrict share lending and recall loaned shares in firms with poor performance and weak governance in order to vote (Aggarwal, Saffi & Sturrgess, 2015). This tend to raise borrowing fees around voting record dates.

of unfavorable price movements, short sellers are asked to update collateral (Mitchel, Pulvino & Stafford, 2001; Jones & Lamont, 2001). Investors without liquid assets to post collateral may need to close a position early. Moreover, under a call to terminate from a counterparty, borrowers will need to either close the position permanently or find another willing lender. Borrowers have three days to return recalled borrowed shares and the average time to re-establish a short is estimated at 23 trading days (D'Avolio, 2002). Due to reputation effects however, recall rates tend to be quite low (2% per month) (D'Avolio, 2002). As with most financial contracts, there is some flexibility in the design. Recall risk can be ameliorated with the use of a fixed term loan which cannot be renegotiated before an agreed upon date. Nevertheless, term loans tend to be infrequent in practice, arguably, due to the low incidence of recalls.

Return swaps or options are an alternative to short selling. Studies show that the use of options increases when short selling is constrained (Evans, Geczy, Musto & Reed, 2008; Battalio & Schultz, 2011). However, sellers tend to transfer short selling costs and risks to the derivative buyer. For example, short sale constraints tend to be reflected in option pricing (Ofek, Richardson & Whitelaw, 2004). This is intuitive as sellers would want to have the choice to hedge positions cheaply. In fact, derivative contracts often contain fee provisions in case of a rise in the underlying loan fees. In a sense, loan prices, derivative conditions and spot prices are jointly determined (D'Avolio, 2002).

2.3. Theoretical links between short selling and mispricing

There is a flourishing literature on the theoretical link between short selling and security prices. Given that anomalies came about as tests of the CAMP, it is important to first note that short selling frictions do not change the predictions of the CAPM. As an equilibrium model, the CAPM predicts that all homogeneous investors hold the market portfolio. Given that short positions cannot be part of this equilibrium, short selling frictions are immaterial for the model's predictions (Elton, Gruber, Brown & Goetzmann, 2009, Ch. 14). Intuitively, the representative investor cannot be short on average just like he cannot be a net lender.

Under investor *heterogeneity* however, overpricing can occur as a combination of differences in opinion and short selling restrictions. The mechanism is simple, short sale constraints prevent negative opinions from being incorporated into prices (Miller, 1977). Reasoning more generally, short leg overpricing can remain persistently strong and reflect the views of primarily optimistic (or irrational) investors if savvy arbitrageurs are unable to profitably execute offsetting trades due to short selling costs. This can lead to prices being biased by the view of optimists for securities with high short selling fees. Relying on similar forms of reasoning, theoretical models often use short selling constraints to sustain differences between prices and fundamentals (Duffie, Garleanu & Pedersen, 2002).

More generally, limits to arbitrage, such as short selling costs, are a fundamental building block of mispricing explanations of anomalies. If investors experience a demand shock that pushes prices away from fundamental values, arbitrageurs will not be able to correct security prices if they face difficulties trading. The demand shock causing price divergence is often modeled in the literature as the result of irrational investor behavior. Limits to arbitrage is, therefore, a key ingredient to behavioral explanations (Barveris & Thaler, 2003). Since demand shocks can also arise for a variety of different reasons, such as institutional frictions relating to contracting and agency (Gromb & Vayanos, 2010), the relevance of short selling frictions for asset pricing is even more comprehensive.

2.4. Arbitrage asymmetry

Exploiting model mispricing in an undervalued security is easy as arbitrageurs can simply make a purchase. In the process, they will cause price pressure until mispricing corrects. However, if short selling frictions are extensive, arbitrageurs will face difficulty profiting from security overpricing. This causes an asymmetry in arbitrage. For anomalies to be explained by arbitrage asymmetry we need to confirm two hypotheses: (1) anomaly profitability is concentrated in short position and (2) it is too costly to profitably exploit.

We need both hypothesis to be confirmed by the data to be able to claim that the persistence of anomalies is explained exclusively by short selling frictions. If only the second hypothesis holds, then arbitrage asymmetry explains the profitability of short positions and we would need to develop a completely different explanation for the profitability of long positions.

The details matter. We are not interested if short selling costs are higher than long-short profitability; even though this is often done in the literature. When long-only investing works, investors can always simply choose not to short sell. Consequently, we need to investigate two implications of arbitrage asymmetry: (1) is there profitability in long positions and (2) how high are costs in short positions relative to their profitability. Finally, we need to understand if there are methods to avoid high short selling costs that do not result in a commensurate drop in profitability.

It is important to note that short selling frictions only have the potential to explain the persistence of anomalies. They cannot account for anomaly existence. In other words, short selling frictions can suggest that trading against model mispricing may be unprofitable for an array of investors, but they do not explain why there is model mispricing in the first place. To motivate why anomalies arise in the first place we would need to model the pricing process of the representative investor. The intuition of this argument can be easily understood through the following simple example. Suppose an agent is willing to sell a 10-dollar bill for 5 dollars in coins. The mispricing of the bill is not tradable if entering the transaction requires a 10-dollar fee to a third party. In this case, the persistence of mispricing can be explained by limits to arbitrage. However, limits to arbitrage will not explain why one of the agents is improperly pricing the 10-dollar bill in the first place. We need either behavioral or rational story to model the initial divergence of prices.

2.5. Anomalies and short selling: the assumptions for frictionless anomaly trading

Papers examining anomaly performance in frictionless markets are implicitly making two assumptions: (1) the size of the collateral posted on borrowed assets is equivalent to their value and (2) the rate paid on borrowed cash is equivalent to the rate received on collateral. Both assumptions are required for long-short anomaly investments to require no initial money outlay and to have no short selling cost.

How would the zero-cost trade work under these two assumptions? First, you borrow 100$ dollars from the market at the borrowing rate (R) and post them as collateral on the short position. On this collateral, you receive an interest rate (r) from the counterparty. This makes you effectively a lender of cash to the security lender; at the same time, you are a borrower from the market. Once you have the asset, you can sell it on the market and obtain 100$ for its sale (assumption 1). Finally, you can use the 100$ from the short sale to buy the long asset. In the final portfolio, you get a rebate rate (r) on your cash collateral and you pay the borrowing rate on your cash borrowings (R). These two rates cancel out (assumption 2) and portfolio performance is determined by the difference between the long and short stock position.

Both assumptions are violated in practice. The market rate is different from the rebate rate. This difference is effectively the short selling cost. Second, the size of the collateral for short positions is higher than the value of the asset (102% for US equities). Consequently, taking a long-short anomaly bet via physical short selling cannot be without an initial money outlay[7] or a short selling cost. This raises the question as to how high are short selling costs in practice and whether they can explain the profitability of short positions in well-known anomalies?

[7] We can also view the addition collateral as a cost and assume that the long position is scaled down to account for the higher collateral requirement.

2.6. *Short selling costs: what do we know?*

Early evidence on the magnitude of short selling costs comes from Jones & Lamont (2001). Using data on 80 actively traded NYSE stocks in the 1926-1933 period, they find substantial time-series and cross-sectional variation in short selling costs. In their sample, most large-cap stocks are inexpensive to short. In addition, expensive to short stocks have lower subsequent returns.

Using data from an institutional lender in a sample covering the 2000-2001 period, D'Avolio (2002) finds that the cost of borrowing a value-weighted loan portfolio is 25 basis points annually. Around 16% of CRSP stocks in his sample can't be borrowed but they account for less than 1% of the market capitalization. Stocks on special represent 9% of the sample and cost around 4.3% annually; they also tend to be small with low institutional ownership. The remaining stocks have loan fees of around 20 basis points annually. For most stocks, there is excess lendable supply (D'Avolio, 2002). D'Avolio argues that shorting fees are not high enough to explain return anomalies or an underlying reluctance to short sell.

An early attempt to estimate the shorting cost of anomalies was made by Geczy, Musto & Reed (2002). Using a year of equity loans data, they find that the short selling costs of big, growth and low momentum firms are small relative to the documented excess returns of the strategies.

Nagel (2005) uses institutional ownership as a proxy for short-selling constraints. Consistent with the view that short selling constraints reduce price efficiency and anomaly performance, Nagel (2005) finds that lower instructional ownership implies more overpricing of short leg securities in equally weighted sorts.

Cohen, Diether & Malloy (2007) use proprietary lending data from a large institution and find an average loan fee of 4% for small stocks and 0.4% for large stocks for the 1999–2003 period. The median holding time for a stock loan position is 3 weeks in their sample. Cohen, Diether & Malloy (2007) find that outward demand shifts, which signal an increase in the amount of negative information coming to the borrowing market, lead to negative future stock returns.

Boehmer, Jones & Zhang (2008) construct a proprietary NYSE panel data of short sales and find that short selling constraints are not widespread. In their 2000-2004 sample, they find that heavily shorted stocks underperform stocks low levels of shorting over a 20-day period.

Drechsler & Drechsler (2015) argue that anomalies disappear for stocks with low lending fees. Their result is contrary to findings by Getczy, Musto & Reed (2002) but in line with the results of Nagel (2005) who finds that (proxied) short selling constraints are associated with more short position overpricing.

Chu, Hirshleifer & Ma (2016) use regulation SHO as a natural experiment to examine the impact of limits to arbitrage on ten stocks anomalies. The examined regulation relaxed constraints on *short selling execution* for a random pilot of NYSE/AMEX stocks. They find that profitability fell by 77 basis points per month for anomaly short positions following the adoption of the regulation. The authors argue that their estimates capture the causal effect of limits to arbitrage. They interpret the findings as being more consistent with mispricing explanations to anomalies.

Overall, short selling investigations give ambiguous evidence on the potential relevance of borrowing costs for anomalies. On the one hand, studies find low average borrowing fees (Jones & Lamont, 2001; D'Avolio, 2002; Cohen, Diether & Malloy, 2007), low shorting costs to anomalies (Getczy, Musto & Reed, 2002) and weak short-selling constraints (Boehmer, Jones & Zhang, 2008). On the other hand, some authors argue that shorting costs are high for anomalies (Drechsler & Drechsler, 2015), that price inefficiency is high when short selling costs are high (Nagel, 2005) and that removing constraints on shorting execution reduces short anomaly profitability (Chu, Hirshleifer & Ma, 2016).

Short selling costs are measured differently across conflicting studies. However, when it comes to the magnitude of short selling costs, this paper reconciles the literature by showing that choices in anomaly construction can have a large impact on the results. More specifically, strategies relying on small stocks (by using equal weights without NYSE breakpoints for example) have much larger borrowing cost. The results show that the difference across construction methods is so large that it can extensively alters the conclusions of the analysis.

2.7. Transaction costs

Investigations of trading and short selling costs tend to be undertaken separately in the literature. Frazzini, Israel, and Moskowitz (2012) show that the *price impact* of short selling is not statistically different from the price impact of selling long. Israel and Moskowitz (2012) find little evidence that variation in the size, value and momentum premiums can be explained by variation in trading costs. Novy-Marx and Velikov (2015) study an array of anomalies and find positive net spreads after incorporating simple transaction cost mitigation techniques into the strategies. Research also suggests that despite the incredible growth rates experienced by smart beta ETFs over the past few years, well known active strategies can still accommodate extensive supplementary growth before the market impact of large fund turnover can annul smart beta profitability (Novy-Marx & Velikov, 2016; Ratcliffe, Miranda, & Ang, 2016). In short, extensive research supports the view that transaction costs cannot account for anomalies. More recently, however, Chen and Velikov (2019) find that anomaly profits after trading costs are small in the period following their publication. While this paper does not explicitly account for transaction costs, the bounds derived in Table 12 can also be interpreted as the total cost (both short selling cost and transaction cost) needed to induce investors to switch from one execution method to another.

3. Anomaly construction and short selling data

3.1. Anomaly construction

Similarly to Fama and French (2008), the paper constructs seven anomalies using CRSP and COMPUSTAT data on US common stocks listed on NYSE, AMEX, and NASDAQ from 07/1963 until 12/2016. Data before the examined time frame is not used as it can be biased towards large successful firms (Fama & French, 1992). To avoid forward-looking bias, fundamental data from the previous fiscal year is conservatively assumed to be available at the end of June. Firms without market capitalization at the period of portfolio formation are excluded. Delisting returns are included whenever available in CRSP to minimize potential biases.

Baseline anomalies are constructed using value-weighted decile sorts with NYSE breakpoints (equal number of NYSE firms across portfolios). Equally weighted portfolios are also considered. However, equally weighted sorts require additional trading each month following return realizations in order to rebalance back to equal weights. Equally weighted sorts also overweight small stocks by construction. As a result, they have two to three times the transaction costs of value-weighted portfolios (Novy-Marx & Velikov, 2015). Similar problems will occur if we do not use NYSE breakpoints or if we assign weights based on the strength of the signal; top and bottom portfolios will end up being overpopulated with small firms as they tend to have extreme values of the characteristics. Intuitively, a small firm is more likely to have extreme characteristics, such as low profitability or investments, relative to a large firm which can be diversified over projects, region, and divisions.

Seven anomalies are reconstructed: size, value, profitability, investment, momentum, accruals, and net issuance. These anomalies also appear in Fama & French (2008). Anomaly portfolio rebalancing is annual except for momentum which is rebalanced monthly. Stocks are excluded if they lack the information to be included in a sort.

Size (SMB) is constructed following Fama & French (1993) whereby portfolios are constructed at the end of June using market capitalization as the sorting signal. The 'me' signal is the log of market capitalization recorded in million. The size anomaly goes long on low market capitalization firms and short on high market capitalization firms.

Value (BTM) follows Fama & French (1993). The signal is formed by dividing book equity with market equity whereby negative book to market firms are excluded. Value goes long on the high book to market firms and short on the low book to market firms. The signal does not take the log of the ratio to improve interpretability.

Operating profitability (OP) follows Fama & French (2015). The operating profitability (OP) signal is constructed as revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity. The operating profitability anomaly goes long high profitability firms and short low profitability firms.

Investments (INV) follows Fama & French (2015). The investments signal is constructed as the change in total assets between two fiscal years divided by the earlier fiscal year. The investments anomaly goes long firms with low investments and short firms with high investments.

Momentum (WML) is constructed using cumulative returns between t-2 and t-12 as the sorting signal (with portfolio formation at t-1) and monthly rebalancing following Jagadeesh and Titman (1993). The momentum anomaly goes long on high cumulative return firms and short on low cumulative return firms.

Accruals (ACC) follows Sloan (1996). The accruals signal is constructed as:

$$Accruals = \frac{(dACT - dCHE - dLCT + dDLC + dTXP - DP)}{\frac{(AT + AT_{-12})}{2}}$$

Where *d*ACT is the annual change in total current assets, dCHE is the annual change in total cash and short-term investments, *d*LCT is the annual change in current liabilities, *d*DLC is the annual change in debt in current liabilities, *d*TXP is the annual change in income taxes payable, *d*DP is the annual change in depreciation and amortization, and (AT+AT−12)/2 is average total assets over the last two years. Companies that do not have information for all variables needed for constructing the signal (except income taxes payable) are excluded. The accruals anomaly goes long on low accruals firms and short high accrual firms.

Net issuance (NI) follows Fama & French (2008). The net issuance signal is constructed as the log ratio of split-adjusted shares outstanding over the two previous consecutive years. Portfolios exclude firms with no change in net issuance. The net issuance signal is the difference between the highest issuance portfolio and a separate negative issuance portfolio.

The market (MKT) is constructed as the value-weighted return in excess of the Treasury bill rate of all US common stocks in NYSE, AMEX, and NASDAQ that have valid data in CRSP. Long-only anomalies (LSMB, LBTM, LWML, LOP, LINV, LAC, LNI) are constructed by only taking the long position in each anomaly. Short-only anomalies (SSMB, SBTM, SWML, SOP, SINV, SAC, SNI) are constructed by taking only the short position in each anomaly. Table 1 shows descriptive statistics of the signals in the data. All signals display considerable cross-sectional variation.

3.2. *Short selling data*

To estimate short selling costs, the paper uses a proprietary cross-sectional database (20/04/2017) from a large financial institution containing the borrowing fee on 7435 equities. The data capture cost quotes between two large financial institutions; that is, it shows the type of fees that a large arbitrageur can expect. Most papers in the literature use proprietary lending databases. However, lending and borrowing fees need not be equivalent due to intermediation costs. Since arbitrageurs also bear these additional costs, the borrowing fee is a better estimate of short selling costs.

The reference value for borrow cost calculation is the overnight bank funding rate (OBFR; 91 BPS). The general collateral rate is 35 BPS below the OBFR reference value. The database also contains information on the number of stocks available for borrowing. Short selling data is matched with accounting data from the previous fiscal year (December). Cost data is available for 96% of securities with market capitalization information in CRSP/COMPUSTAT. Securities without market capitalization information are excluded.

The borrowing cost data is useful for understanding differences in characteristics between cheap and expensive to borrow securities. However, given the opaque nature of the borrowing market and the cross-sectional nature of the data, it is prudent to corroborate analysis conclusions using a proxy. The empirical analysis suggests that market capitalization is a useful proxy for short selling costs. The intuition is that non-lending investors are less likely to dominate the ownership of large stocks. Consequently, large stocks are cheaper and easier to borrow.

Table 2 summarizes information in the short selling database. Around 17.8% of the shares outstanding are available for borrowing. Most of them are stocks on GC where 17.2% of total shares outstanding are available for borrowing. Using market values rather than shares outstanding gives a similar picture; 19.4% of market capitalization is available for shorting. The result suggests that the data provider is a large player in the market.

The most important result is the difference between the value-weighted and equally weighted average borrowing cost. The value-weighted borrowing cost is only 46 basis points (BPS) which is close to the GC rate of 35 BPS. In comparison, the equally weighted borrowing cost is 416 BPS. This is nine times larger![8] Figure 1 illustrates the issue. Most securities above the median market

[8] The equally weighted mean borrowing fee is close its full sample counterpart which does not exclude firms that are not in CRSP.

capitalization (vertical line in Figure 1) are on GC while extreme values for borrowing costs are common for small market capitalization stocks. In fact, the smallest stocks are almost never on GC. The average cost of stocks above the median market capitalization is 70 basis points (Figure 1 difference between intercept and above median market capitalization dummy).

The mean value of stocks on special is 1060 BPS. Even though 37.3% of stocks in the sample are on special, they represent only 2.9% of total market capitalization. The most important result it is that high borrowing costs are concentrated in small market capitalization firms.

Portfolio sorts are the same as non-parametric cross-sectional regressions (Cochrane, 2011) and they are particularly well suited to give a clear picture of how characteristics vary across different levels of short selling costs. Table 3 shows the variation of characteristics across ten portfolios sorted on borrowing costs. As expected, portfolios with high borrowing costs are small market capitalization firms with relatively fewer lendable shares relative to outstanding. Accruals and investments do not seem related to borrowing fees. Moreover, value stocks seem to be associated with higher short selling costs than growth stocks. On the other hand, unprofitable loser firms that invest extensively and issue shares are associated with high short selling costs. Nevertheless, we also need to keep in mind that results can be driven by market capitalization as small firms tend to have both high fees and extreme values of the characteristics.

The important thing to note from Panel B in Table 3 is that stocks above the median market capitalization have low equally weighted borrowing fees. The finding that large stocks are inexpensive to short is consistent with preceding investigations that use proprietary data (Jones & Lamont, 2001; D'Avolio, 2002). This is intuitive as non-lending investors are less likely to absorb the entire share issue in larger companies. Moreover, short selling costs for small stocks may also be unreliable as a large arbitrageur can move the market. The intuition and empirical findings suggest that size is a good proxy for short selling costs. Using this proxy, we can extend the analysis for the full sample period. Resultantly, the paper will form portfolios that exclude firms below the median market capitalization as a mechanism for excluding hard to borrow securities.

3.3. Portfolio performance

Table 4 shows summary statistics for long-short portfolios. Net issuance and momentum have the highest risk-adjusted performance with an M2 of 11.2 % and 10.5% respectively. On the other side of the spectrum are size (SMB) and operating profitability (OP) with the lowest risk-adjusted performance as stand-alone investments. In fact, their raw excess returns are not statistically significant. On average, anomaly skewness is positive. Excess kurtosis on the other hand, is an issue for all the strategies. The maximum drawdown measure indicates that extreme crashes are especially problematic for size and momentum.

Table 14 in the appendix shows portfolio statistics for taking a long position in the short side of anomalies. As expected, the Sharpe ratio of the short side of anomalies is much lower than that of the long side of anomalies. Furthermore, the short side of anomalies experiences even higher drawdowns on average than the long side. The drawdown of 99% for low momentum really stands out. High drawdowns suggest that undiversified counterparties to individual anomaly bets face considerable crash risk.

Table 5 shows that the average correlation between long-short strategies is very low. The highest individual correlation are value-investments (0.51) and operating profitability-net issuance (0.38). On average, the equity premium is the least correlated strategy. The result can be expected given the historical development of anomalies as tests of the CAPM whereby researchers discover anomalies using the equity premium as an aggregate wealth proxy.

The average correlation among stock strategies rises considerably in the long-only setting (Table 6). Surprisingly, the market reverses its role and becomes the most correlated strategy. Individual correlations between the market and operating profitability, investments, accruals and net issuance are all above 0.9. This severely limits the diversification potential of long-only strategies. Intuitively, whenever you invest in a stock, whether that stock is a value stock or a low issuance stock, you are also investing in the stock market. Therefore, the equity premium is implicitly included in all long-only anomalies. Correlations among short strategies are even higher than their long-only counterparts. Again, the market has the highest average correlation among short strategies.

Finally, the diagonal in Table 6 shows the correlation between the long and short leg of the same anomaly. High correlations are desirable in this case. A perfect correlation would imply arbitrage; the long and short portfolio would move together whilst providing different average returns. Net issuance has the highest correlation between the long and short leg. This can in part explain net issuance's low variance and drawdown. On the other hand, low and high momentum portfolios have a relatively low correlation. Given that the performance of the long and short momentum portfolios can significantly diverge, the strategy has a high standard deviation and a large maximum drawdown.

4. Anomaly alpha and short selling costs

4.1. Alphas

Anomaly alphas with respect to the equity premium are positive and statistically significant for six out of the seven examined anomalies[9] (Table 7). An exception is size, which has an economically small and a statistically insignificant alpha. The average alpha t-statistic across anomalies is 3.68. Five of the anomalies have a long-short alpha t-statistic larger than 3.

When it comes to the alphas of long-only anomalies, we see a significant decrease in both economic and statistical significance. Average alpha falls by more than half for long-only portfolios. Book to market, momentum, investments and net issuance have statistically significant long-only alphas. Surprisingly, value's long-only alpha is more significant than its long-short counterpart. While average alphas fall by more than half in the long-only setting, the average t-statistics of alphas has a much smaller decline. This occurs as the market model is a much better fit in the long-only setting (an average R2 of 77% compared to 6% for the long-short setting) which reduces the standard errors of anomaly alphas and raises their statistical significance.

Time-series regressions reveal that 63% of long-short profitability comes from the short side using this construction method. Five from the seven examined anomalies have statistically significant negative alphas. Statistical significance is even higher than in the long-short setting for accruals and operating profitability.

Momentum, investments and net issuance have significant alphas from both the long and short position. Book to market seems to be the only anomaly deriving its alpha primarily from the long side. On the other hand, operating profitability and accruals get their alpha primarily from the short position. Finally, size portfolios are well explained by the market model and do not have significant alphas.

CAPM alphas are the most relevant assessment metric. Estimating alphas to benchmarks such as the Fama-French five factor model would have to assume that investors already hold the benchmark anomalies in their portfolio (since alphas imply that the left-hand side asset improves risk-adjusted performance when added in a portfolio containing the right-hand side assets). Making this assumption is problematic as the goal is to establish whether anomalies that enter the benchmark are also tradable after costs.

[9] A t-statistic threshold of 2 is more appropriate as the data-mining adjusted hurdle of 3 refers to new discoveries (Harvey, Liu & Zhu, 2016).

4.2. Short selling costs

Table 8 contains the borrowing fee of stocks in long and short positions. The results broadly confirm the intuition obtained from the sorts in Table 3. For size and value there is higher short selling cost in the long position. In addition, unprofitable and low momentum portfolios are the most expensive to short sell as expected. The annual short selling cost is 110 and 116 BPS for momentum and profitability respectively. Investments, accruals and net issuance do not exhibit high short selling costs or notable differences between cost in the long and short position. On average, short selling costs are only 15.4% of average short alpha and 13.6% of the average significant short alpha. Overall, costs are low relative to short anomaly profitability.

4.3. Equally weighted portfolios without NYSE breakpoints

Researchers often use equally weighted portfolios without NYSE breakpoints to investigate the cross-section of securities without a special focus on large market capitalization enterprises. It is prudent to consider how this alternative construction method affects the estimates. Table 9 reports alphas and shorting costs.

Equally weighted portfolios have three times the average long position alpha of value-weighted sorts. Especially the long position of size becomes strongly significant. This is intuitive as the approach emphasizes small stocks which allow the size anomaly to shine. This is further evidence that there is significant profitability in long positions. In fact, for small stocks, there seems to be more profitability in long than short positions.

Short alphas in equally weighted sorts are almost equivalent to their value-weighted counterparts. In short, all the added profitability from overweighting small caps comes from long positions. However, short selling costs for short positions are fourteen times larger! Only investments and book to market have short alphas higher than their associated borrowing cost. The increase in short selling costs comes from the large cross-sectional difference between the short selling costs of small and large market capitalization firms.

The results also suggest that it might be sensible to execute the long position using equally-weighted portfolios while the short positions using value-weighted portfolios. In this manner, investors can capture the higher positive alphas in small stocks whilst avoiding high short selling costs by exploiting negative alphas only in big firms.

4.4 Restricted value-weighted portfolios

High borrowing costs are concentrated in small stocks (see Table 3 and Figure 1). This section investigates how cost and profitability are affected by excluding small stocks from the analysis.

More specifically, anomalies are reconstructed without stocks below the market capitalization median. Results are shown in Panel B Table 9.

The average short and long position cost are respectively 4.32% and 4.15% smaller than the -5.10% cross-sectional average that includes all securities (Table 9 Panel B). The average short alpha is reduced by 54 BPS annually relative to the value-weighted approach without size restrictions (Table 9). Again, the reduction in profitability from excluding small market capitalization stocks is minimal in the short position. Costs also fall by 13 BPS relative to the unrestricted value-weighted sort and are only 20 BPS away from the GC rate. Restricting the investment universe by excluding small market capitalization firms has a small detrimental effect on profitability and a minor positive effect on borrowing costs. Value weights and NYSE breakpoints are already emphasizing large enterprises extensively. Consequently, additional restrictions to remove small firms only have a limited impact on the results. The regression results that include dummy variables if stocks enter the long or short portfolio, also confirm that portfolios constructed using value weights with NYSE breakpoints are very effective at reducing costs in the extreme portfolios relative to the cross-section.

5. Scenarios

What is the impact of short selling restrictions on the joint profitability of anomalies? To investigate this question, several scenarios based on different short selling and investment restrictions are considered. Differences in risk-adjusted performance determine constraint relevance. There are four base scenarios: (1) market (long market), (2) long-only (includes long-only anomalies), (3) synthetic short (allows short selling the market portfolio) and (4) long-short (allows short selling individual securities).

Sharpe ratio improvements across scenarios are compared using two portfolio construction methods: (1) in-sample maximum Sharpe ratio and (2) equally-weighted. The equally weighted approach (EW) can be considered out-of-sample as it does not incorporate any future data for execution. In fact, past research suggests that EW is superior to out-of-sample alternatives due to the sensitivity of optimization procedures to estimation error (DeMiguel, Garlappi, & Uppal, 2009). The goal is to not to compare performance between construction methods but between scenarios with different assumptions and restrictions. The statistical significance of differences in Sharpe ratios is assessed with the Ledoit & Wolf (2008) bootstrap procedure which accounts for non-normality and serial correlation. Since we are not constructing a new anomaly and have evaluated the merits of each signal individually, we do not have to account for potential biases arising from selecting n out of k predictors (Novy-Marx, 2015).

Trading anomalies in reverse order, such as long growth short value, is disallowed across scenarios as there is no empirical or theoretical justification to motivate a reverse bet. All scenarios are dollar positive with weights that sum to 100%. Scenarios with short positions assume 100% collateral at the risk-free rate[10]. The analysis starts without considering short selling costs. Latter sections derive the cost bounds that would cause a switch between execution methods.

5.1. *Market: traditional investing*

The simplicity of the market scenario makes it the default choice for many investors. In this base setting, anomaly investments are not utilized, and investors simply hold a passive long position in the market.

5.2. *Long-only: including anomalies*

Above and beyond instrument availability, investors often face regulatory or self-imposed leverage and short selling restrictions that make long only anomaly investing a valid real-world approximation. The widespread availability of long-only smart beta ETFs and anomaly replicating mutual funds have made this approach commonplace. The equally weighted approach assigns equal weight to all the available investments. In the Max Sharpe approach constraints take the following form:

$$\sum_{j}^{J} w_j = 1$$

$$0 \le w_j \le 1$$

where

$$j = [LMKT, LSMB, LBTM, LWML, LOP, LINV, LACC, LNI]$$

5.3. *Synthetic short*

Ideally, investors want to buy positive alpha whilst short selling negative alpha securities. In practice, investors can often only easily short sell the market. In other words, investors can only easily short securities in their value-weighted proportions. The paper proposes a synthetic-short approach to anomaly investing as a substitute to short selling individual securities. Investors can use a market short to remove beta and overexposure to the equity premium. In addition, a market short can also help exploit overpricing.

[10] Placing a 102% collateral requirement does not materially influence the results.

Intuitively, combining a long decile position in the highest alpha portfolio with a market short implies a net short position on all stocks in the remaining nine deciles. Shorting securities that do not have negative alphas is suboptimal. However, the biggest concern is shorting positive alpha securities which can often accompany the second highest alpha decile. To ameliorate the issue, the paper uses a synthetic long-short bet which includes a modest purchase of the second highest alpha portfolio. The goal is to reduce the strong negative weight in the intermediate portfolio relative to a pure long-market-short approach. This can reduce the risk of short selling positive alpha securities. Including an intermediate portfolio using this simple method causes an improvement of 7% in-sample and 5% out-of-sample relative to a pure market short approach. The proposed strategy is as follows:

$$R^{synthetic} = \frac{2R^{l} + R^{i}}{3} - R^{m} + R^{f}$$

Where $R^{synthetic}$ is the long-short synthetic position. R^{l} is the highest alpha decile portfolio. R^{i} is a value-weighted intermediate portfolio containing stocks that are in the second decile with the highest alpha. R^{m} is the (short position) in the market and R^{f} is the risk-free rate capturing the interest on market short collateral. Effectively, imposing a 100% collateral requirement makes only the short position self-financed.

In the max Sharpe approach, constraints take the following form (where SMBS, for example, refers to the synthetic size bet):

$$\sum_{i}^{I} w_i = 1$$

$$0 \leq w_i$$

where

$$i = [LMKT, SMBS, BTMS, WMLS, OPS, INVS, ACCS, NIS]$$

5.4. *Long-short*

In the long-short scenario, investors can take short positions in anomalies, but they must post 100% collateral at the risk-free rate. This effectively deleverages the portfolio as investors are forced to hold a significant investment in the risk-free asset (like moving down the capital allocation line). Moreover, in this scenario, short position must equal long positions in anomalies; that is, anomalies cannot be unbundled. This can happen in practice if investors only have access to format-fixed long-short investments that attempt to harvest a premium. Removing the unbundling constraint does not significantly improve performance. Moreover, removing the collateral restriction also has a limited impact on Sharpe ratios. The constraint moves the investor down the capital allocation line as it forces investment in the risk-free asset. In the in-sample Max-Sharpe setting constraints take the following form:

$$\sum_{i}^{I} w_i = 1$$

$$0 \leq w_i$$

where

$$i = [LMKT, SMB, BTM, WML, OP, INV, ACC, NI]$$

6. Scenario Results

6.1. *Sharpe ratios*

Table 10 shows the returns, standard deviation, Sharpe ratios and p-values for portfolios across scenarios. Several notable results emerge. First, there is a large improvement in Sharpe ratios when we include long-only anomalies. The Sharpe ratio raises by 32% in the EW case and 60% in the Max Sharpe approach. Improvements are statistically significant at the 1% level. The result implies that anomalies can add to performance even in a long-only setting.

Second, enabling a market short also improves performance. EW Sharpe ratios rise by 40% relative to the long-only setting. The improvement is significant at the 2% level. Sharpe ratios in-sample increase by 80% and are significant at the 1% level. Overall, the results suggest that the synthetic short approach is superior to long-only investing.

Third, allowing for the short selling of individual securities whereby investors are forced to hold collateral at the risk-free rate leads to a significant improvement. The out-of-sample EW Sharpe ratio further increases by 64% and is statistically significant at the 2% level. The in-sample Sharpe increases by 24% and is significant at the 5% level. In frictionless markets, short-selling individual securities is very profitable. Overall, all the constraints have an economically large impact on performance.

6.2. *Weights*

Table 11 shows the weights assigned to anomalies across scenarios and portfolio construction methods. It is first important to note that the market portfolio is redundant in the presence of long-only anomalies. This suggests that anomalies and the market are substitutes when anomaly shorting is prohibited. Intuitively, you always want to invest in the outperforming long-only anomaly portfolio that already embeds a significant equity premium exposure (Table 7). In fact, removing overexposure to the equity premium is the intuition behind the construction of the synthetic short. The conclusion that passive investments and anomalies are substitutes does not hold in long-short space as long-short anomalies tend to have low or negative market betas (Table 7).

As expected, in the long-only scenario, significant weight is assigned to the anomalies with the highest long alpha. Book to market, momentum and net issuance are the only strategies receiving a positive long-only weight. This can explain why value and momentum are so popular among mutual funds and ETF providers while anomalies that require significant short positions, such as accruals, operating profitability and investment are yet to gain significant traction as standalone products in practice.

The investment anomaly receives the smallest weight across scenarios. This can be expected given its high cross-correlation with other investments (see correlation Table 5 and 6). The finding suggests that the investment anomaly is irrelevant from an investment perspective in the examined setting. On the other hand, net issuance receives a substantial weight across scenarios.

7. Cost bounds and the limitations

Investigations of short selling costs face several noteworthy limitations. First, the decentralized nature of the borrowing market makes the matching of the universe of anomaly stocks to a meaningfully lengthy historical record of borrow fees a futile quest. Proprietary databases are inherently brief. This prevents us from drawing conclusions about the time-series variation of short selling costs during the anomaly backtest period. Second, the cost of borrowing can vary between broker-lender relationships (Kolasinski, Reed & Ringgenberg, 2013). Rebate rates are not competitive prices and are thus inherently relationship specific. Consequently, what was available to one borrower may not be applicable to another. Finally, even the perfect short selling data would only capture the marginal cost of borrowing. The marginal cost can be markedly different from the cost faced by large arbitrageurs that move the market for borrowing stocks. These issues are common to the literature; the structure of the borrowing market makes the derivation of a 'true' cost estimate difficult and investor specific.

Fortunately, shorting costs are known in advance. In addition, the decision to short sell individual securities or the market need not be constant. The optimal execution method can depend on prevailing market conditions. Interested arbitrageurs can estimate their own concurrent shorting costs before deciding how to execute an anomaly trade. Along this line of reasoning, it is more interesting to estimate the total cost bounds (both trading and short selling costs) at which switching from one method of execution to another is optimal.

It is important to keep in mind that long-short investing can be successfully approximated with the use of a synthetic-short which circumvents the entire messy business of short selling individual securities. It is therefore prudent to use the synthetic short approach as a benchmark (rather than long-only). A conservative annual cost of 45 BPS for shorting the market is assumed based on the value-weighted shorting cost in the data (investors would execute a market short via a future for example). A useful way to think of the market short is as a value-weighted short on all stocks. Alternatively, shorting via derivative contracts or (reverse) ETFs is another easy way to obtain short market exposure.

The alternative to the synthetic-short benchmark is the leverage constrained long-short method with 102% rebate bearing collateral. Adding the market collateral level of 102% additionally reduces the attractiveness of shorting in the presence of costs. Demanding additional collateral magnifies shorting costs as it induces rebate bearing collateral on a larger position.

Table 12 shows the results. First, it is evident that at low levels of borrowing costs, there is undeniably a lot of benefit to short selling. Improvements are statistically significant both in-sample and out-of-sample for GC and value-weighted (VW) short selling costs. The statistical significance of improvements disappears at the 5% level when shorting costs exceed 125BPS annually. The economic usefulness of shorting individual equities disappears at an annual shorting cost of approximately 300BPS. The cost bound is large relative to the average anomaly short selling cost of 68BPS. This implies that in normal times the cost of short selling is small relative to the profitability of short positions in individual anomaly securities. Alternatively, the bound in Table 12 can be interpreted as the total cost bound (sum of all anomaly trading costs).

To conclude, investors have a high degree of confidence that they should execute an anomaly trade using a security-short approach when annual short selling costs are below 125 basis points annually. Executing a market short becomes economically more viable when annual shorting costs exceed 300 basis points annually. Estimates of average anomaly borrowing costs imply that they are small relative to the profitability contribution of security-short selling.

8. Final remarks

The short selling cost associated with anomaly strategies can be partly offset by revenue received via the lending of stocks in long positions. The analysis assumed that investors are unable to use this income as incorporating lending fees requires information on lending utilization rates. Moreover, for a fair comparison, any income from the lending market would also need to be incorporated in the passive benchmark. In other words, the relevant question is whether stocks in long anomaly positions can deliver higher lending income than stocks in a passive value-weighted index. This auxiliary question is left for future research.

For future work, it would also be interesting to investigate the short selling costs of the betting against beta anomaly (Frazzini & Pedersen, 2014). More specifically, in the spirit of Hong and Sraer (2016), it would be interesting to examine how short selling costs vary with aggregate disagreement.

9. Conclusion

An explanation of anomalies grounded on arbitrage asymmetry implies two hypotheses: (1) anomaly profitability should be concentrated in short positions and (2) exploiting this profitability should be too costly. The paper finds evidence against both claims. Long-only investing is profitable and can be further improved via a synthetic short. High short selling costs tend to be concentrated in small stocks and can be easily avoided through the use of value-weighted sorts with NYSE breakpoints. The profitability of security-short positions that do not overweigh small market capitalization securities is large relative to their borrowing cost; that is, costs are only a small fraction relative to short position alphas. Short selling costs are only large enough to annul short position profitability of small stocks. Nevertheless, small stocks are not necessary for obtaining large short anomaly alphas.

Arbitrageurs interested in anomaly investing can compare their concurrent borrowing costs to estimated cost bounds for switching between execution methods. If short selling individual securities takes more than 125 BPS annually, investors are no longer confident that a security-short will outperform a synthetic short. Synthetic-short investing becomes economically more profitable when short selling costs exceed 300BPS. The cost bounds are much larger than the estimated borrowing cost associated with value-weighted anomalies.

The paper makes three contributions: (1) it shows that long only investing works and can be significantly enhanced using a synthetic short (2) it demonstrates how overreliance of small stocks in anomaly construction can overstate short selling costs to the extent that it alters analysis conclusions and (3) it derives cost bounds for switching between execution methods and compared them to recent borrowing fees. Overall, the results suggest that short selling frictions cannot explain anomaly persistence and are inconsistent with the predictions of arbitrage asymmetry.

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Tables and Figures

Table 1: Characteristics. This table shows the mean and dispersion of anomaly signals for the 07/1963-12/2016 period. me is the signal for size (in million and log). Mom is the cumulative momentum signal for momentum. bm is the book to market signal for value. prof is the signal for profitability. inv is the signal for investment. acc is the signal for accruals. ni is the signal for net issuance. Average (ew) is the timef series average of the equally weighted cross-sectional average of the characteristic. High signal portfolio (vw) is the time-series average of the value-weighted cross-sectional average in the decile sorted portfolio with the highest value of the characteristic. Low signal portfolio (vw) is the time-series average of the value-weighted cross-sectional average in the decile sorted portfolio with the lowest value of the characteristic. CS dispersion is the time-series average of the cross-sectional standard deviation of characteristics.

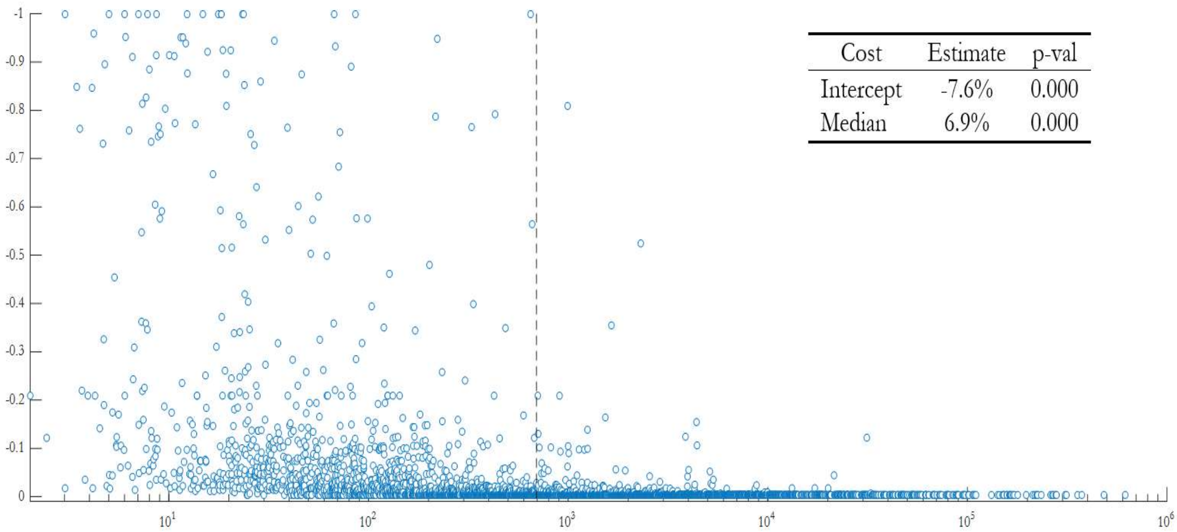
Time-series average of characteristics (07/1963 - 12/2016)							
	me	mom	bm	prof	inv	acc	Ni
High signal portfolio (vw)	9.87	1.91	2.25	0.85	0.76	0.10	0.32
Average (ew)	4.49	1.14	0.94	0.17	0.17	-0.03	0.04
Low signal portfolio (vw)	3.61	0.64	0.19	-0.29	-0.15	-0.14	-0.02
Time-series average of cross-sectional dispersion							
CS dispersion	1.93	0.57	1.26	8.61	0.98	0.11	0.14

Table 2: Borrowing costs and share availability. This table shows summary statistics for borrowing costs and the shares available for borrowing. Borrowing costs are annual. Firms without market capitalization in CRSP are excluded. VW Mean is the value-weighted mean of borrow costs. % on special is the number of stocks that are not on general collateral (GC) relative to the total. Available/Outstanding is the average total number of shares available for borrowing relative to the total number of shares outstanding. Available GC/Outstanding is average the total number of shares on general collateral relative to total shares outstanding. Capitalization Special/Market is the total market capitalization of stocks on special relative to the total market capitalization of stocks in the sample.

Borrow Costs			
Number of stocks	3497	Max	-0.35%
GC	-0.35%	10th percentile	-8.37%
VW Mean	**-0.46%**	1st percentile	-87.6%
Mean	**-4.16%**	Min	-99.9%
Median	-0.35%	S.D.	13.2%
Mean (Specials)	-10.6%	% on Special	37.3%

Available			
Shares		$	
Available/Outstanding	17.8%	Available/Market	19.4%
Available GC/Outstanding	17.2%	Available GC/Market	19.3%
		Capitalization Special/Market	2.9%

Figure 1: Borrowing costs and market capitalization. This table shows borrowing costs (y-axis) and market capitalization (x axis-log scale recorded in million). The dotted vertical line is the median of market capitalization. The table shows a regression of short selling costs on an intercept and a Median dummy variable that takes the value 1 when a stock is above the median market capitalization.



Cost	Estimate	p-val
Intercept	-7.6%	0.000
Median	6.9%	0.000

Table 3. Borrow costs and characteristics. This table shows the equally weighted average of characteristics in ten portfolios sorted on borrow costs with market capitalization as a secondary sort (when borrow costs are equivalent) in Panel A and sorted on market capitalization in panel B. Includes stocks for which anomalies are constructed. Cost is the annual borrowing cost. A/O is average of the firm values of shares available for borrowing relative to shares outstanding. Mc is market capitalization recorded in million. Bm is the book to market ratio. Mom is cumulative momentum. Op is operating profitability. Inv is investments. Acc is accruals. Ni is net share issuance.

Panel A-Sort on cost										
Decile	Securities	Cost	Mc	A/O	Bm	Mom	Prof	Inv	Acc	Ni
1	350	**-31.78%**	**247**	**2%**	**1.07**	**0.87**	**-1.32**	0.18	-0.04	**0.18**
2	349	-5.07%	269	4%	1.06	0.99	-0.18	0.17	-0.04	0.08
3	350	-1.85%	576	6%	1.17	1.05	0.59	0.11	-0.05	0.07
4	350	-0.80%	858	10%	0.75	1.09	0.05	0.17	-0.04	0.04
5	350	-0.35%	749	16%	0.82	1.26	0.21	0.07	-0.05	0.02
6	349	-0.35%	1521	21%	0.61	1.20	0.22	0.15	-0.05	0.03
7	350	-0.35%	2122	24%	0.62	1.25	0.24	0.13	-0.05	0.02
8	350	-0.35%	3537	27%	0.64	1.20	0.30	0.08	-0.05	0.01
9	349	-0.35%	7230	28%	0.65	1.23	0.30	0.13	-0.05	0.02
10	350	-0.35%	46733	23%	0.61	1.21	0.35	0.06	-0.05	0.00
μ	3497	-4.16%	6401	16.1%	0.79	1.14	0.10	0.12	-0.05	0.04
p-val (10=1)		0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.48	0.00

Panel B-Sort on market capitalization										
Decile	Securities	Mc	Cost	A/O	Bm	Mom	Prof	Inv	Acc	Ni
1	350	286	-21.85%	1%	**1.71**	**0.99**	**-0.63**	0.08	-0.05	**0.11**
2	349	400	-10.90%	4%	0.96	1.01	0.43	0.18	-0.06	0.09
3	350	346	-3.40%	8%	0.80	1.05	-0.27	0.14	-0.03	0.07
4	350	619	-2.37%	12%	0.77	1.11	-0.05	0.17	-0.04	0.05
5	350	950	-0.92%	16%	0.70	1.14	0.09	0.09	-0.05	0.03
6	349	1567	-0.58%	21%	0.58	1.18	0.19	0.19	-0.05	0.05
7	350	2168	-0.44%	24%	0.62	1.24	0.19	0.11	-0.05	0.02
8	350	3533	-0.38%	27%	0.64	1.20	0.29	0.10	-0.05	0.01
9	349	7146	-0.37%	28%	0.66	1.22	0.29	0.13	-0.05	0.02
10	350	46806	-0.35%	22%	0.61	1.21	0.35	0.06	-0.05	0.00
μ	3497	6401	-4.16%	16.1%	0.79	1.14	0.10	0.12	-0.05	0.04
p-val (10=1)		0.00	0.00	0.00	0.00	0.00	0.00	0.55	0.95	0.00

Table 4: Data summary for long-short portfolios. This table shows the summary statistics for long-short anomalies for the period 07/1963-12/2016. D.D. is downside deviation with zero as the target. M2 is the annual volatility matched (to the equity premium) return. μ is the average across anomalies. MKT is the equity premium, SMB is size, BTM is value, WML is momentum, OP is profitability, INV is investment, ACC is accruals and NI is net issuance.

	MKT	SMB	BTM	WML	OP	INV	ACC	NI	μ
R	0.50%	0.28%	0.38%	1.34%	0.30%	0.38%	0.31%	0.55%	0.51%
t-stat	*2.84*	*1.46*	*2.26*	*4.87*	*1.69*	*2.86*	*2.44*	*5.12*	2.96
σ	4.44%	4.81%	4.22%	6.93%	4.44%	3.30%	3.23%	2.69%	4.23%
Sharpe	0.12	0.06	0.09	0.18	0.07	0.12	0.10	0.20	0.12
M2	6.3%	3.2%	5.0%	10.5%	3.9%	6.4%	5.5%	11.2%	6.5%
Skew	**-0.53**	0.74	0.49	-1.46	0.37	0.35	0.19	0.07	**0.11**
t-stat	*-5.43*	*7.63*	*5.11*	*-15.11*	*3.82*	*3.62*	*1.93*	*0.75*	1.11
Ex. Kurt.	1.94	4.41	1.76	7.81	4.20	1.83	1.74	0.75	3.21
t-stat	10.05	22.79	9.10	40.39	21.71	9.44	8.98	3.90	16.62
Max	16%	32%	21%	23%	26%	17%	13%	10%	20%
Min	-23%	-21%	-15%	-46%	-23%	-13%	-12%	-9%	-20%
Drawdown	56%	84%	53%	81%	65%	36%	34%	29%	55%
D.D	3.05%	2.99%	2.59%	4.96%	2.92%	2.04%	2.05%	1.58%	2.73%
Sortino	0.17	0.09	0.15	0.26	0.11	0.19	0.16	0.35	0.19

Table 5: Correlations long-short. This table shows the correlations between long-short portfolios**.** Numbers below the diagonal are Pearson correlation coefficients. Numbers above the diagonal are p-values.

Rho/P-val	MKT	SMB	BTM	WML	OP	INV	ACC	NI
MKT		0.00	0.12	0.00	0.00	0.00	0.00	0.00
SMB	0.17		0.00	0.04	0.00	0.00	0.00	0.00
BTM	-0.06	0.33		0.00	0.00	0.00	0.06	0.98
WML	-0.18	-0.08	-0.17		0.00	0.17	0.33	0.00
OP	-0.39	-0.54	-0.18	0.16		0.94	0.11	0.00
INV	-0.24	0.15	0.51	0.05	0.00		0.00	0.00
ACC	-0.17	-0.20	0.07	0.04	0.06	0.21		0.00
NI	-0.39	-0.34	0.00	0.21	0.38	0.30	0.20	
μ	-0.18	-0.07	0.07	0.01	-0.07	0.14	0.03	0.05

Table 6: Correlations long only and short only. Numbers above the diagonal are the cross correlations between short only anomalies. Numbers below the diagonal are correlations between long only anomalies. Numbers in the diagonal are correlations between the short and long leg of the same anomaly. μ (L) is the average correlation for long anomalies. μ (S) is the average correlation between short anomalies. The intersection of μ (L) and μ (S) is the average long correlation divided by the average short correlation.

Correlation Long only/Short only									
RhoL/RhoS	MKT	SMB	BTM	WML	OP	INV	ACC	NI	μ (S)
MKT		0.98	0.93	0.79	0.88	0.94	0.92	0.92	**0.91**
SMB	0.78	0.66	0.93	0.74	0.80	0.90	0.86	0.88	0.87
BTM	0.83	0.78	0.67	0.72	0.82	0.92	0.90	0.84	0.86
WML	0.85	0.76	0.69	**0.55**	0.79	0.79	0.78	0.79	0.77
OP	0.93	0.69	0.75	0.78	0.76	0.86	0.86	0.84	0.83
INV	0.90	0.82	0.86	0.80	0.83	0.84	0.94	0.92	0.90
ACC	0.90	0.74	0.74	0.81	0.84	0.82	0.85	0.88	0.88
NI	0.95	0.70	0.83	0.77	0.91	0.87	0.81	**0.88**	0.87
μ (L)	**0.88**	0.75	0.78	0.78	0.82	0.84	0.81	0.84	0.94

Table 7: Anomaly alphas. This table shows the slope and the monthly intercept from time-series regressions of value-weighted anomaly portfolios on the equity premium. T-statistics are calculated using heteroskedasticity and autocorrelation consistent standard errors.

LS	SMB	BTM	WML	OP	INV	ACC	NI	μ
ά	0.19%	0.42%	1.42%	0.53%	0.48%	0.39%	0.67%	0.59%
β	0.18	-0.06	-0.28	-0.40	-0.18	-0.12	-0.23	-0.16
t (ά)	1.02	**2.52**	**5.41**	**3.15**	**3.72**	**3.15**	**6.79**	3.68
t (β)	3.52	-1.09	-3.24	-8.36	-4.99	-3.92	-9.40	-3.93
R2	2.9%	0.4%	3.2%	15.3%	5.7%	2.9%	15.0%	6.5%

Long	LSMB	LBTM	LWML	LOP	LINV	LACC	LNI	μ
ά	0.16%	0.31%	0.48%	0.11%	0.19%	0.04%	0.23%	0.22%
β	1.11	1.00	1.17	0.96	1.09	1.14	0.91	1.05
t (ά)	1.01	**2.70**	**3.78**	1.58	**2.05**	0.38	**4.46**	2.28
t (β)	25.7	26.0	32.0	47.6	41.8	42.3	63.1	39.79
R2	60%	70%	72%	86%	81%	80%	91%	77%

Short	SSMB	SBTM	SWML	SOP	SINV	SACC	SNI	μ
ά	-0.03%	-0.11%	-0.94%	-0.42%	-0.29%	-0.35%	-0.44%	-0.37%
β	0.93	1.06	1.45	1.35	1.27	1.26	1.14	1.21
t (ά)	-0.85	-1.47	**-4.98**	**-3.24**	**-3.60**	**-3.74**	**-5.35**	-3.32
t (β)	88.8	49.7	23.0	39.1	59.8	51.8	51.5	51.98
R2	95%	86%	63%	78%	89%	84%	86%	83%

Table 8: Short selling costs. This table shows the annual borrowing costs associated with long and short value-weighted anomaly positions. Borrowing cost calculations are made on sorts that exclude firms without borrowing cost data. Short/Long ά is the average annualized alpha where bolded coefficients are the statistically significant gross alphas.

VW	SMB	BTM	WML	OP	INV	ACC	NI	μ
Cost Short	-0.38%	-0.42%	-1.10%	-1.16%	-0.47%	-0.64%	-0.61%	-0.68%
Cost Long	-3.56%	-0.67%	-0.53%	-0.39%	-0.68%	-0.67%	-0.48%	-1.00%
Short ά	0.38%	1.32%	**11.24%**	**5.04%**	**3.48%**	**4.26%**	**5.28%**	4.43%
Long ά	1.88%	**3.71%**	**5.81%**	1.32%	**2.28%**	0.45%	**2.74%**	2.60%

Table 9: Market capitalization and anomaly performance. Panel A shows average annual alpha and short selling costs for equally weighted portfolios without NYSE breakpoints. Panel B shows the annual alpha for value-weighted portfolios that exclude stocks below the median market capitalization. Long and Short are the coefficients from regressing costs on dummy variables that take the value 1 for stocks that enter long and short portfolios respectively.

Panel A - EW without NYSE breakpoints								
	SMB	BTM	WML	OP	INV	ACC	NI	μ
Long ά	12.48%	10.17%	8.52%	3.94%	7.12%	4.92%	7.35%	**7.79%**
t (ά)	*4.44*	*4.93*	*4.23*	*3.08*	*2.55*	*2.06*	*5.92*	*3.89*
Short ά	0.27%	-6.30%	-6.00%	-1.27%	-7.94%	-3.77%	-7.26%	**-4.61%**
t (ά)	*0.56*	*-3.24*	*-1.71*	*-0.40*	*-4.38*	*-1.93*	*-3.67*	*-2.11*
Short EW Cost	-0.41%	-4.07%	-17.32%	-17.66%	-4.88%	-9.15%	-14.36%	**-9.69%**
Intercept	-4.19%	-4.78%	-4.27%	-4.24%	-4.47%	-4.52%	-5.22%	-4.53%
p-val	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	
Long	-18.07%	-2.58%	0.35%	2.31%	-8.67%	-5.17%	4.29%	-3.93%
p-val	*0.00*	0.00	*0.57*	*0.00*	*0.00*	*0.00*	*0.00*	
Short	3.78%	0.71%	-13.05%	-13.43%	-0.40%	-4.64%	-9.14%	-5.17%
p-val	*0.00*	*0.28*	*0.00*	*0.00*	*0.53*	*0.00*	*0.00*	

Panel B -VW Size Restricted								
	SMB	BTM	WML	OP	INV	ACC	NI	μ
Long ά	2.06%	3.56%	5.85%	1.31%	1.75%	0.41%	5.07%	**2.86%**
t (ά)	*1.40*	*2.75*	*3.70*	*1.55*	*1.80*	*0.37*	*5.25*	*2.40*
Short ά	-0.31%	-1.09%	-9.53%	-4.04%	-3.57%	-3.76%	-4.89%	**-3.89%**
t (ά)	*-0.67*	*-1.18*	*-4.80*	*-4.78*	*-3.65*	*-3.27*	*-4.92*	*-3.32*
Short VW Cost	-0.70%	-0.39%	-0.60%	-0.68%	-0.44%	-0.50%	-0.51%	**-0.55%**
Intercept	-5.08%	-5.05%	-5.06%	-5.05%	-5.05%	-5.02%	-5.40%	-5.10%
p-val	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	
Long	4.32%	4.47%	4.57%	4.55%	3.60%	3.77%	4.95%	4.32%
p-val	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	
Short	4.73%	4.05%	3.58%	3.91%	4.23%	4.01%	4.58%	4.15%
p-val	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	

Table 10: Scenarios. This table shows monthly performance across scenarios and optimization methods. Long-only allows for investments in long anomaly position. The synthetic short constrained scenario goes long the highest two alpha portfolios (at different weights) whilst short selling the market with a 100% collateral at the risk-free rate. The long-short scenario allows short selling but requires 100% interest bearing collateral at the risk-free rate. P–values are based on the Ledoit and Wolf (2008) bootstrap procedure and are calculated relative to the previous scenario.

μ (R)	Max Sh	EW
Market	0.9%	
Long-Only	1.3%	1.1%
Synthetic Short	0.6%	0.6%
Long-Short	0.9%	0.9%

Sh	Max Sh	EW
Market	0.12	
Long-Only	0.18	0.15
Synthetic Short	0.33	0.21
Long-Short	0.41	0.35

σ	Max Sh	EW
Market	4.4%	
Long-Only	5.0%	4.7%
Synthetic Short	0.7%	1.0%
Long-Short	1.2%	1.5%

p	Max Sh	EW
Market		
Long-Only	0.00	0.00
Synthetic Short	0.00	0.02
Long-Short	0.04	0.02

Table 11: Portfolio weights across scenarios. This table shows portfolios weights across optimization techniques and scenarios. 'Max Sh' is in-sample optimization for the maximum Sharpe ratio. 'EW' is equally weighted.

	Long-Only		Synthetic-Short Constrained		Long-Short Constrained	
	Max Sh	EW	Max Sh	EW	Max Sh	EW
MKT	0.0%	12.5%	6.8%	12.5%	21.4%	12.5%
SMB	0.0%	12.5%	1.5%	12.5%	12.5%	12.5%
BTM	18.3%	12.5%	20.9%	12.5%	6.6%	12.5%
WML	53.9%	12.5%	5.2%	12.5%	7.8%	12.5%
OP	0.0%	12.5%	1.0%	12.5%	12.2%	12.5%
INV	0.0%	12.5%	0.6%	12.5%	0.0%	12.5%
AC	0.0%	12.5%	3.3%	12.5%	10.6%	12.5%
NI	27.8%	12.5%	60.6%	12.5%	28.9%	12.5%
Sum	100%	100%	100%	100%	100%	100%

Table 12. Shorting cost variation and performance. This table shows portfolio performance for different short selling cost assumptions. Cost is the annual rebate rate. Portfolios are leverage constrained and short positions require 102% rebate bearing collateral. Anomaly unbundling in optimization is prohibited. The benchmark for the p-values is the market short method with an annual market short cost of 45 BPS. 45 VW is the value-weighted cost of short selling in the sample. 35 GC is to the general collateral rate in the short selling sample. P–values are based on the Ledoit and Wolf (2008) bootstrap procedure.

Cost (BPS)	Max Sharpe		EW	
	Sharpe	p-val	Sharpe	p-val
Base Long-Short	0.41		0.35	
35 (GC)	0.39	*0.00*	0.32	*0.00*
45 (VW Cost)	0.38	*0.00*	0.32	*0.01*
65	0.37	*0.01*	0.31	*0.01*
85	0.36	*0.02*	0.30	*0.02*
105	0.35	*0.02*	0.29	*0.03*
125	0.34	***0.05***	0.28	***0.04***
150	0.33	*0.11*	0.27	*0.07*
200	0.30	*0.32*	0.24	*0.18*
300	0.26	*0.83*	0.19	*0.70*
Synthetic Short (-45BPS)	0.27		0.18	
Base Synthetic Short	0.33		0.21	

Appendix – Supplementary tables and figures

Table 13: Data summary for long-only portfolios. This table shows summary statistics for long only anomalies minus the risk-free rate for the period 07/1963-12/2016. D.D. is downside deviation with zero as the target. M2 is the annual volatility matched (to the equity premium) return. μ is the average across anomalies. LSMB is small, LBTM is high book to market, LWML is winners, LOP is profitable, LINV is low investment, LACC is low accruals and LNI is negative share issuance.

	LSMB	LBTM	LWML	LOP	LINV	LAC	LNI	μ
R	0.73%	0.82%	**1.08%**	0.60%	0.75%	0.62%	0.69%	0.76%
t-stat	*2.91*	*3.93*	*4.51*	*3.34*	*3.55*	*2.81*	*4.18*	3.60
σ	6.33%	5.30%	6.07%	4.55%	5.35%	5.61%	**4.20%**	5.35%
Sharpe	0.11	0.16	0.18	0.13	0.14	0.11	0.17	0.14
M2	6.33%	8.60%	10.03%	7.22%	7.75%	6.07%	9.09%	7.87%
Skew	-0.15	-0.02	-0.46	-0.46	-0.39	-0.45	-0.48	**-0.34**
t-stat	*-1.57*	*-0.23*	*-4.78*	*-4.75*	*-4.05*	*-4.62*	*-4.94*	-3.56
Ex. Kurt.	2.47	3.55	1.87	2.29	2.45	1.69	2.16	2.35
t-stat	12.76	18.35	9.65	11.86	12.69	8.73	11.18	12.17
Max	29%	30%	21%	17%	21%	18%	16%	22%
Min	-30%	-26%	-27%	-25%	-29%	-25%	-21%	-26%
Drawdown	80%	56%	54%	57%	59%	77%	51%	62%
D.D	4.20%	3.38%	3.99%	3.06%	3.54%	3.85%	2.77%	3.54%
Sortino	0.17	0.24	0.27	0.20	0.21	0.16	0.25	0.22

Table 14: Data summary for short only portfolios. This table shows summary statistics for the short leg of anomalies minus the risk-free rate for the period 07/1963-12/2016. D.D. is downside deviation with zero as the target. M2 is the annual volatility matched (to the equity premium) return. μ is the average across anomalies. SSMB is big, SBTM is growth, SWML is losers, SOP is unprofitable, SINV is high investment, SACC is high accruals and SNI is high share issuance.

	SSMB	SBTM	SWML	SOP	SINV	SAC	SNI	μ
R	0.45%	0.43%	**-0.19%**	0.27%	0.36%	0.29%	0.14%	0.25%
t-stat	*2.68*	*2.18*	*-0.61*	*1.02*	*1.53*	*1.22*	*0.67*	1.24
σ	4.21%	5.04%	**8.07%**	6.80%	5.96%	6.08%	5.45%	5.95%
Sharpe	0.11	0.09	-0.02	0.04	0.06	0.05	0.03	0.05
M2	5.74%	4.66%	-1.27%	2.17%	3.27%	2.59%	1.42%	2.65%
Skew	-0.36	-0.25	0.61	-0.56	-0.48	-0.52	-0.35	-0.27
t-stat	*-3.77*	*-2.63*	*6.35*	*-5.77*	*-4.94*	*-5.33*	*-3.57*	-2.81
Ex. Kurt.	1.73	1.60	4.22	1.84	1.37	1.74	1.45	1.99
t-stat	2.68	2.18	-0.61	1.02	1.53	1.22	0.67	1.24
Max	18%	24%	45%	19%	19%	18%	20%	23%
Min	-20%	-23%	-26%	-33%	-28%	-31%	-25%	-27%
Drawdown	61%	69%	**99%**	**91%**	75%	75%	79%	78%
D.D	2.88%	3.46%	5.54%	4.93%	4.25%	4.36%	3.92%	4.19%
Sortino	0.15	0.13	-0.04	0.06	0.08	0.07	0.04	0.07

Chapter 3: The pricing implications of shareholder voting

Abstract

The paper investigates the pricing implications of shareholder voting using a US sample of management and shareholder sponsored resolutions covering environmental, social, and governance issues. We uncover two robust asset pricing anomalies: (1) firms with a shareholder meeting provide positive risk-adjusted returns in the month of the meeting, as well as the months leading up to the meeting and (2) sorts on abnormal shareholder support in the month following the shareholder meeting, have an annualized long short alpha of 15.1%, with high support firms experiencing particularly poor stock market performance.

1. Introduction

Shareholder meetings are a key corporate event relevant to a variety of stakeholders. Management relies on meetings to share their corporate vision and to obtain approval for policy. For shareholders, meetings offer an opportunity to challenge management and to express dissent through the voting process. This paper investigates how shareholder meetings and voting outcomes affect stock valuation.

We investigate the pricing implications of shareholder voting using a US sample of 437,742 management and shareholder sponsored resolutions covering environmental, social, and governance topics from 2003 to 2016. To capture the information content from voting behavior, we construct a novel measure of (abnormal) shareholder support: the average of excess vote support relative to a historical topic-specific benchmark. This measure enables us to consider the full array of resolutions under consideration by all firms, as each resolution is benchmarked against a representative sample of proposals. The aim of the measure is to capture 'abnormal' shareholders support (or disapproval) towards the firm.

The data reveals two robust and independent asset pricing anomalies: (1) a voting period premium, whereby firms that will have a shareholder meeting have positive risk-adjusted returns in the month of the vote as well as the months leading up to the vote and (2) an abnormal shareholder support premium, whereby firms that had abnormally high shareholder support experience negative risk-adjusted returns in the month after the meeting.

More specifically, using the abnormal shareholder support measure as a signal, we construct value-weighted decile portfolios, with monthly rebalancing as a bassline investment strategy, and find that firms with the highest level of shareholder support experience a negative alpha in the month following the vote. In other words, abnormally high shareholder support leads to abnormally poor stock market performance. The long-short strategy is statistically significant with an annualized long-short alpha of 15.1%.

The profitability of the abnormal shareholder support anomaly is robust to the benchmarking method with significant alphas across the CAPM, Fama-French three factor, Fama-French five factor and the Fama-French five factor model augmented with momentum. Moreover, robustness tests reveal a consistent pattern in subsamples that consider only management and shareholder sponsored resolutions, as well as subsamples that use data only from annual general meetings (AGM). Since the subsamples have limited overlap in topics, the results also suggest that alphas are not topic-specific.

More sophisticated construction methods, such as increasing the signal-fading frequency (how long stocks can remain in a portfolio following the initial vote) or the way abnormal support is aggregated across resolutions, yield an even stronger conclusion. For example, using a two-month fading signal with maximum aggregation, which implies that abnormal shareholder support in a meeting is obtained by averaging the three most extreme votes (rather than the all-resolution average), yields an annualized long-short alpha of 16.9% with an associated t-statistic of 4.

The impact of shareholder support reverses before the vote. Firms that will experience high abnormal shareholder support in a forthcoming meeting have positive risk-adjusted return in the months preceding the meeting that turn negative in the month following the vote. Alphas disappear on longer horizons (more than three months) both before and after the meeting.

In addition to the stock price response to shareholder support, we investigate the general pricing impact associated with the incidence of shareholder meetings. In the period before the meeting, the agenda will be revealed and the voting recommendations from management and proxy advisory agencies will be distributed to shareholders. Moreover, share ownership for the purposes of voting will be established. The data suggest that there are positive and significant alphas in the month of the vote as well as the months leading up to the vote regardless of shareholder support. The voting period premium is strongest for small companies and special meetings but is also present in annual meeting and large stocks. For example, the annualized FF5+ momentum alpha of firms with a shareholder meeting in the upcoming month is 6.5% with a t-statistic of 3.2.

The voting period premium is broadly in line with findings that examine the within-firm time-series, whereby predictable events where information is revealed, such as dividend and earnings announcements, are associated with positive risk-adjusted returns. A unique feature of the voting period premium is that it is not concentrated exclusively in the month of the vote but also in the three months preceding the vote.

Time-series regressions suggest that the voting period premium and shareholder support premium are independent. This is intuitive as the voting period premium selects all stocks that have a shareholder meeting and the shareholder support premium selects a subset of those stocks in the month after. Time-series regressions suggest that the equity premium is subsumed by the voting period premium. This is intuitive as above average performance in the voting period implies below average performance in the rest of the year.

Keeping in mind the inherent non-testability of rational and behavioral explanations (Bekjarovski, 2017), we discuss the consistency of the results with a variety of theories. More specifically, we consider the extent to which agency theory, strategic information disclosure by management, the investor attention hypothesis, and time-varying risk premiums and loadings (to unobserved factors) can explain the uncovered price pattern. The behavioral theories are not mutually exclusive, and they often provide overlapping predictions that are partially consistent with the observed pricing pattern. However, no single explanation seems to account for the full range of empirical findings and we speculate that multiple forces are at play. Strategic information disclosure by management appears to be the most consistent theory when it comes to the abnormal shareholder support premium. On the other hand, the attention hypothesis seems the most plausible when it comes to the voting period premium.

Strategic information disclosure by management suggests that corporate news is opportunistically disclosed prior to relevant meeting dates. Intuitively, management has incentives to disclose good information before meetings and bad information after meetings to avoid dissenting shareholders. The hypothesis implies positive risk-adjusted returns prior to shareholder meetings that are stronger for firms that are about to experience high abnormal shareholder support. Intuitively, management releases positive information which raises stock prices and boosts shareholder approval. Similarly, we can expect negative risk-adjusted returns following the vote for companies that have had high abnormal shareholder support. Following the vote, management will start to release negative information as shareholders are unable to quickly challenge management. The predicted pricing pattern is broadly consistent with the shareholder support premium.

The investor attention hypothesis, combined with Miller's (1977) theory that investor heterogeneity combined with short selling frictions can lead to prices that are biased by the view of optimists, suggests that we should see positive risk-adjusted returns for firms in the spotlight. The hypothesis is consistent with the voting period premium as well as the increased trading volume we uncover around meeting dates. It is also corroborated by the fact that the voting period premium is stronger in small stocks firms which have higher short selling frictions (Bekjarovski, 2018).

An alternative explanation for the voting period premium is the hypothesis of downward sloping demand curves. Investors interested in influencing voting outcome are going to actively acquire shares in the months prior to the vote. For example, we know that (institutional) investors recall loaned shares (which are often sold short) prior to proxy dates in order to exercise their voting rights (Aggarwal, Saffi, & Sturgess, 2015)[11]. Similarly, battling for corporate control in proxy fights and special meetings with M&A resolutions should induce price pressure prior to record dates. The resulting 'extra' demand for shares of voting firms may create upward price pressure in the presence of slow-moving capital (Duffie, 2010). The hypothesis predicts positive performance before shareholder meetings which is consistent with the data. Moreover, the fact that the voting period premium is stronger in small firms is also consistent with a supply-demand effect.

Strategic information disclosure, investor inattention and slow-moving capital should be combined with an error in expectations explanation on the part of market participants to account for the fact that markets have not formed unbiased expectations of prices. For example, if markets anticipated strategic information disclosure they would not be surprised by the inflow of asymmetric news. Similarly, providers of capital should be surprised by excess demand on seemingly predictable events. An anticipated event should not create a price response.

Finally, rational explanations would suggest that we are excluding a relevant pricing factor for which betas change rapidly between periods. For example, a potential explanation is that the beta to an unobserved factor switches abruptly in the month after the vote to obtain the reversal pattern for the shareholder support premium. Omitted factors concerns are less problematic for the voting period and shareholder support premiums, relative to other anomalies based on persistent accounting data, as the explanation requires that the betas to the missing factor change monthly. If high abnormal shareholder support firms had a positive beta to an unobserved factor with a positive premium before the meeting, it is necessary that the beta to the unobserved factor abruptly changes signs for the sign of alpha to switch right after the meeting. This explanation remains a possibility and we do observe some modest variation in betas to controlled factors around voting dates. While no anomaly paper can definitively exclude risk explanations, the structure of the voting anomalies makes a rational explanation excessively convoluted.

[11] The effect is strongest for firms with poor performance and governance.

2. Data and methodology

2.1. Data

Voting information comes from the 'Company Vote Result' database provided by ISS (formerly known as RiskMetrics). The ISS Voting database is merged with CRSP and Compustat using CUSIP as a matching identifier to obtain price and financial statement information. The ISS database contains vote information on 437,742 US resolutions covering 10767 unique films for the period 1/2003 to 12/2016. The data composition is reported in Table 1, whereby infrequent data classifications, as well as missing data, are included in 'other' for the sake of brevity. As expected, most of the resolutions are sponsored by management. Shareholder sponsored proposals account for 2.33% of the data and are primarily governance-related. They are relatively more common in proxy contests when activist shareholders propose their own candidates for the board of directors (Table 3).

Public companies in the US are required by federal securities law to hold at least one shareholder meeting each year. Meetings enable shareholders an opportunity to express their views on policy and performance. Most resolutions are tabled in annual general meetings (AGMs) Table 1). Special meetings, also known as extraordinary meeting, occur infrequently and are usually scheduled to address matters that cannot wait until the subsequent AGM, such as resolutions regarding mergers and acquisitions (Table 3). State laws and corporate bylaws determine who has the right to call a special meeting. In fact, shareholders can vote on this matter.

A significant proportion of resolutions address the election of directors via plurality voting; which implies that the candidate director with the highest number of votes gets elected. Majority voting is the second most common requirement for a vote to pass and it applies for approximately 38.9% (9%) of the management (shareholder) proposals (Table 1). The data also contains a small sample of votes that require various degrees of supermajorities.

Management recommendations are disclosed on the proxy card and stand for the voting recommendation given to shareholders by the board of directors. The board of directors supports management-sponsored proposals on average in 98.5% of the cases, which entails that in a small proportion of the management proposals, the board of directors recommends voting against. In general, negative voting recommendations on management resolutions can reflect disagreement between the board and CEO, disagreement between board members or disapproval for a resolution tabled due to procedural necessity (such as adjourning a meeting). The most frequent management-sponsored topic with a negative recommendation from the board of directors is 'say on pay'.

The board of directors is generally hostile towards shareholder proposals, with only 15.6% of resolutions receiving a positive voting recommendation. The largest jump in management support for shareholder-sponsored proposals came in the crisis year of 2008 and has remained higher ever since. The topic behind this rise in positive recommendations is the election of shareholder proposed directors.

Activist shareholders incur a cost when they undertake independent voting research while the benefits are dispersed across the shareholder base. The proxy advisory industry arose to tackle this free rider problem by reducing the cost of informed voting. Institutional shareholder services (ISS) is the most well-known proxy advisory agency and they issue voting recommendations to clients. For 84.3% of the management resolutions, ISS recommends voting in support of a proposal. The second most common recommendation is to withhold votes (9% of resolutions). ISS is more supportive towards shareholder-sponsored resolutions relative to the board of directors, with 60.2% of resolutions receiving a favorable voting recommendation.

Calculating the support rate for each resolution requires specifying the votes that will constitute the voting base. Information on the appropriate denominator is available in the data. The most common method for calculating the voting denominator is to take 'For + Against' votes. This vote base is used to determine whether a proposal passes in 73.7% (48.4%) of the management (shareholder) proposals (Table 1). Abstaining votes are also added to the denominator in 22.2% (48.0%) of the management (shareholder) proposals. Other denominators, such as shares outstanding are rare (1.4% and 2.1% for management and shareholder respectively). When constructing the vote support rate, we adopt the company's choice regarding the voting base (be it 'For + Against' or 'For + Against + Abstain').

'Frequency on say on pay' is a management-sponsored resolution whereby shareholders vote on how often to vote on executive compensation. This resolution is mandated by the Dodd-Frank Act enacted in 2010 which requires companies to hold both an advisory (not binding) vote on executive compensation and an advisory vote on the frequency at which shareholder vote on executive compensation. Frequency on say-on-pay has the number of recommended years as an outcome and this outcome refers to the frequency at which say-on-pay votes should take place. In total there are 4963 say-on-pay frequency proposals in the data and we exclude them from the analysis due to the unique nature of their outcome (one/two/three years). Consistent with the anomalies literature, we also exclude votes for entities that are not US common stocks listed on NYSE, Amex, and NASDAQ.

Around 84.4% of management-sponsored proposals pass while the failure rate is only 0.5%. Resolutions can also be withdrawn before the vote (neither pass or fail). In contrast, the pass rate for shareholder sponsored proposals is only 20.6% with 67% failing to gather the necessary support.

An ideal vote benchmarking method should allow us to make use of votes with very high or low levels of support. This is relevant as most management-sponsored resolutions end up with more than 90% shareholder support (Figure 1). In addition to having high support, management proposals also have a low standard deviation of shareholder support (Table 2). Shareholder sponsored resolutions on the other hand, most frequently end with less than 10% support (Figure 1), and they have up to three times the standard deviation of support rates relative to management-sponsored proposals (Table 2). Support for shareholder proposals has varied between 26% and 45% over the years. Changes in average support rates over time can capture both changes in approval and changes in the incidence of topics with varying average support rates.

Participation rates are high on average for both management and shareholder sponsored resolutions (Figure 1). Moreover, participation rates for shareholder-sponsored proposals have been stable over the years. On the other hand, participation in management-sponsored proposals has decreased extensively since 2010 (Table 2), likely due to increasing restrictions on uninstructed broker voting. Brokers can vote on certain items on behalf of their clients if they have not received voting instructions within 10 days of the vote (allowed by NYSE)[12]. Such 'uninstructed' broker votes are allowed only on 'routine' items. The scope of topics that qualify for uninstructed broker voting has been reduced over time. For example, brokers can no longer vote on adopting majority rules for director elections, providing rights to call a special meeting, eliminating supermajority requirements, etc. Bethel and Gillan (2002) show that broker votes tend to be skewed in favor of management. Therefore, the growing restrictions on uninstructed voting increase the relevance of shareholder views.

Most resolutions cluster around April, May, and June (Figure 2). This is effectively the US 'proxy season'. However, a meaningful proportion of resolutions also occur off-season and throughout the year. Resolutions in special meetings tend to be distributed more evenly across the calendar year.

2.2. *Timeline for annual shareholder meetings*

Share ownership for the purposes of voting is established on the record date (Figure 4). Companies must schedule the record date at most 60 days ahead of the annual shareholder

[12] A 'broker-non-vote' is when brokers did not receive voting instructions from owners and they are not allowed to cast uninstructed votes. Along with abstentions they are sometimes used to determine if a quorum is present.

meeting. SEC Proxy Rules 14a-13 stipulates that companies must also give notice of at least 20 business days to all brokers before the record date.

The mail date is when companies dispatch proxy materials. Companies usually allow 7-14 calendar days between record and mailing date, but they can dispatch material even one business day after the record date. The meeting date must be at least 30 days after the mail date. Companies usually mail 40 to 45 days in advance for non-routine proposals to ensure participations when uninstructed broker votes are unavailable. Corporate bylaws and exchange regulations can add addition restriction on the timeline. ISS provides reports to clients between 13 to 30 calendar days before the meeting.

The rules ensure that proxy materials, which reveal the agenda items to be considered during the upcoming meeting as well as the recommendation of the board of directors, are distributed to shareholders well in advance. Proxy voting, whereby shareowners authorize agents to cast votes on their behalf, is a widespread practice in the US. A broad geographic shareholder base implies that most shareholder will not attend meetings and can only exercise their rights as beneficial owners through proxy voting. The proxy solicitation process taking place before the meetings is therefore crucial for high participation.

Most publicly traded shares in the US are held in 'streets name'. Approximately 85% of exchange-traded shares are held by securities intermediaries (broker-deals and banks) the majority of which are deposited in the Depository Trust Company (DTC)[13]. Usually, this implies that there is no specific share directly associated with the beneficial owner. Nevertheless, when intermediaries such as DTC receive proxy material, they are obligated to pass on the information to beneficial owners reflecting their overall voting rights[14].

Shareholders that hold at least 2000$ worth of securities or 1% of voting stocks (Rule 14a-8) can submit their own proposal 120 calendar days before the anniversary of the date when proxy materials were delivered to shareholders in the previous AGM. The company can omit proposals after this date. Alternatively, when companies wish to exclude shareholder-sponsored proposals based on their content, they often ask the SEC for a 'no-action' letter which indicates that regulatory staff members do not recommend taking legal actions against the company should they exclude the proposal.

[13] Information available on the SEC website (www.sec.gov/spotlight/proxyprocess/proxyvotingbrief.htm)

[14] Double voting can occur when the beneficial owner does not know that his shares have been lent by the broker-custodian; this can result in both the original owner and the share borrower casting a vote (Christoffersen, Getczy, Musto & Reed, 2007).

Information about the occurrence of a meeting, its content, and even the outcome of upcoming resolutions can be approximated well in advance. For example, annual shareholder meetings tend to happen 11 to 13 months after the previous annual shareholder meeting (Figure 8). Moreover, additional relevant information, such as the voting recommendations of management and ISS, is disclosed in advance of meetings. Resultantly, we will also investigate performance in the months leading up to the meeting to obtain a complete picture of the market response.

2.3. *Defining abnormal shareholder support*

How do we determine if shareholders support a proposal? Routine resolutions have high average support rates and will resultantly almost always pass. Consequently, using average support rates or vote outcomes as a measure of shareholder support is comparable to selecting resolution topics. Adopting this approach will always pick resolutions such as 'ratifying auditors' as having the highest level of shareholder support (Table 3). Resultantly, an investment strategy would pick companies that have a large incidence of high support topics as the companies that have large shareholder support. Moreover, simple support rates do not capture how novel information is to markets. If the market anticipated 98% voting support for a resolution to ratify auditors, then we can expect no reaction following the outcome.

To summarize, using plain support rates as a measure of shareholder support will simply select vote topics without bringing 'fresh' information into the analysis. A simple method common in the literature when analyzing voting behavior is to omit 'routine topics' or even management resolutions altogether. This approach results in a needless loss of information. Optimally, we want a measure that takes topic-specific effect into account when determining shareholder support without placing extreme restrictions on the sample. To achieve this objective, we propose the following simple measure of shareholder support:

$$s_{k,i,t} = \frac{V_{k,i,t} - \mu_{j,t-1}}{\sigma_{j,t-1}}$$

Where $s_{k,i,t}$ is shareholder support for vote k, firm i and period t. $V_{k,i,t}$ is the vote support rate, $\mu_{j,t-1}$ is the average vote support level in previous votes on the same topic j (whereby the topics are assigned and classified by ISS) and $\sigma_{j,t-1}$ is the standard deviation of vote support in previous votes on the same topic j.

We construct a recursive benchmark whereby we include all previous votes on the same topic for constructing the average and standard deviation. The recursive benchmark allows us to build a better measure of expected support for infrequent resolutions. In contrast, using a rolling yearly window would exclude most topics that have a limited number of resolutions in an arbitrarily defined time frame. Our goal is to provide a simple measure that maximizes the use of the available data whilst limiting the set of arbitrary choices that the researcher needs to make.

The average and standard deviation measures are lagged to avoid forward-looking bias in the analysis. This is required to make investable strategies and to capture the information available to investors at the time of the vote. We only lose the first month of signal data to make the first topic-specific average. This helps maximize our sample length. Moreover, since we have a topic-specific benchmark, we can use all the eligible resolutions in the sample and therefore obtain more general results.

The measure is intuitive. For a given voting outcome, shareholder support for the resolution is low if: (1) average support rates for the same topic were higher in previous years (effect of μ_{t-1}) and (2) standard deviation of support for votes on the same topic was low (effect of σ_{t-1}).

Although a lot of the proposals have very high support rates, we still want to use this information. If a proposal passes with low support rates relative to past voting on a similar topic, shareholders are less pleased with this firm's corporate policy on this issue. A low standard deviation implies that an outcome strongly deviates from past voting observations and should therefore not be considered 'normal'; that is, the signal is stronger since most similar votes in the past have clustered around the average.

Topics explain around 55% of the variation in voting outcomes (Table 10). We do not use a within firm benchmark as we would be averaging across very different proposal types, some of which persistently attract either very high or low shareholder support. Alternatively, within-firm benchmarking on a specific topic would leave us with too few observations for infrequent proposals and we would end up analyzing only a small subset of resolution types.

The following numerical example illustrates how the measure works. If vote support for an elect director resolution was 70% while the average support rate in previous years for similar votes was 90% with an associated standard deviation of 10%, then shareholder disproval is -2.

$$s_{k,i,t} = \frac{70\% - 90\%}{10\%} = -2$$

For comparison, a vote such as declassifying the board of directors can have a much lower support rate of 55% but if this resolution topic has an average support rate of 80% and a standard deviation of 25%, then shareholder disapproval is -1.

$$s_{k,i,t} = \frac{55\% - 80\%}{25\%} = -1$$

In other words, even though the proposal to declassifying the board of directors has lower support, the outcome is less contentious and surprising than the elect director vote. Intuitively, support of only 70% for director elections can be considered very contentions given a high historical average with little variation across outcomes. Adopting this approach enables us to make extensive use of information in routine votes to capture shareholder approval.

Figure 3 shows the distribution of abnormal shareholder support for management and shareholder sponsored resolutions. Since most management-sponsored resolutions have shareholder support above 90%, the potential for high negative disruptions (extreme disapproval) is larger. This is observable by the skewed distribution of the management-sponsored abnormal shareholder support measure (Figure 3).

2.4. *Average abnormal shareholder support*

Firms tend to have multiple votes during a single shareholder meeting. To construct a single measure of shareholder support per firm-period, we use the firm's average of all the available abnormal shareholder support measures within a period.

$$S_{i,t} = \frac{1}{K}\sum_{k=1}^{K} s_{k,i,t}$$

$S_{i,t}$ is our support rate for firm i in period t and we average across the k abnormal support measures across resolutions in the same month and firm.

By using the full array of resolutions under consideration we get a clearer picture of overall support for corporate policy. In contrast, unaccounted agenda items are a common concern when focusing on a single resolution type. More specifically, markets may be responding to correlated but unaccounted resolutions during the same shareholder meeting. We know that firms can be subject to (vote no) dissent campaigns (Bach & Metzger, 2016). Consequently, low support in one proposal is likely associated with low support across all proposals. Alternatively, high support may be resolution specific and not reflective of general views towards the firm. We avoid this issue by basing our measure of shareholder support on all the voted resolutions.

2.5. *Maximum abnormal shareholder support*

An alternative to averaging abnormal shareholder support across all resolutions is to average across the n votes with the 'maximum' level of absolute abnormal support:

$$S_{i,t} = \frac{1}{3}\sum\nolimits_{1}^{3} s_{i,k,t}$$

where the three resolutions used are the ones with the largest absolute abnormal support. The average approach may play down the outcomes of very high disagreement resolutions by placing the amalgamated outcome around the middle of the shareholder support distribution. On the other hand, high disapproval in a resolution need not reflect an overall negative view of the company. For example, high disagreement on a resolution may signal dissatisfaction with the election of a specific director rather than general displeasure with corporate policy. We will use the 'maximum' measure as a robustness check whilst keeping in mind that it can capture a different feature of shareholder support.

2.6. Rebalancing frequency and signal fading

The baseline shareholder support strategy is rebalanced monthly using a one-month fading signal. A one-month fading signal implies that firms with vote information can remain in a portfolio for one-month following the creation of the signal. A strategy in the literature that uses a similar signal fading and rebalancing is short term reversal (Jegadeesh, 1990; Da, Liu & Schaumbaug, 2013).

Reasoning more generally, the optimal frequency should depend on the horizon at which we expect markets to incorporate information. As voting is a corporate event, we can expect the pricing consequences of events to be incorporate 'quickly'. With this perspective in mind, the use of a one-month fading signal can be considered as 'long term' pricing consequences relative to event studies which focus on performance in the days around the event. Nevertheless, the strategy can be considered high frequency investing relative to anomalies that rely on financial statement information with annual rebalancing. We also investigate potential long-run effects by iterating the signal fading frequency.

Companies are required to disclose vote outcomes within four business days of the meeting by filling Form 8-K (the form is used to notify shareholders of relevant events). Typically, it is revealed during the meeting if a vote has passed the approval threshold. Preliminary support rates are also often disclosed during the meeting as significant proportion of votes tend to be cast in advance of the meetings. In other words, there is no significant lag between the vote outcome and its availability to investors and the public. Therefore, assuming voting results are known to the public at the end of the month cannot be expected to induce meaningful forward-looking bias in the abnormal support signal. As a robustness check, we also investigate the performance of the strategy if we include only firms with a meeting in the first half of the month. With this approach, we assume that voting information is available to investors at least 15 days after the day of the meeting.

2.7. Anomaly construction

At the end of each month, we rank securities based on the abnormal shareholder support signal and we construct ten value-weighted decile portfolios with NYSE breakpoints (equal number of NYSE firms across portfolios) as a baseline strategy. Value weights are more appropriate for making tradable portfolios with low transaction costs (Novy-Marx & Velikov, 2015) and short selling fees (Bekjarovski, 2018). We also investigate how performance is affected by restrictions on the universe based on firm size.

First, we do a univariate sort on abnormal shareholder support in the full sample. Firms with the highest average abnormal shareholder support across resolutions and meetings enter the top decile and firms with the lowest are placed in the bottom decile. We then analyze the properties of the top and bottom portfolios as well as the long-short strategy. As a robustness check, we split the universe into shareholder-sponsored and management-sponsored proposals and reconstruct the average abnormal shareholder support signal. Moreover, we check if the pricing pattern changes across different meeting types.

3. Abnormal Shareholder Support Anomaly

3.1. Performance of baseline strategy

The baseline strategy has a large and significant negative alpha in the low abnormal shareholder support portfolio. The alpha relative to the five factor Fama-French model augmented with momentum is -1.08% monthly with an associated t-statistic of 3.28. A long-short annual alpha of 14.4% is large relative to other well-known asset pricing anomalies. The magnitude of model mispricing makes statistical significance possible even in a short sample.

The abnormal shareholder support anomaly is negatively related to the value and momentum premium; nevertheless, the statistical significance of alpha is not extensively affected by the benchmarking method.

The effect of abnormal shareholder support is asymmetric with a one-month signal-fading frequency. Most of the profitability is concentrated on the short side. Moreover, the relationship between risk-adjusted performance and abnormal voting support is not monotonic. Nevertheless, alphas for portfolios in the middle are mostly insignificant across benchmarking methods. Moreover, some of the performance spikes for in-between portfolios disappear as we account for firm size. The absence of a monotonic relationship is more consistent with behavioral explanations than rational linear asset pricing models.

3.2. Firm sizes and standard error robustness checks

Excluding stocks below the market capitalization median does not significantly alter the conclusions (Table 6). It seems that most of the model mispricing found in the baseline shareholder support anomaly is in large market capitalization securities. This is relevant as small stocks tend to have very higher short selling costs while large stocks tend to be on general collateral (cheap to short) (Bekjarovski, 2018).

Accounting for heteroskedasticity and autocorrelation using Newey-West standard errors does not meaningfully impact the results. Alternatively, removing early sample years (2004 and 2005 for example) to have a better historical benchmark also does not meaningfully impact the results (not reported).

3.3. Subsamples based on meeting type and resolution sponsor

Using the abnormal shareholder support signal only from the annual shareholder meeting still yields economically and statistically significant findings (Table 7). This implies that the conclusions are not exclusively driven by special meetings and proxy contests; although they evidently contribute to the relevance of the baseline anomaly.

Using signals from meetings only in the first part of the month (first 15 days) yields an economically stronger result. This suggests that the findings are not driven by forward-looking bias as this approach assumes that each signal is available at least half a month after the meeting.

3.4. Signal fading and the maximum aggregation measure

Signal fading refers to how long stocks are eligible for portfolio assignment after the vote. Using a two-month fading signal has two effects. On the one hand, it reduces the alpha of the high shareholder support portfolio. On the other hand, it raises the alpha of the low shareholder support portfolio. The two effects partly cancel out and the long-short strategy is still economically and statistically significant (Table 5). Overall, the results show that the effect is robust to the anomaly construction method. Model mispricing disappears with a six-month fading signal for large firms. This is consistent with the idea that voting information is incorporated 'quickly' after the vote.

Table 5 also shows alphas if we combine multiple disagreement votes for the same firm in the same period using the average of the three most extreme abnormal vote outcomes. Using this measure, we still find large and significant model mispricing. The effect is particularly strong with two-month signal fading whereby the long short alpha is 1.40% monthly with a t-statistic of 3.96.

Using the absolute value of only the extreme abnormal shareholder support resolution within a firm-period as a signal does not work (not reported). We need to incorporate at least a few voting outcomes in constructing the abnormal shareholder support measure. This is consistent with the idea that the alpha is not associated with resolution specific outcomes.

3.5. Abnormal shareholder support before meetings

To the extent that market participants are anticipating the outcome of shareholder votes, by revising their estimates based on ISS and management recommendation, we can expect enterprises with high support to experience price appreciation ex-ante. The intuition suggests increases in firm value before voting dates with the strongest effect for firms with high approval.

Table 8 shows the alpha of portfolios sorted on shareholder support across time. The months before the vote tend to be associated with significant alphas. As expected, alphas are strongest for firms that are about to experience positive abnormal shareholder support during the upcoming corporate meeting. The effect reverses after the vote for large firms, with high support stocks experiencing negative alpha and low support stocks experiencing positive alpha. It is important to note that sorts of abnormal shareholder support before the meeting rely on information revealed during the vote and are resultantly not tradable in the months prior to the vote. Nevertheless, the result can help us understand the overall pricing reaction around voting dates. We find that in the three months preceding the meeting, firms with high shareholder support have positive alphas. The effect is most pronounced for large firms (Figure 5) and disappears in periods further from the vote.

3.6. Relevant stakeholders

Table 9 shows the relevant participants in the voting process. 'Agreement' occurs when all stakeholders are in either support or disapproval of a resolution. When management is against a proposal, but ISS and shareholders are for, we define such an outcome as 'Dissent'. If both shareholders and ISS are on the same side, they can challenge management and provide both discipline and monitoring through the voting mechanism. When shareholders go against the recommendations of the board and ISS we define such an outcome as 'Disagreement'. This is the strongest form of shareholder disapproval of corporate policies. When ISS is against a proposal, but shareholders and management are for, we define such an outcome as 'ISS Dissent'. This outcome implies that ISS was not able to sway the opinions of shareholders. ISS often consults their largest clients, such as large asset owners, before issuing recommendations. Therefore, to the extent their recommendation contains the opinion of large institutional clients, ISS dissent can be viewed as the disagreement between large and small shareholders.

The intuition of the definitions is not dependent on the sponsor. Shareholders can vote in support of a shareholder-sponsored proposal when management and ISS recommend voting against. Alternatively, they can vote against a management-sponsored proposal when management and ISS are recommending support. Both outcomes capture disagreement.

Table 10 provides some evidence on the impact of management and ISS recommendations on shareholder support (we include only resolutions with valid shareholder support data). Consistent with intuition, we find that positive recommendations are correlated with higher support. Voting recommendations happen before the vote. Nevertheless, claiming causation here is difficult as the recommendations themselves can be influenced by forecasted shareholder support. However, the results suggest that votes that receive positive recommendations will tend to end up with higher abnormal support while votes that receive negative recommendations will end up in the lower abnormal support portfolios. In other words, recommendations can be predictive of shareholder support. In the next section, we discuss how performance is affected if we incorporate recommendations in the vote benchmarking method for the shareholder support premium.

3.7. Sophisticated forecasts of shareholder support

Variables which are not utilized in the forecast will affect the firm's abnormal shareholder support signal. For example, if both ISS and management are against a resolution, we can expect low abnormal shareholder support relative to the topic benchmark (Table 10). In other words, unaccounted variables, such as the management and ISS recommendations, will determine which votes end up being classified as high or low shareholder support.

Relying on topics as a benchmark produces a robust return predictor. Nevertheless, it is interesting to examine if performance can be improved if we use more information in the formation of an expected voting outcome. For example, an alternative method of constructing abnormal shareholder support ($s_{k,i,t}$) is to define it as the deviation of vote support from a regression-derived prediction:

$$s_{k,i,t} = V_{k,i,t} - E[V_{k,i,t}]$$

Relative to the topic average, the regression gives more freedom in choosing predictors. Moreover, since the panel regression uses additional information in forming the forecast, we can expect it will lead to more accurate predictions of vote outcomes. On the downside, the regression approach needs a longer sample to estimate the initial coefficients which reduces the length of the time-series. In a sense, we can also think about the historical topic average as a monthly rolling panel regression with topic dummies as predictors.

Sophisticated methods for forecasting vote outcomes can potentially lead to enhanced investment results. An important point to consider is the extent to which market participants are using the additional variables in forming their forecast. The abnormal shareholder support measure is trying to capture the response of market participants to 'abnormal voting outcomes'. The task of the model is not to make the perfect prediction. The task of the model is to give an indication of what market participants find abnormal. Resultantly, a more accurate model need not be closer to the objective of capturing market expectations of voting outcomes. If market participants are not utilizing a sophisticated model, then they may find an outcome abnormal while the model classifies it as ordinary given forecasting information. In other words, the model would 'properly' forecast the outcome and not place it in the extreme portfolios.

For example, if the low shareholder support is exclusively driven by a negative ISS recommendation, and if the market is not using this information when forming the vote forecast, then market participants will be surprised by the vote outcome and will resultantly reassess firm valuation. If the forecasting model of the econometricians includes ISS recommendations as a predictor, then the vote outcome would be classified as normal and will not be placed in the investable extreme portfolios. Consequently, it is not clear a-priori whether forecast accuracy will result in improved strategy profitability. In this section, we proceed to test the way improved forecasts of voting outcomes affect the profitability of strategies.

In our analysis, we amalgamate the ISS recommendations 'withhold', 'do not vote', 'none', 'abstain', and 'against' and treat them as negative ISS signals in the analysis ('refer' is omitted as its meaning is ambiguous). The same assumption is made for management recommendations. Once we obtain the residuals from the in-sample vote forecasting regressions, specifications 1 and 2 shown in Table 10, we average them within a firm-month. We then use the average abnormal residual to form univariate value-weighted quintile portfolios with monthly rebalancing. The alphas and t-statistics of the portfolios sorted on the residual of shareholder support are shown in Table 11. Overall, the alphas are comparable to the alphas in the sorts using a simple rolling topic benchmark. High abnormal support leads to positive alphas before the vote and negative alphas after the vote. Alphas in the period after the vote for the high support portfolio are negative and statistically significant if we use either topics or topics and recommendations as predictors. Sophisticated in-sample forecasts of voting outcomes seem not to improve strategy profitability. Switching to decile sorts does not alter this conclusion.

4. The voting period anomaly

4.1. The within firm time-series

The literature has documented a general tendency across investigations to find significant abnormal returns around recurring predictable events such as earnings and dividend announcements. Hartzmark, Solomon and Soltes (2016) advocate for comprehensive investigation of anomalies that rely on the within-firm time-series. They show that most of the predictable event anomalies are evident in value-weighted portfolios and occur on the long side. For example, Hartzmar and Solomon (2013) find a dividend month premium while Barber, George, Lehavy, and Trueman (2013) document an earnings announcement premium in multiple countries across the world. Similarly, Heston and Sadaka (2006) find seasonality in the cross-section of stock returns whereby stocks that outperform in a particular month continue to do so in the same month the following year.

Evidence that returns are not equivalent throughout the calendar year is not exclusive to the cross-section of stocks. Ai and Bansal (2018) show that stock returns around scheduled market announcements, such as employment reports or Federal Open Market Committee statements, capture 55% of the equity premium. They argue that announcements carry information about prospects of future economic growth and are consequently the periods in which the equity premium gets realized. Similarly, Lucca and Moench (2015) document large excess returns for stocks in the period around monetary policy decisions.

In the following sections, we document the voting period premium by showing that the incidence of a predictable event, such as shareholder meetings, is associated with positive risk-adjusted returns regardless of the voting outcomes. The findings are analogous to the investigations to Ai and Bansal (2018) as well as Lucca and Moench (2015), who find a connection between the equity premium and macroeconomic announcements, and our results whereby we document that a significant proportion of returns at the firm level is earned in the period surrounding shareholder meetings.

4.2. Shareholder meetings and valuation

Since the voting period premium is a long-only strategy that does not require short-selling, we can investigate alphas for both the value-weighted and equally weighted portfolios of stocks that experience a shareholder meeting in period t (Table 12). The value-weighted portfolio has a significant positive alpha in the month of the vote. Moreover, there seem to be positive alphas leading up to the meeting (with only t-3 being statistically significant). The pattern reverses after the vote with negative, albeit not statistically significant, alphas.

Equally weighted portfolios have a stronger positive effect. The alphas leading up to the shareholder meeting are economically larger relative to the value-weighted case. For example, the FF + Momentum alpha for an equally weighted portfolio of firms with a shareholder meeting in two months is 0.89% monthly with a t-statistic of 5.69. The positive alpha for equally weighted portfolios remains positive even after the meeting (with only t+3 being statistically significant). The results are not extensively affected by the benchmarking method.

4.3. Fama-MacBeth regressions

Table 13 shows the Fama-MacBeth regressions of stock returns on the voting period dummies. Consistent with the portfolio results, we find a voting premium in the month of the vote and the months preceding the vote (column 1 Table 13). The results are economically and statistically significant.

We also replicate an array of controls form the literature for the full sample covering the period from 07/1963 to 12/2016 (column 2 Table 13). The full sample replication results are in line with the original studies. However, the predictors from the literature are not statistically significant in the restricted sample for which there is voting data (column 3 Table 13). A drop is significance is somewhat expected given that we reduce the number of sample years from 53 to 13 and the number of firms from 8285 to 5921. The important thing to note is that when we control for well-known return predictors, the voting premium becomes even stronger (column 4 Table 13). Including all firms in CRSP/Compustat increases the significance of the voting dummies (not reported). In this case, the comparison sample includes firms that do not have voting data.

The regression in column 5 Table 13 splits the sample into AGM, special meetings (3107 in total) and proxy contests (309 in total). Returns in the month of the vote are only statistically significant in annual general meetings. Interestingly, special meetings and proxy contests have a particularly strong performance before the meeting. As special meetings are evenly distributed across the calendar year, the results are unlikely to capture a seasonal pattern, such as the January effect (Rozeff and Kinney, 1976; Bouman & Jacobsen, 2002). Contrary to AGM, firms with a proxy contest or a special meeting have s particularly poor average performance in the months after the vote.

Premiums such as size, which are significant even in the restricted sample, are subsumed when we control for the meeting type. This implies that part of the size premium is captured by the strong positive returns of small firms in the period running up to special meeting and proxy contests.

4.4. *Anomaly independence and the equity premium*

Time-series regressions reveal that the shareholder support and voting period premium are independent (Table 14). This is consistent with intuition as the two strategies select stocks in different time periods. More specifically, the voting period premium selects all stocks in the month of the vote and the shareholder support premium selects a subset of those stocks in the month following the vote. Interestingly, the excess return of the voting period premium is considerably larger than its alpha as well as the excess return for the value-weighted portfolio of securities (Table 14).

The time-series regressions reveal that the equity premium has a negative alpha when regressed on the voting period premium. The fact that the intercept for the equity premium becomes negative when we control for the voting period premium is in fact intuitive. The equity premium selects all securities in the universe and the voting period premium selects all stocks that have a shareholder meeting (see more on sample selection bias in section 5.2). Firms are required to have at least one annual shareholder meeting. Consequently, higher than average returns in the month of the vote imply lower than average returns in other periods. This reasoning is consistent with theories arguing that the risk-reward trade-off is not constant but concentrated in periods when uncertainty gets resolved.

4.5. *Proxy season and mixed strategy*

Table 14 shows time-series regressions for the mixed voting period and shareholder support premium strategy whereby we also include a dummy variable for the proxy season. The dummy variable takes the value 1 in April, May, and June. Alphas outside of proxy seasons are still economically large and statistically significant. Proxy season alphas can be obtained as the sum of the intercept and the season dummy coeffect and they are much smaller across strategies. This is supportive of attention narratives as off-season meetings face less competition for the spotlight. Nevertheless, given the short sample, we cannot reject the null hypothesis that alphas in the two periods are equivalent.

Finally, we construct a mixed tradable strategy that goes long firms that will have a shareholder meeting next month and short firms that had high abnormal shareholder support in the previous month. The information to construct these strategies is theoretically available to investors in real time. The mixed strategy has an off-season monthly alpha of 1.86% with a t-statistic 4.61. Again, we observe that proxy season alphas are economically smaller, but the coefficient is not statistically significant.

5. Theory

5.1. The rational-behavioral debate

The rational-behavioral debate is not readily testable without eliciting the preferences and valuation process of the representative investor. In other words, market data cannot definitively discriminate if model mispricing is compensation for an unaccounted time-varying risk or the result of irrational investor behavior. Keeping this limitation in mind, shareholder meetings and abnormal shareholder support seem to provide independent return forecasting information and we discuss the extent to which various explanation can account for this pricing pattern.

5.2. Sample selection and survivorship bias

A potential concern is sample selection during data collection. If the data provider is collecting voting information only on surviving firms, then we will end up with a biased sample of outperforming firms when constructing the voting anomalies. To rule out sample selection during data collection, we investigate the performance of firms that have voting data relative to the standard anomaly investment universe. We construct a value-weighted portfolio of all securities that have at least one meeting in the ISS database and we regress it on a value-weighted portfolio of US common stocks in the CRSP/Compustat universe. We subtract the risk-free rate from both long-only portfolios for the regression. The intercept, slope, and t-statistics (in brackets) from the time-series regression are reported below:

$$R_{+votedata} = \underset{(4.51)}{0.00021} + \underset{(794)}{0.99} R_{universe}$$

The test has a lot of power since the two portfolios have extensive overlap (R2 is high, beta almost 1) so the high significance is expected, but a monthly alpha of 0.021% is not economically meaningful (especially in comparison to the alphas of the anomalies). The result suggests that the data provider has not been systematically omitting historically unsuccessful firms during the vote collection procedure.

Another noteworthy concern is that the abnormal shareholder support anomaly simply selects stocks with positive idiosyncratic news before the shareholder meeting. These stocks have higher returns due to chance. The high returns induce abnormal voting support. However, this mechanical explanation cannot account for the reversal pattern. An arbitrary sample of successful firms would not experience a systematic reversal in the month after the vote following multiple months of positive performance.

We also run a simulation to ensure that the alphas three months before the vote are not driven by survivorship bias. Intuitively, investing in firms that will have a shareholder meeting three months in the future implies forward-looking bias whereby the algorithm knows which entities will continue to exist. All investigation of pre-event performance can bias return estimates upwards as the strategy has knowledge which firms will not go bankrupt in the near future. It is usually implicitly assumed in empirical work that this bias is negligible. We confirm this with a simple simulation.

We assign a pseudo meeting for 10% of the firms in the 2003-2016 period and we lag this signal three months. Consequently, the placebo strategy invests in an arbitrary sample of firms that will not go bankrupt in the following three months. We repeat the simulation 1000 times and collect the times series alphas from regressions of the value-weighted placebo strategy on the market benchmark to examine the strength of the bias. Figure 6 plots the distribution of t-stats. The average alpha in the simulation is 0.01% percent annually and it represents a tiny fraction of the voting period alphas. Naturally, the bias will be even smaller if we move closer to the month of the vote.

5.3. Strategic information disclosure

The abnormal shareholder support anomaly is consistent with strategic information disclosure by management. Intuitively, management has incentives to disclose positive information before meetings in order to avoid dissenting shareholder resolutions and votes (Dimitrov and Jain, 2011). Using analogous reasoning, management has incentives to delay disclosing negative information until after the meeting. This type of asymmetric information release should lead to positive stock market performance of firms before the meeting. We can also expect negative information to be released after the vote with additional negative information for firms with high shareholder support. Intuitively, the higher the support the more likely that management did not release negative information beforehand and the more leeway management has with shareholders. The hypothesis is broadly consistent with the data. We find positive alphas before meetings that are larger for firms with high abnormal shareholder support. Moreover, we find that after the meeting, firms with high abnormal shareholder support experience the biggest drop in performance.

To further investigate this hypothesis, we recreate the abnormal shareholder support anomaly using only outcomes in management and shareholder sponsored resolutions; that is, the abnormal shareholder support signal for the subsamples assumes that a meeting only has management (shareholder) resolutions and constructs abnormal support by ignoring outcomes in shareholder (management) resolutions. This approach yields fewer signals and we, therefore, construct tercile portfolios for the shareholder-sponsored portfolio. Moreover, the approach suffers from 'omitted resolutions' concerns given that only a subset of resolutions is considered when constructing the signal. Nevertheless, the approach allows us to examine if there are differences in pricing patterns across the subsamples. If management is strategically disclosing voting information to gain approval, we should notice a positive price response for both firms with high support in management-sponsored resolutions and low support for shareholder-sponsored resolutions (given that a large fraction of shareholder-sponsored resolutions receives negative voting recommendations from the board).

The intuition of the strategic information disclosure hypothesis is supported by the data (Table 17). Management-sponsored resolutions receive positive alphas for the high support portfolio in the period running up to the meeting and negative alphas in the period after the meeting which is consistent with positive news disclosure by management. In contrast, the firms with high support in shareholder-sponsored resolutions have much smaller alphas in the period running up to the meeting.

5.4. Investor attention and divergence of opinions

An alternative behavioral explanation is that shareholder meetings grab investor attention. In the presence of heterogeneous agents and short selling frictions (Miller, 1977), we can expect prices to reflect the views of more optimistic investors as negative views are not incorporated into prices. Even if the average price by all investors is 'correct', investor attention, in combination with short selling frictions, implies that the view of the most optimistic investors will be incorporated into prices. Investor attention is central to the explanation as it expands the set of investors for which the most optimistic valuation will be incorporated. In addition to the price response, we also know that stocks that are in the news will have high trading volume (Barber and Odean, 2007). To the extent that firms with a meeting are more likely to be in the spotlight, especially in proxy fights and special meetings with M&A activity, we can expect a similar pattern in returns and trading volume.

Divergence of opinion can have the same effect as investor attention. Diverging views in the presence of short selling restrictions will raise prices as the view of more optimistic investors will be incorporated. In addition, the greater the disagreement among traders the larger the level of the trading volume; that is, high trading volume implies disagreement between heterogeneous investors (Kim & Verrecchia, 1997).

Both explanations can account for the positive returns before and during shareholder meetings as investors focus on and disagree about the agenda items and voting outcomes. They are also consistent with the finding that performance preceding shareholder meetings is stronger for small firms which are known to have high short selling costs (Bekjarovski, 2018). Higher short selling costs imply additional difficulty for investors to express pessimistic views. This implies that small firms will experience larger price appreciation in the presence of investor heterogeneity and increased attention which is consistent with the result that the voting period premium is stronger in equally weighted portfolios.

5.5. Trading volume

To further examine the validity of the various theories, we investigate trading volume around corporate votes. We define trading volume as shares traded divided by shares outstanding (we use CRSP/Compustat for constructing our measure). Panel A of Table 15 compares the average trading volume around voting dates only for companies that have a vote in month T. Panel B and Panel C show full sample regressions of trading volume on dummy variables capturing abnormal shareholder support. There are four main takeaways.

First, based only on a sample of stocks that have a voting event at T, we see that average trading activity peaks in the month of the vote relative to months surrounding the vote (Table 15, Panel A). Second, lower abnormal shareholder support is associated with higher trading activity (Table 15, Panel B). Third, high trading activity is not specific to the voting month, but it is also higher in the three months before and after the vote (Table 15, Panel C). The lead and lag dummies suggest that trading activity is higher than the sample average for an extended period surrounding the vote[15]. Forth, trading activity is highest for special meetings and proxy contests which are more contentious.

The investor attention (and divergence of opinion) explanation for the voting period premium is in line with the trading volume results. Shareholder meetings are associated with an increase in trading volume. Moreover, special meetings and proxy contests, which are arguably associated with the greatest divergence of opinions and investor attention, tend to produce the strongest pricing pattern for the voting period anomaly. An alternative rational explanation is that high trading volume is indicative of noise trader risk for which risk-averse investor demand a premium (Hong & Yu, 2006).

Contrary to the abnormal support anomaly, we find that low abnormal support stocks have higher trading volume. According to the attention hypothesis, low support stocks should have

[15] The higher before period trading can be associated with share recall by asset managers that are interested in voting; this channel forces short sellers to close their positions which increases trading volume.

higher (and not lower) returns relative to high support stocks. Consequently, the investor attention and divergence of opinion theories do not fit the abnormal shareholder support anomaly well. Moreover, they cannot explain the post-meeting results such as the reversal pattern for high abnormal support firms and the fact that trading volume is still larger in the months following the meeting. A potential explanation for the persistent increase in trading volume after the meeting is given by Kim and Verrecvhia (1991) who hypothesize both higher pre-event trading on private information and higher post-event trading as event outcomes change trader's beliefs.

5.6. Demand effect

Active owners interested in influencing firm votes or taking over the firm will seek to increase their share ownership before shareholder meetings. In the presence of slow-moving capital (Duffie, 2010), the extra demand can create temporary price distortions. For example, in an extreme process known as empty voting, investors can obtain significant voting rights by purchasing shares whilst simultaneously reducing price exposure through offsetting trades in the derivative market (Hu & Black, 2006).[16] Such a process can create significant price distorting effects around shareholder meetings. Alternatively, if funds that hold voting stocks outperform in early months preceding the shareholder meeting, then fund inflows, which are persistent and follow good performance, will cause funds to increase their positions in existing stocks and therefore further push prices (Coval, & Stafford, 2007). Resultantly, good performance in the early months preceding the meeting (example at month t-3) would be followed by good performance in later months (example at t=0) due to the price pressure induced by fund flows. Either empty voting, fund flow persistence or active ownership can induce a demand effect consistent with the voting period premium.

[16] This can potentially induce investors to vote in a manner that is not consistent with corporate interests and markedly different from the behavior of investors that are exposed to the price risk of bad decisions.

5.7. Agency costs and management response

If expressing preferences or sending a signal (to management and markets) through voting has value, then the prices of stocks in the voting period should increase. In other words, the predictions of agency theory are consistent with the voting premium in the period preceding the shareholder meeting. The effect of shareholder support on valuation through the prism of agency theory is ambiguous.

On the one hand, low shareholder support can be a source of new negative information that points out high agency costs and extensive shareholder disapproval of corporate decision making. If this were the case, we would expect poor stock market performance. of reprimanded firms. On the other hand, low shareholder support can induce a positive stock price response if the pressure of shareholders motivates management to take value increasing actions (even though a winning vote by shareholders is not necessarily legally binding). Similarly, high shareholder approval can be a positive signal insofar as it suggests alignment between corporate policy and shareholder preferences. Alternatively, it can be taken as a negative signal if it implies that management is given too much leeway. In other words, the price response to shareholder support depends on the effect it has on management and the extent to which it conveys new information to markets with regards to agency costs.

5.8. Errors in expectations

Eades, Hess, and Kim (1985) propose underestimation of the probability of positive outcomes as an explanation for the high returns around dividend announcements. The explanation can be extended to the anomalous returns associated with the voting anomalies by arguing that investors have biased expectations with regards to shareholder support, shareholder meetings, strategic disclosure by management, demand effects or the effects of investor attention on valuation. When information gets revealed, investors get 'surprised' and update their beliefs. For example, investors can be surprised by the positive news disclosed by management before meetings. This causes a positive price response. The bias comes from the fact that investors did not properly anticipate the general pricing pattern whereby more good news is strategically disclosed before shareholder meetings. The consistency in 'surprises' leads to consistency in price behavior. The biggest challenge is that errors in expectation explanations are easily amendable to explain any pricing pattern ex-post.

5.9. *Time-varying risk loadings and premiums*

The voting anomalies are incompatible with static risk models. Intuitively, firm-specific events should not affect a stock's expected returns in static models as they are unrelated to betas or risk premiums by construction. Consequently, a rational explanation to the voting anomalies must rely either on time-varying quantity of risk or a time-varying price of risk.

A potential rational explanation is that firms in anomalous portfolios are riskier as the firm's betas to unobserved factors with a positive premium are time-varying and higher in the investigated periods of outperformance. A narrative along these lines could claim that firms with high approval votes have negative alphas because their betas change in the month following the vote and are therefore not representative of their full sample counterparts.

In general, however, high-frequency anomalies are more difficult to reconcile with rational explanations as they require risk to change rapidly; in our case, it would need to change on a monthly frequency. For example, high shareholder support firms would need to have higher betas before and during the meeting to justify their high returns. Then their beta would have to immediately drop after the meeting to justify their anomalously low returns. The betas estimated for a portfolio of voting firms over time (Table 16) suggests only modest variation in betas to observed factors.

Alternatively, betas could be constant, but the premiums associated with a given quantity of risk can change through time. This form of argument was initially made by Robichek & Mayers (1966) and the trading of financial claims to cargo ships with an uncertain outcome and known date of arrival. Intuitively, the risk of the voyage is concentrated in the period when the ship is expected to return. At that moment, cash flow uncertainty is reduced. Intuitively, risk per unit of time need not be constant and can increase in periods when extensive new information gets released. If this risk is not diversifiable, risk-averse investors would require higher expected returns around information events. Kalay and Loewenstein (1985) find abnormal returns around dividend announcements and interpret the results as supportive of the idea that expected returns can increase around predictable events with high information content. The stock market also has much higher returns on days in which macroeconomic announcements are made (Savor & Wilson, 2013). Similarly, firms scheduled to report quarterly earnings have an abnormal annualized alpha (Beaver, 1968; Lamont & Frazzini, 2007; Savor & Wilson, 2016). Savor and Wilson (2016) argue that covariance between firm-specific and market cash flow news is higher around announcements which makes these firms riskier.

If announcements are expected and the risk associated with announcements is not diversifiable, then rational (mean-variance) investors should demand a premium for bearing announcement risk

(Cohen, Dey, Lys, & Sunder, 2007). Shareholder meetings are a predictable corporate event in which relevant information is released in markets. However, for the systematic announcement risk hypothesis to hold, this risk should not be diversifiable. This is harder to prove as the number of announcing firms can be small relative to the investment universe. For example, Cohen, Dey, Lys, and Sunder (2007) show that the risk associated with earnings announcements is diversifiable. The standard deviation of the portfolio of firms in the month of the vote is also quite small relative to periods before and after the vote (Table 16). Moreover, the voting anomalies tend to have negative betas across factors. Consequently, an increase in the price of risk should make them even more anomalous.

The market beta of a portfolio of firms that have a shareholder meeting is the smallest relative to the beta in the months preceding and after the vote (Table 16). Similarly, the portfolio of firms that have a shareholder meeting has the lowest standard deviation of returns. Betas and standard deviations suggest that firms are least 'risky' in the month when they vote. The results do suggest that there is some variation to betas to observable factors (Figure 9 appendix), potentially giving rise to concerns that the beta to an omitted factor is also time-varying to an extent that it annuls anomaly alphas. While no anomaly paper can definitively exclude risk explanations, the structure of the voting anomalies makes a rational explanation excessively convoluted, and in our view, unlikely.

6. Conclusion

We uncover two noteworthy price patterns. First, firms with a shareholder meeting have positive alphas in the month of the meeting as well as the months preceding the meeting. Second, firms with high abnormal shareholder support have negative alphas in the month after the vote. The attention hypothesis and divergence of opinions theories show the most promise in explaining the voting period premium while strategic information disclosure seems to be the most consistent with the abnormal shareholder support anomaly.

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Figures

Figure 1. Shareholder Support and Participation. The figure shows the distribution of shareholder support and participation for management and shareholder sponsored resolutions. Support is defined as the number of votes in support of a proposal divided by the vote specific denominator as base. Voter participation is defined as the sum of votes in support and against a proposal relative to shares outstanding.

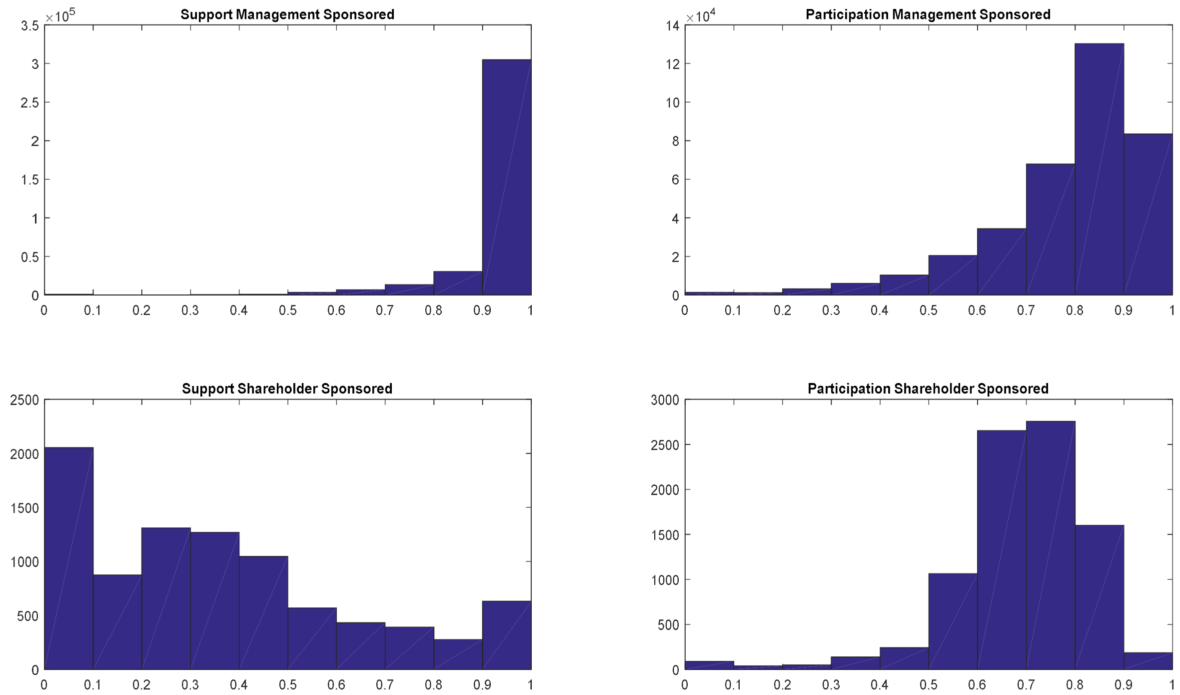


Figure 2. US Proxy Season. This figure shows the distribution of resolutions throughout the year in annual meetings (left-hand axis), proxy contest, and special shareholder meetings. Resolutions from annual meetings and proxy contests cluster around April, May, and June. Resolutions from special meetings are more evenly distributed throughout the calendar year.

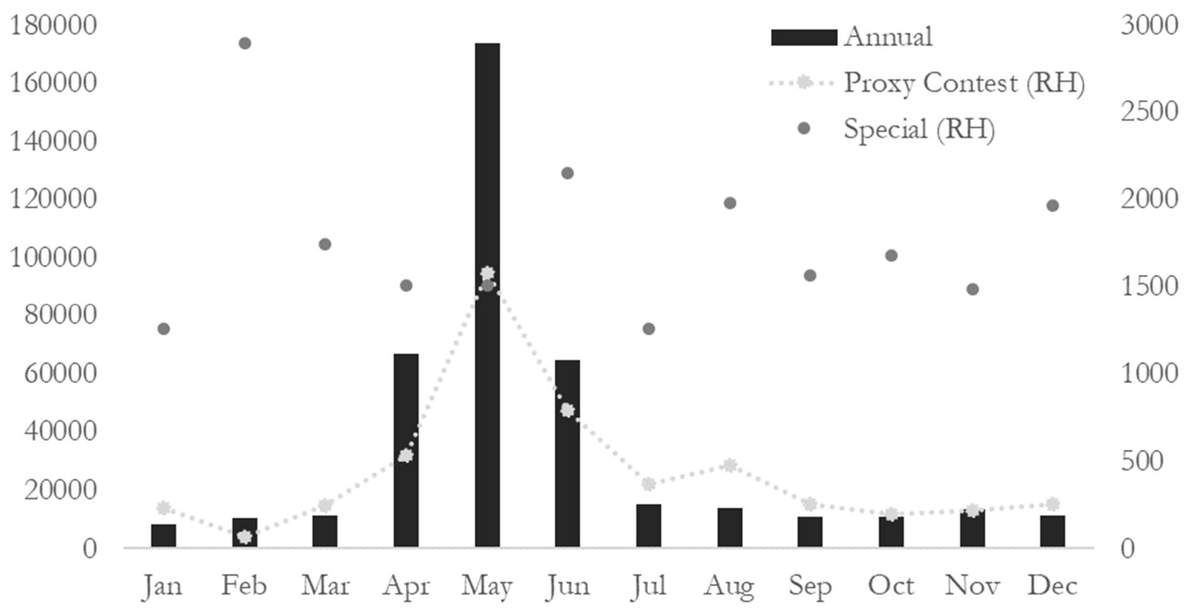


Figure 3. Abnormal shareholder support. This figure displays the full sample pooled distribution of the abnormal shareholder support signal for management and shareholder sponsored resolutions. Shareholder support is the number of votes in support of a proposal relative to the vote specific denominator as base. The abnormal shareholder support signal is constructed as the firm-period average of the difference between shareholder support and a topic-specific benchmark divided by the standard deviation of voting outcomes for the same topic. The signal is winsorized in the figure at 10 for visualization.

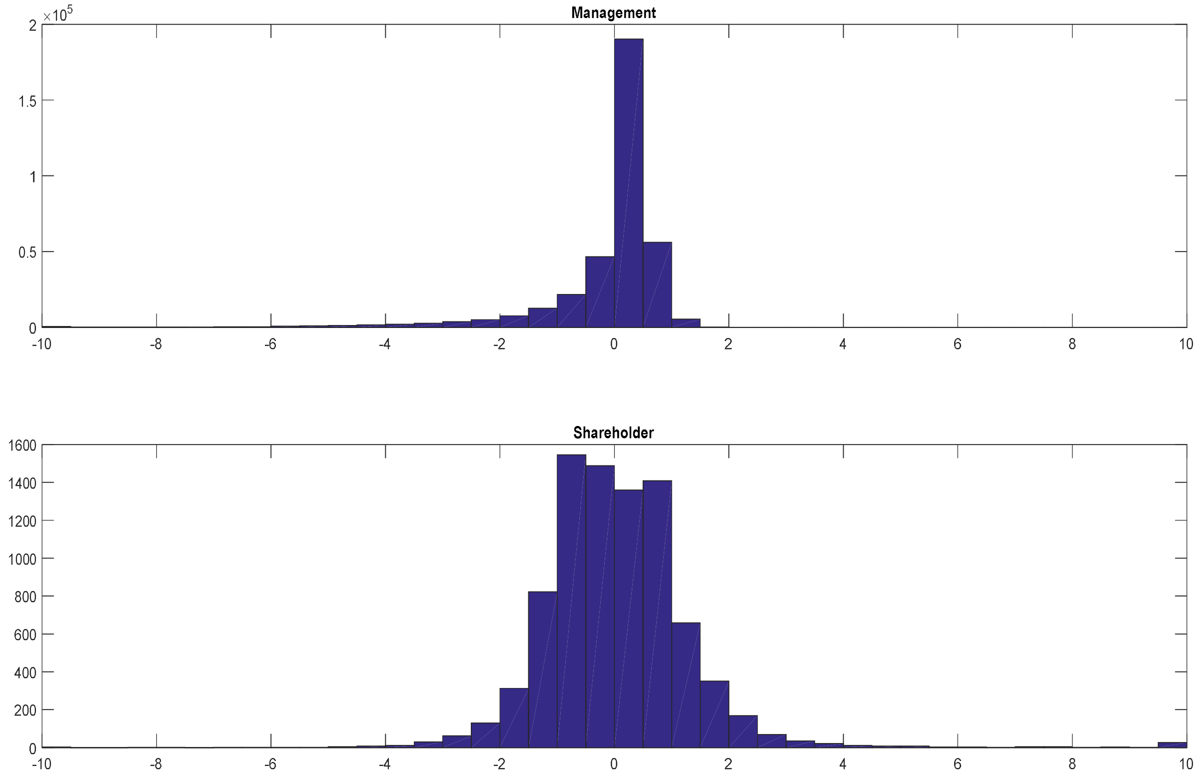


Figure 4. Timeline. This figure gives an example of a timeline for an annual US shareholder meeting. Shareholders are required to submit proposals at least 120 days before the anniversary of the date at which proxy materials were mailed to shareholders. Companies are required to: (1) inform brokers at least 20 days before the record date, (2) mail proxy materials to shareholders at least 30 days before the meeting date, (3) set the record date at most 60 days before the meeting date, and (4) disclose results within four business days. Additional time restrictions can apply depending on corporate bylaws and exchange requirements.

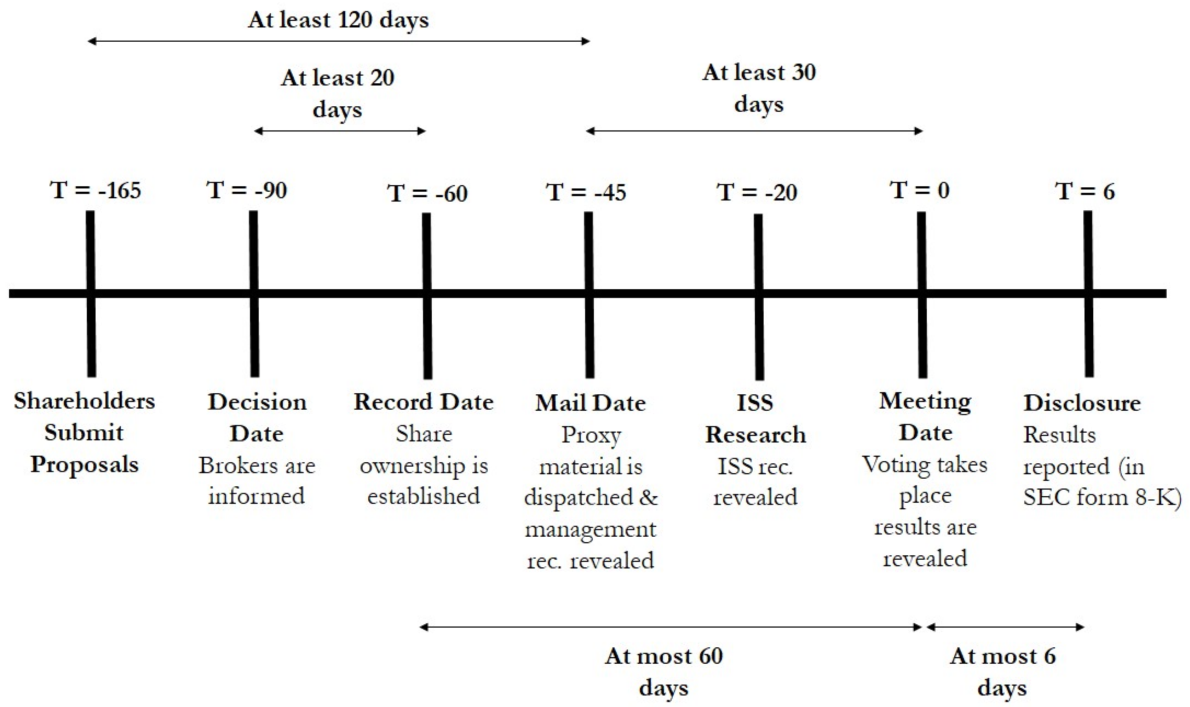


Figure 5. High shareholder support. Shows alphas (left-hand axis) and t-statistics (right hand axis) from time-series regressions of the high abnormal shareholder support decile on the Fama-French five factor model augmented with momentum. The portfolio is constructed using value-weights, NYSE breakpoints, stocks above the market capitalization median and monthly signal fading. Period 0 is the month of the vote.

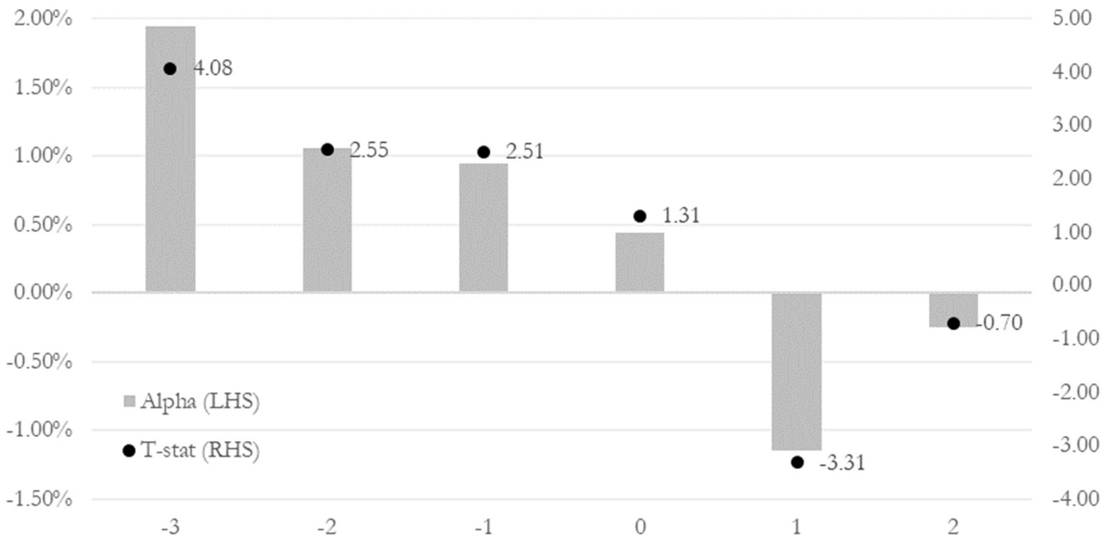
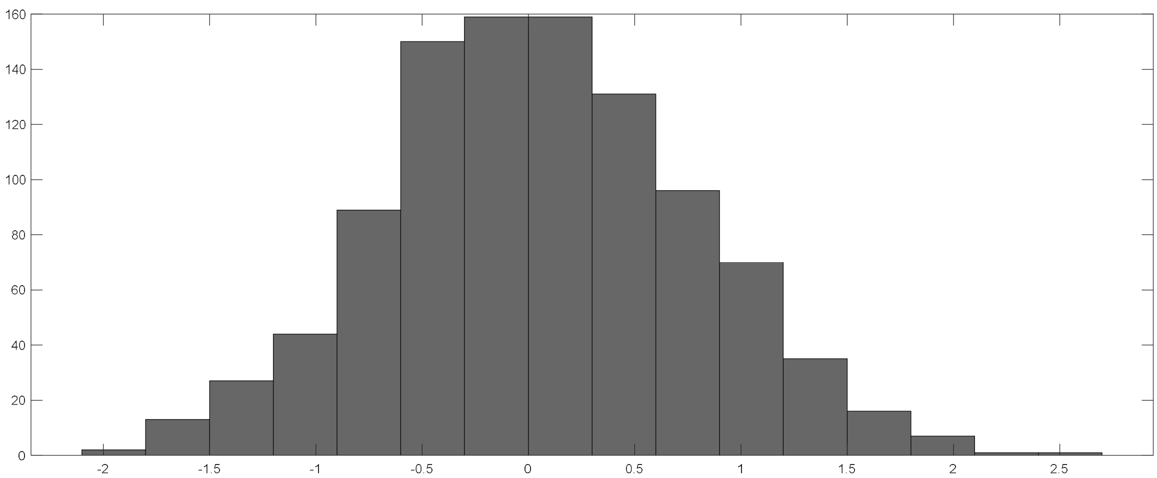


Figure 6. Alpha t-statistics distribution for portfolios with forward-looking bias. This figure shows the distribution of CAPM alpha t-statistics from 1000 simulations in which we construct a value weight portfolio from 10% of the securities in the universe with a pseudo shareholder meeting in three months. The strategy aims to select companies that will not go bankrupt within three months. The average alpha in the simulation is 0.01% annually highlighting minimal forward-looking bias.



Tables

Table 1. Data Summary. This table shows the most common characteristics across key measures in the full unfiltered voting sample (1/2003-12/2016). Descriptive statistics are displayed as percent of total resolutions. 'Vote base' is the denominator in the calculation of support rates. 'F' stands for support of a proposal, 'A' is against a proposal and 'AB' is abstain. 'Outstanding' is the total number of shares eligible to vote during a meeting. 'Vote requirement' is an indication of the kind of majority required for a proposal to pass. 'Plurality vote' refers to (elect director) votes where a majority is not required; obtaining more votes than the alternative is enough for the proposal to pass. The ISS recommendation comes from ISS's proxy research report. 'Vote result' comes from the comparison of the support rate and the required support threshold disclosed by the company. Management recommendation is the board of director's vote recommendation disclosed in the proxy card. Rare outcomes and missing data are included in 'other' for the sake of brevity.

Meetings	60268	Resolutions	437742
Unique Firms	10767	Management	427558
Unique Topics	409	Shareholder	10184

Management-sponsored		Shareholder Sponsored	
Meeting Type		**Meeting Type**	
Annual	94.0%	Annual	79.7%
Proxy Contest	0.7%	Proxy Contest	19.7%
Special	4.9%	Special	0.6%
Other	0.4%	Other	0.1%
Vote Requirement		**Vote Requirement**	
Plurality Vote	50.4%	Plurality Vote	83.3%
0.5	38.9%	0.5	9.0%
Other	10.7%	Other	7.7%
Management Recommendation		**Management Recommendation**	
For	98.5%	For	16.8%
Against	0.1%	Against	81.0%
Other	1.4%	Other	2.2%
ISS Recommendation		**ISS Recommendation**	
For	84.3%	For	60.2%
Against	3.9%	Against	28.0%
Withhold	9.0%	Withhold	1.6%
Do not vote	0.4%	Do not vote	9.9%
Other	2.4%	Other	0.4%
Vote Base		**Vote Base**	
F+A	73.7%	F+A	48.4%
F+A+AB	22.2%	F+A+AB	48.0%
Outstanding	1.4%	Outstanding	2.1%
Other	2.7%	Other	1.4%
Vote Result		**Vote Result**	
Pass	84.4%	Pass	20.6%
Fail	0.5%	Fail	67.0%
Other	15.2%	Other	12.4%

Table 2. Evolution of Voting Behavior. Panel A displays descriptive statistics across years for management-sponsored proposals, while Panel B does so for shareholder-sponsored proposals. 'Firms' is the number of unique firms with at least one proposal. 'Proposed' refers to the total number of resolutions. 'P/F' is the average number of proposals per firm. 'Voted' refers to proposals with valid vote data. Not all proposed resolutions are voted (as they can also be withdrawn). 'Support' is the average support rate calculated using the resolution specific denominator as the base. 'SD' is the standard deviation in support rates. 'Participation' is the average participation rate with shares outstanding as the denominator ((for+against)/outstanding). 'Mgmt. For' is the average number of 'for' recommendations issued by the board of directors. 'ISS For' is the average 'for' recommendations issued in ISS proxy research reports. 'Average' is the average across years.

Panel A: Management-sponsored Proposals									
Year	Firms	Proposed	P/F	Voted	Support	SD	Participation	Management For	ISS For
2003	2761	18098	6.6	17187	97.7%	7.6%	84.0%	99.9%	81.7%
2004	2740	19243	7.0	16993	97.3%	7.9%	85.4%	99.9%	86.5%
2005	2614	18885	7.2	18608	94.0%	9.1%	87.7%	99.9%	87.8%
2006	2822	20565	7.3	20016	94.6%	10.0%	87.3%	99.9%	89.3%
2007	2890	21886	7.6	19566	94.5%	9.0%	87.1%	99.9%	89.2%
2008	2893	22761	7.9	20071	94.3%	10.9%	86.7%	99.8%	89.5%
2009	3022	24639	8.2	22723	92.7%	11.7%	89.3%	99.8%	84.2%
2010	2971	24171	8.1	23508	93.8%	10.0%	76.7%	99.8%	87.1%
2011	3473	35272	10.2	29209	93.9%	9.5%	75.5%	91.0%	80.6%
2012	3882	36303	9.4	32887	93.9%	10.9%	75.5%	98.9%	84.4%
2013	4434	46516	10.5	34299	94.4%	9.1%	73.7%	97.3%	81.9%
2014	4507	47443	10.5	35347	95.0%	8.6%	74.0%	99.1%	83.6%
2015	4564	46410	10.2	35914	94.9%	8.7%	74.3%	99.2%	82.7%
2016	4553	45341	10.0	35050	94.8%	8.7%	76.2%	99.0%	82.2%
Average	3438	30538	8.6	25813	94.7%	9.4%	81.0%	98.8%	85.1%

Panel B: Shareholder Sponsored Proposals									
Year	Firms	Proposed	P/F	Voted	Support	SD	Participation	Management For	ISS For
2003	295	579	2.0	571	30.6%	23.7%	69.7%	1.9%	50.3%
2004	316	644	2.0	599	26.7%	24.1%	70.1%	1.1%	42.7%
2005	269	568	2.1	550	28.7%	23.5%	70.0%	2.5%	52.1%
2006	298	620	2.1	598	32.5%	23.4%	71.4%	1.3%	60.6%
2007	308	678	2.2	643	30.7%	22.3%	70.0%	3.2%	58.7%
2008	327	774	2.4	679	37.0%	28.2%	67.8%	18.9%	56.7%
2009	349	835	2.4	726	42.5%	28.5%	66.9%	20.0%	65.4%
2010	358	847	2.4	649	37.3%	25.1%	68.6%	24.0%	64.3%
2011	290	599	2.1	538	41.2%	28.8%	68.3%	20.7%	67.3%
2012	338	804	2.4	596	41.1%	29.5%	69.5%	25.9%	58.2%
2013	344	837	2.4	669	45.0%	32.0%	67.5%	28.9%	62.6%
2014	334	762	2.3	643	43.1%	31.3%	68.7%	27.2%	66.5%
2015	393	871	2.2	678	37.9%	26.6%	70.5%	21.5%	67.2%
2016	377	766	2.0	631	36.2%	28.6%	69.5%	22.1%	61.9%
Average	328	727	2.2	626	36.5%	26.8%	69.2%	15.6%	59.6%

Table 3. Most common agenda items. Panel A exhibits the five most common voted resolution types for management and shareholder sponsored proposals. Panel B exhibits the most common voted resolution types in special meetings and proxy contests. ISS classifies resolutions into 410 unique topics. 'Voted' is the number of remaining resolutions with disclosed voting outcomes in the post-processed data. 'Average Support' is the average support for resolutions on the same topic with the company-specific denominator as the base for each resolution. 'SD Support' is the standard deviation of vote support. 'Omnibus stock plan' resolutions encompass a range of performance-based incentives for employees, executives and board members. 'Declassify the Board of Directors' resolutions aim to prevent directors from serving different term lengths (which enables preventing takeovers). 'Require a Majority Vote for the Election of Directors' aims to end the practice whereby nominees receiving the most votes are elected even if the majority of the votes cast are not supportive of the appointment. 'Advisory Vote to Ratify Named Executive Officers' Compensation' is say-on-pay. 'Advisory Vote on Golden Parachutes' is a non-binding vote related to the approval of executive compensation arrangements in M&A arrangements.

Panel A			
Management Resolutions	Voted	Average Support	SD
'Elect Director'	240642	95%	8%
'Ratify X as Auditors'	37076	98%	3%
Advisory Vote to Ratify...Compensation'	17108	91%	12%
'Amend Omnibus Stock Plan'	7095	83%	13%
'Approve Omnibus Stock Plan'	4253	83%	13%
Shareholder Resolutions	Voted	Average Support	SD
'Require Independent Board Chairman'	590	30%	12%
'Declassify the Board of Directors'	547	68%	18%
'Elect Directors (Opposition Slate)'	535	89%	16%
'Political Contributions Disclosure'	487	22%	12%
'Require a Majority Vote for...Directors'	447	55%	18%

Panel B			
Special Meeting	Voted	Average Support	SD
'Approve Merger Agreement'	1030	89%	18%
'Adjourn Meeting'	694	91%	10%
'Advisory Vote on Golden Parachutes'	629	81%	17%
Proxy Contest	Voted	Average Support	SD
'Elect Director (Management)'	973	92%	12%
'Elect Directors (Opposition Slate)'	524	89%	16%

Table 4. Baseline Anomaly. Panel A shows intercepts from time-series regressions of the voting strategy constructed using value-weighted decile portfolios with NYSE breakpoints, monthly rebalancing and one-month fading abnormal shareholder support signal on the CAPM, the Fama-French three factor model (FF3), the Fama-French five factor model (FF5) and the Fama-French five factor model augmented with momentum (FF5+Mom). Panel B shows loadings and t-statistics of the baseline anomaly on the augmented Fama-French five factor model. Portfolio 10 is the high abnormal shareholder support portfolio. Alphas are monthly.

Panel A								
Portfolio	CAPM		FF3		FF5		FF5+Mom	
	Alpha	*t-stat*	Alpha	*t-stat*	Alpha	*t-stat*	Alpha	*t-stat*
10	**-1.09%**	***-3.36***	**-1.10%**	***-3.45***	**-1.06%**	***-3.21***	**-1.08%**	***-3.28***
1	0.08%	*0.25*	0.05%	*0.17*	0.11%	*0.33*	0.12%	*0.36*
LS	**1.17%**	***2.44***	**1.15%**	***2.42***	**1.18%**	***2.37***	**1.20%**	***2.46***

Panel B						
Coeff	MKT	SMB	HML	RMW	CMA	MOM
10	1.04	0.20	0.39	-0.09	-0.21	0.15
1	0.91	0.43	-0.21	-0.15	0.15	-0.13
LS	-0.13	0.24	-0.60	-0.06	0.36	-0.28

t-stat	MKT	SMB	HML	RMW	CMA	MOM
10	*10.65*	*1.27*	*2.45*	*-0.44*	*-0.81*	*1.91*
1	*9.00*	*2.72*	*-1.30*	*-0.70*	*0.56*	*-1.59*
LS	*-0.91*	*1.04*	***-2.55***	*-0.19*	*0.94*	***-2.39***

Table 5. Alternative strategies. This table shows time-series regressions of the CAPM, Fama-French three factor model (FF3), the Fama-French five factor model (FF5) and the Fama-French five factor model augmented with momentum (FF5+Mom) on the voting strategy constructed using various methods. 'Maximum' refers to strategies where abnormal shareholder support is constructed using the average of the three most extreme support measures. Signal fading refers to the number of months a stock can remain in a portfolio. Portfolio 10 (1) is the high (low) abnormal shareholder support portfolio. Alphas are monthly.

Portfolio	CAPM		FF3		FF5		FF5+Mom	
	Alpha	*t-stat*	Alpha	*t-stat*	Alpha	*t-stat*	Alpha	*t-stat*
Two Months Fading								
10	-0.54%	***-2.00***	-0.56%	***-2.11***	-0.45%	*-1.65*	-0.47%	*-1.74*
1	0.43%	*1.52*	0.41%	*1.47*	0.50%	*1.75*	0.50%	*1.76*
LS	0.97%	***2.75***	0.97%	***2.74***	0.95%	***2.59***	0.97%	***2.68***
Maximum								
10	-0.87%	***-3.01***	-0.89%	***-3.09***	-0.84%	***-2.83***	**-0.85%**	***-2.83***
1	-0.34%	*-1.00*	-0.35%	*-1.03*	-0.21%	*-0.59*	-0.20%	*-0.57*
LS	0.53%	*1.17*	0.53%	*1.17*	0.64%	*1.35*	0.65%	*1.37*
Maximum-Two Months Fading								
10	-0.81%	***-3.40***	-0.82%	***-3.45***	-0.87%	***-3.52***	-0.89%	***-3.69***
1	0.37%	*1.37*	0.36%	*1.36*	0.50%	*1.80*	0.51%	*1.87*
LS	1.18%	***3.30***	1.19%	***3.31***	1.37%	***3.73***	1.40%	***3.96***

Table 6. Robustness checks. This table shows time-series regressions of the CAPM, Fama-French three factor model (FF3), the Fama-French five factor model (FF5) and the Fama-French five factor model augmented with momentum (FF5+Mom) on the abnormal shareholder support anomaly constructed using various methods. Unless otherwise stated, strategies are constructed using value-weights, NYSE breakpoints, monthly rebalancing, and monthly fading signal. The 'without small' strategy excludes all firms below the market capitalization median. 'Newey West SE' refers to t-statistics based on heteroskedasticity and autocorrelation consistent standard errors. 'Two months fading' refers sorts where stocks can remain in a portfolio for two months after the initial signal. Alphas are monthly. Portfolio 10 is the high abnormal shareholder support portfolio.

Without Small								
Portfolio	CAPM		FF3		FF5		FF5+Mom	
	Alpha	*t-stat*	Alpha	*t-stat*	Alpha	*t-stat*	Alpha	*t-stat*
10	-1.17%	***-3.44***	-1.18%	***-3.51***	-1.13%	***-3.24***	-1.14%	***-3.31***
1	-0.11%	*-0.31*	-0.13%	*-0.36*	-0.01%	*-0.02*	-0.01%	*-0.03*
LS	-1.06%	***-2.02***	1.05%	***2.01***	1.12%	***2.07***	1.13%	***2.10***

Two Months Fading-Without Small								
10	-0.71%	***-2.51***	-0.73%	***-2.60***	-0.60%	***-2.11***	-0.62%	***-2.20***
1	0.63%	***2.41***	0.62%	***2.37***	0.72%	***2.66***	0.72%	***2.68***
LS	1.34%	**3.91**	1.35%	**3.92**	1.32%	**3.71**	1.34%	**3.83**

Newey-West SE								
10	-1.09%	**-3.13**	-1.10%	**-3.26**	-1.06%	**-3.16**	-1.08%	**-3.25**
1	0.08%	0.24	0.05%	0.16	0.11%	0.32	0.12%	0.34
LS	1.17%	**2.21**	1.15%	**2.23**	1.18%	**2.21**	1.20%	**2.27**

Table 7. Subsamples. This table shows time-series regressions of the CAPM, Fama-French three factor model (FF3), the Fama-French five factor model (FF5) and the Fama-French five factor model augmented with momentum (FF5+Mom) on abnormal shareholder support sorted portfolios. Unless otherwise stated, portfolios are constructed using value-weights, NYSE breakpoints, monthly rebalancing, and a monthly fading signal. 'Management' constructs abnormal shareholder support using only management-sponsored resolutions. 'Shareholder' constructs abnormal shareholder support using only shareholder-sponsored resolutions and sorts assets into EW terciles due to the smaller amount of stocks. 'Annual meeting' constructs portfolios using signals only from annual meetings. 'Meeting in the first half of the month' constructs portfolios with signals from meetings that take place in the first half of the month. 'Conditioned on management recommendation' multiplies abnormal shareholder support measure with 1 when management is for and -1 when management is against (or when management recommends not voting/abstaining). Alphas are monthly. Portfolio 10 is the high abnormal shareholder support portfolio.

	Annual Meeting							
Portfolio	CAPM		FF3		FF5		FF5+Mom	
	Alpha	*t-stat*	Alpha	*t-stat*	Alpha	*t-stat*	Alpha	*t-stat*
10	-0.84%	**-2.30**	-0.87%	**-2.42**	-0.88%	**-2.37**	-0.89%	**-2.40**
1	0.07%	0.20	0.04%	0.13	0.17%	0.50	0.17%	0.51
LS	0.91%	1.90	0.91%	1.90	1.05%	**2.12**	1.06%	**2.14**
	Meetings only from the first half of the month							
10	-1.11%	**-2.49**	-1.13%	**-2.58**	-1.08%	***-2.37***	-1.09%	***-2.41***
1	-0.59%	-1.30	-0.60%	*-1.33*	-0.57%	*-1.22*	-0.58%	*-1.23*
LS	0.52%	0.84	0.53%	*0.88*	0.50%	*0.81*	0.51%	*0.82*

Table 8. Abnormal support and period effects. Shows alphas and t-statistics of decile portfolios sorted on abnormal shareholder support regressed on the Fama-French five factor model augmented with momentum. The portfolios are constructed using value-weights, NYSE breakpoints, monthly rebalancing, and monthly signal fading. Period 0 is the month of the vote.

	Alpha							
Period	-4	-3	-2	-1	0	1	2	3
1	0.39%	0.23%	0.06%	0.05%	0.41%	0.12%	0.32%	-0.09%
10	0.43%	1.75%	1.02%	0.72%	0.47%	-1.08%	-0.65%	-0.16%
LS	0.04%	1.51%	0.97%	0.68%	0.06%	-1.20%	-0.96%	-0.06%

	t-stat							
Period	-4	-3	-2	-1	0	1	2	3
1	1.07	*0.67*	*0.15*	*0.14*	*1.16*	*0.36*	*0.86*	*-0.24*
10	1.12	***3.91***	***2.60***	***1.96***	*1.37*	***-3.28***	*-1.84*	*-0.48*
LS	0.07	***2.78***	*1.71*	*1.37*	*0.12*	***-2.46***	*-1.80*	*-0.12*

Table 9. The Dimensions of Disagreement. This table shows the dimension of disagreement for relevant stakeholders in the voting process. ISS For (Against) implies that the institutional shareholder services (ISS) recommend voting for (against) the proposal. Management For (Against) implies that the board of directors recommends voting For (Against) the proposal. Shareholders For (Against) implies that shareholders are in support of (against) the proposal. Shareholders views are reflected in the vote. Management and ISS recommendations precede the corporate vote.

	ISS For		ISS Against	
	Shareholder For	Shareholders Against	Shareholder For	Shareholder Against
Management For	Agreement	Disagreement	ISS Dissent	Dissent
Management Against	Dissent	ISS Dissent	Disagreement	Agreement

Table 10. Voting support. This table shows results from regressing shareholder support on dummy variables for resolution sponsor ('Shareholder'), management recommendation ('MGMT For'), proxy advisory recommendation ('ISS For'), meeting type, calendar year, month and topic. The sample covers the period from 01/2003 to 12/2016.

Shareholder Support		Estimate	*t-stat*	Estimate	*t-stat*
MGMT For		8.5%	**10.6**	9.7%	***12.1***
ISS For		6.8%	**5.6**	6.7%	***5.7***
MGMT For*ISS For		5.9%	**4.8**	6.4%	***5.4***
Shareholder		-33.3%	**-37.9**	-31.5%	***-36.1***
Shareholder*MGMT For		17.6%	**16.3**	16.8%	***15.5***
Shareholder*ISS For		13.1%	**10.5**	13.5%	***11.1***
Shareholder*ISS For*MGMT For		-4.9%	**-3.6**	-6.2%	***-4.6***
Topic FE	Yes	Yes		Yes	
Month FE	No	No		Yes	
Year FE	No	No		Yes	
Meeting Type FE	No	No		Yes	
Industry FE	No	No		Yes	
NT	339289	338700		338700	
R2 Adj	57.4%	67.9%		69.8%	

Table 11. Sorts on residual vote support. Shows FF5 + Momentum time-series alphas and t-statistics for value-weighted quintile portfolios. The portfolios are sorted on the residual from an in-sample vote forecasting regression using topics and voting recommendations as predictors ('recommendation & Topic Res.'). '[-6,-4]' ('[4,6]') captures alphas for stocks that fall in a particular quintile during the period from -6 to -4 (4 to 6) before (after) the month of the vote (used as a placebo/robustness check). 'Topic Res.' refers to sorts on residuals in regressions with only topics as predictors. Period 0 is the month of the vote and alphas showed for this period are for portfolios created at the end of the previous month. Portfolio 5 is the high abnormal support portfolio.

	Recommendations & Topic Res.									Topic Res.
	Alpha							Alpha		Alpha
Period	-3	-2	-1	0	1	2	3	[-6,-4]	[4,6]	1
1	0.28%	-0.30%	0.14%	0.26%	0.11%	0.16%	0.36%	-0.21%	0.12%	0.33%
5	1.60%	1.70%	0.41%	0.85%	-0.76%	-0.36%	-0.46%	0.16%	-0.09%	-0.67%
LS	1.33%	2.01%	0.27%	0.59%	-0.87%	-0.52%	-0.82%	0.37%	-0.21%	-1.01%
	T-stat							*T-stat*		*T-stat*
1	*0.78*	*-0.91*	*0.44*	*0.91*	*0.33*	*0.51*	*0.98*	-0.92	0.48	1.09
5	**4.38**	**5.22**	1.47	**3.13**	**-2.59**	-1.21	-1.43	0.71	-0.45	**-2.21**
LS	***2.74***	***4.31***	*0.62*	*1.59*	***-2.19***	*-1.23*	*-1.59*	1.15	-0.63	**-2.37**

Table 12. Voting Period Anomaly. The table shows alpha and t-statistics form times series regressions of the returns of a value-weighted (VW) and equally weighted (VW) portfolio minus the risk-free rate regressed on the CAPM and Fama-French five factor model augmented with momentum. Period 0 is the month of the meeting.

CAPM Alphas							
Period	-3	-2	-1	0	1	2	3
Alpha VW	0.54%	0.25%	0.23%	0.51%	-0.04%	-0.23%	-0.15%
t-stat	**3.24**	1.53	*1.14*	***3.18***	-0.20	-1.37	-0.77
Alpha EW	1.21%	0.78%	0.58%	0.44%	0.15%	0.07%	0.30%
t-stat	**5.36**	**3.45**	**2.88**	**2.37**	0.73	0.36	1.48

FF5 + Mom Alphas							
Period	-3	-2	-1	0	1	2	3
Alpha VW	0.56%	0.23%	0.28%	0.54%	-0.04%	-0.24%	-0.12%
t-stat	**3.25**	1.42	*1.38*	***3.18***	-0.22	-1.35	-0.63
Alpha EW	1.30%	0.89%	0.65%	0.53%	0.22%	0.11%	0.38%
t-stat	**7.32**	**5.69**	**4.47**	**3.75**	1.56	0.74	**2.69**

Table 13. Returns around shareholder meetings. This table shows average slopes (λ) and t-statistics from monthly cross-sectional regressions to predict stock returns. The predictive variables are defined as: 'MET(-3,-1)' (meeting) is a dummy variable that takes the value 1 in the three months before shareholder meetings, 'MET(0)' is a dummy variable that takes the value 1 in the month of the shareholder meeting, 'MET(1,3)' is a dummy variable that takes the value 1 in the three months after the shareholder meeting, 'MC' (market capitalization) is the natural log of market capitalization, 'B/M' (book-to-market) is book equity from last fiscal year divided by market equity in December, 'Mom' (momentum) is cumulative momentum from t-12 to t-2, 'Inv' (investment) is the change in total assets from the fiscal year ending in year t-2 to the fiscal year ending in t-1, 'Op' (operating profitability) is revenue minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity, 'Acc' (accruals) is accruals following Sloan (1996), 'Ni' (net issuance) is the change in the natural log of split-adjusted shares outstanding between two fiscal years; 'Annual', 'Proxy' and 'Special' are dummy variables that take the value 1 for annual, special and proxy shareholder meeting in the three months before the meeting for (-3,1), the month of the meeting for (0) and the three months after the meeting for (1,3). 'Int' (intercept) is the (average) regression intercept. The full sample includes all US common stocks from 07/1963 to 12/2016. The restricted sample (Res. Sample) contains US common stocks that have voting data (restricts the universe from 8285 to 5921 firms in the period from 01/2003 to 12/2016). T-statistics are based on the time-series standard deviation of monthly slopes.

Stock Returns	Res. Sample		Full Sample		Res. Sample		Res. Sample		Res. Sample	
	λ	*t-stat*	λ	*t-stat*	λ	*t-stat*	λ	*t-stat*	λ	*t-stat*
Int	1.05	***2.48***	1.30	***3.22***	2.44	***3.48***	2.40	***3.36***	1.20	*1.06*
MET (-3,-1)	0.75	***5.91***					1.06	***8.21***		
MET (0)	0.37	***2.61***					0.54	***3.78***		
MET (1,3)	0.18	*1.57*					0.42	***3.46***		
MC			-0.18	***-5.24***	-0.16	***-3.90***	-0.21	***-4.92***	-0.09	*-1.50*
B/M			0.12	***2.09***	0.05	*0.39*	0.05	*0.38*	-0.08	*-0.46*
Mom			0.54	***3.24***	-0.43	*-1.09*	-0.42	*-1.04*	-0.92	*-1.28*
Inv			-0.59	***-6.62***	-0.47	***-3.38***	-0.46	***-3.24***	-0.12	*-0.59*
Op			0.49	***4.55***	-0.01	*-0.08*	-0.05	*-0.29*	0.15	*0.76*
Acc			-1.19	***-4.99***	-0.31	*-0.59*	-0.22	*-0.41*	0.04	*0.05*
NI			-1.27	***-5.32***	-0.47	*-0.95*	-0.38	*-0.75*	-1.69	***-2.35***
Annual (-3,-1)									0.75	***3.57***
Annual (0)									0.44	***1.99***
Annual (1,3)									0.37	*1.83*
Proxy Contest (-3,-1)									2.07	***2.38***
Proxy Contest (0)									-0.28	*-0.24*
Proxy Contest (1,3)									-1.13	*-1.56*
Special (-3,-1)									3.69	***8.46***
Special (0)									1.30	*1.19*
Special (1,3)									-1.33	***-3.38***

Table 14. Voting anomaly independence. Panel A shows mean excess returns and intercepts in time-series regressions for the voting period premium ('VP-Rf'), shareholder support premium ('SMD.LS'), and the equity premium ('MKT'). Controls include the FF5 + momentum factors. VP-Rf' is the baseline value-weighted voting period premium whereby all stocks that have a meeting in the following month are held in a value-weighted portfolio. 'SMD.LS' is the support minus dissent long-short baseline investment strategy whereby stocks are sorted on average abnormal shareholder support at the end of the month of the vote and stocks with high support enter the short portfolio. **Panel B** shows the mixed strategy that is long stocks that will have a meeting next month and short stocks that had high abnormal shareholder support last month. 'Season' is a dummy variable that takes the value 1 in the proxy season (April, May, and June).

Panel A

Strategy		Intercept/Mean	MKT	VP-Rf	SMD.LS	Controls	R2 Adj
VP-Rf	Coef.	1.11%					
	t-stat	**3.43**					
SMD.LS	Coef.	1.13%					
	t-stat	**2.41**					
MKT	Coef.	0.78%					
	t-stat	**2.47**					
VP-Rf	Coef.	0.55%	0.89		-0.03	No	76%
	t-stat	**3.36**	**22.8**		-1.22		
SMD.LS	Coef.	1.28%	0.19	-0.27		No	0%
	t-stat	**2.62**	0.8	-1.16			
MKT	Coef.	0.80%			-0.02	No	0%
	t-stat	**2.5**			-0.43		
MKT	Coef.	-0.17%		0.85		No	76%
	t-stat	-1.05		**23**			
MKT	Coef.	-0.07%		0.76	0.02	Yes	78%
	t-stat	-0.44		**17.3**	0.64		

Panel B

Strategy		Alpha	Season	MKT	SMB	HML	RMW	CMA	MOM	R2 Adj
VP-SMD.S	Coef.	1.51%		-0.17	-0.2	-0.43	0.04	0.29	-0.19	7.30%
	t-stat	**4.29**		-1.63	-1.18	-2.51	0.19	1.04	**-2.3**	
VP-SMD.S	Coef.	1.86%	-1.37%	-0.18	-0.18	-0.44	0.05	0.23	-0.21	8.40%
	t-stat	***4.61***	-1.74	*-1.74*	*-1.07*	***-2.6***	0.21	0.83	**-2.55**	

Table 15. Trading volume. Panel A shows the average trading activity (shares traded/shares outstanding) for stocks experiencing a vote in month t (and have trading data form t-3 to t+3). P-values are calculated for differences between means relative to month t (the month of the vote). Panel B shows coefficient estimates for the full sample of firms from 01/2003 to 12/2016 with trading volume (share volume divided by shares outstanding) as the dependent variable. 'Low (mid/high) before (after) is a dummy variable that takes the value 1 if the company falls in the bottom (middle/top) tercile of the shareholder support signal in the three months before (after) the meeting. Panel C shows coefficients from regressing trading volume on dummy variables that capture proxy contests, special meetings, and annual meetings. 'Proxy' is a dummy variable that takes the value 1 if there was a proxy contest. 'Special' (before/after) is a dummy variable that takes the value 1 if there was a special meeting. 'Before' ('After') indicates that a dummy variable takes the value 1 three months before (after) the meeting. Standard errors are clustered by year and industry.

Panel A

shvol/shrout	μ	*p-val*
t-3	19.5%	*0.00*
t-2	19.6%	*0.00*
t-1	19.4%	*0.00*
T	20.2%	
t+1	19.6%	*0.00*
t+2	19.6%	*0.00*
t+3	20.0%	*0.21*

Panel B

shvol/shrout	b	t-stat
Low Before	5.2%	4.37
Low	6.0%	4.91
Low After	5.6%	4.51
Mid Before	4.2%	3.79
Mid	4.5%	3.65
Mid After	4.0%	3.05
High Before	3.0%	3.62
High	3.8%	3.65
High After	3.1%	3.00
Year FE	Yes	
NT	664092	

Panel C

shvol/shrout	B	t-stat
Special Before	10.5%	6.26
Special	5.6%	4.58
Special After	4.7%	2.00
Proxy Before	7.5%	2.98
Proxy	9.2%	3.75
Proxy After	14.4%	1.57
Annual Before	3.3%	3.12
Annual	4.2%	3.40
Annual After	3.6%	2.79
Year FE	Yes	
NT	664092	

Table 16. Risk measures for the portfolio of voting firms. This table shows the betas and standard deviation of a value-weighted (vw) and equally-weighted (ew) portfolio of firms that have a shareholder meeting in period t=0.

Betas VW							
Period	-3	-2	-1	0	1	2	3
MKT	0.98	1.09	0.94	0.87	1.04	1.11	1.10
t-stat	***19.10***	***22.50***	***15.56***	***17.28***	***18.10***	***21.35***	***18.91***
SMB	0.12	0.09	0.11	0.00	0.06	0.08	0.09
t-stat	*1.47*	*1.21*	*1.13*	*-0.02*	*0.69*	*0.98*	*0.95*
HML	-0.02	-0.20	-0.02	-0.03	0.18	-0.15	0.00
t-stat	*-0.24*	***-2.50***	*-0.17*	*-0.41*	*1.95*	*-1.79*	*0.00*
RMW	-0.08	0.00	-0.10	-0.06	0.01	0.02	0.01
t-stat	*-0.68*	*0.03*	*-0.77*	*-0.50*	*0.10*	*0.16*	*0.07*
CMA	-0.09	0.02	-0.30	0.07	-0.17	-0.02	-0.20
t-stat	*-0.64*	*0.13*	*-1.87*	*0.51*	*-1.12*	*-0.16*	*-1.28*
MOM	0.03	0.02	0.01	-0.04	0.06	-0.02	-0.05
t-stat	*0.85*	*0.53*	*0.25*	*-1.04*	*1.30*	*-0.57*	*-1.13*

Betas EW							
Period	-3	-2	-1	0	1	2	3
MKT	0.98	0.95	0.96	0.88	0.95	1.10	1.01
t-stat	***18.8***	***20.4***	***22.3***	***21.1***	***23.0***	***26.1***	***24.1***
SMB	0.69	0.80	0.75	0.61	0.80	0.71	0.75
t-stat	***8.10***	***10.7***	***10.9***	***9.2***	***12.2***	***10.7***	***11.3***
HML	0.07	-0.18	-0.03	0.02	0.14	-0.16	-0.01
t-stat	*0.77*	***-2.31***	*-0.39*	*0.31*	***2.11***	***-2.31***	*-0.17*
RMW	-0.15	-0.35	-0.25	-0.26	-0.22	-0.16	-0.19
t-stat	*-1.28*	***-3.43***	***-2.64***	***-2.89***	***-2.44***	*-1.75*	***-2.10***
CMA	-0.17	0.29	-0.05	-0.04	-0.14	0.08	-0.13
t-stat	*-1.22*	***2.31***	*-0.42*	*-0.34*	*-1.31*	*0.73*	*-1.19*
MOM	-0.24	-0.21	-0.13	-0.14	-0.11	-0.15	-0.21
t-stat	***-5.89***	***-5.79***	***-3.89***	***-4.15***	***-3.23***	***-4.46***	***-6.37***

SD							
Period	-3	-2	-1	0	1	2	3
VW	4.62%	4.83%	4.72%	4.17%	4.94%	5.00%	5.21%
EW	5.99%	5.99%	5.72%	5.26%	5.78%	6.01%	5.98%

Table 17. Subsamples of management and shareholder sponsored resolutions. This table shows sorts on abnormal shareholder support constructed by using only outcomes in management and shareholder sponsored resolutions. Abnormal shareholder support in shareholder-sponsored resolutions is constructed in terciles due to the lower number of firms. Portfolio 10 (3) is high support while portfolio 1 is low support. Alphas are calculated relative to the FF five factor model augmented with momentum.

Management-sponsored Resolutions							
Alpha							
Period	-3	-2	-1	0	1	2	3
1	0.22%	0.41%	0.28%	0.23%	0.27%	0.71%	0.01%
10	2.24%	1.79%	0.94%	0.46%	-0.55%	-0.35%	-0.71%
LS	2.02%	1.38%	0.65%	0.23%	-0.82%	-1.06%	-0.73%

t-stat							
Period	-3	-2	-1	0	1	2	3
1	*0.59*	*0.98*	*0.86*	*0.70*	*0.73*	*1.71*	*0.03*
10	***4.67***	***4.46***	***2.77***	*1.39*	*-1.61*	*-1.06*	***-2.09***
LS	***3.46***	***2.28***	*1.39*	*0.47*	*-1.56*	***-2.03***	*-1.29*

Shareholder Sponsored Resolutions							
Alpha							
Period	-3	-2	-1	0	1	2	3
1	0.14%	1.50%	0.99%	0.87%	0.90%	-0.68%	0.68%
3	-0.29%	0.01%	0.52%	0.81%	-0.91%	-0.05%	0.63%
LS	-0.42%	-1.50%	-0.47%	-0.06%	-1.81%	0.62%	-0.05%

t-stat							
Period	-3	-2	-1	0	1	2	3
1	*0.26*	***2.30***	*1.91*	*1.79*	*1.56*	*-1.07*	*1.02*
3	*-0.51*	*0.01*	*1.15*	*1.45*	*-1.77*	*-0.13*	*1.27*
LS	*-0.55*	*-1.72*	*-0.71*	*-0.08*	***-2.46***	*0.79*	*-0.06*

Appendix - Additional tables and figures

Figure 7. New signals across time. This figure shows the incidence of new monthly signals in the sample (y-axis). The average abnormal support across votes per firm in a month is a new signal. The large spikes are the proxy seasons.

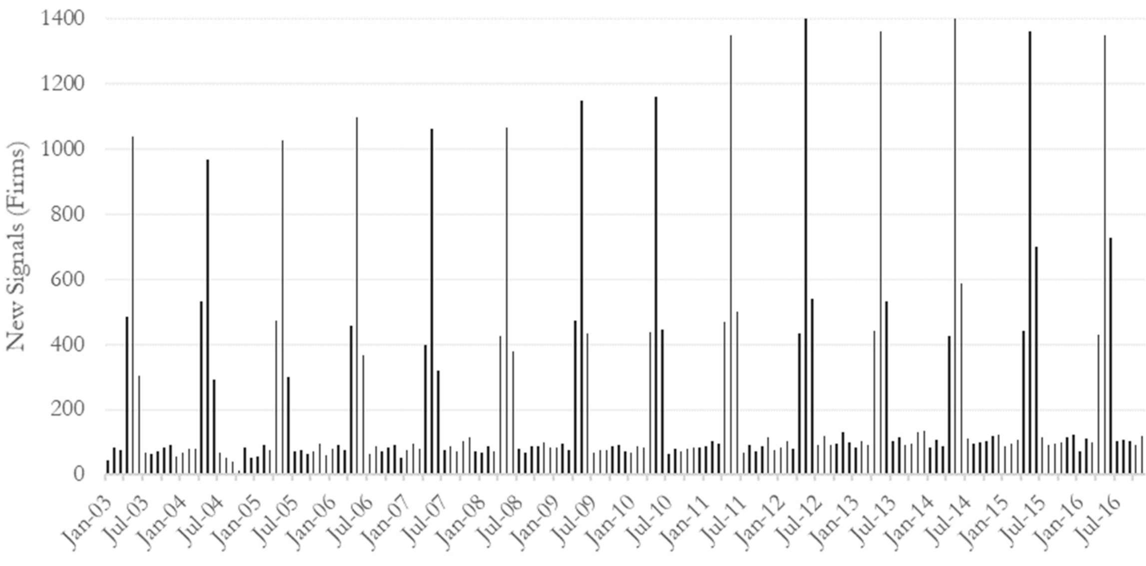


Figure 8. Distance between two consecutive shareholder meetings. This figure shows a histogram of the monthly distance between two consecutive shareholder meetings in the data. Annual meetings tend to occur within 11 to 13 months from the previous annual meeting. Special meetings tend to occur between two consecutive annual meetings.

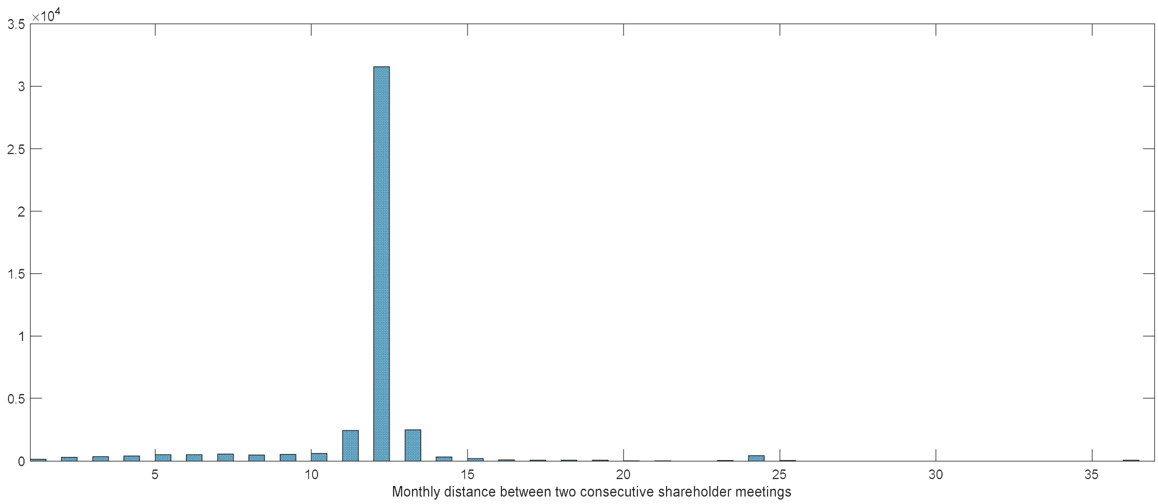


Figure 9. Beta variation for the abnormal shareholder support anomaly. This figure shows t-statistics from time-series regressions of the high minus low abnormal support portfolio at period t on the benchmark factors. Period 0 is the month of the shareholder meeting.

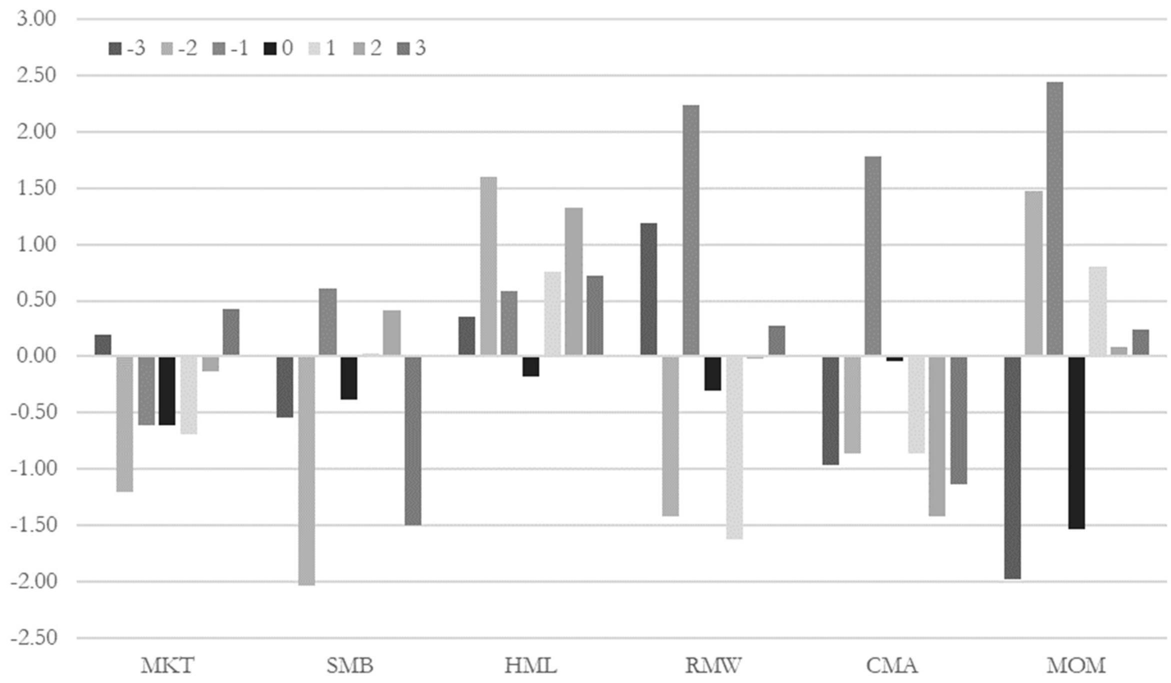


Table 18. Fama-MacBeth abnormal support. Shows coeffects and t-stats from Fama-MacBeth regressions of stock returns on dummy variables capturing abnormal support deciles for big stocks. Period 0 is the month of the vote. Controls include market capitalization, book to market, investments, profitability and cumulative returns.

	Coeff	t-stat	Coeff	t-stat
Intercept	1.13	**2.67**	1.93	**2.06**
Low -3	0.96	**2.93**	1.10	**3.23**
Low -2	0.52	1.73	0.54	1.76
Low -1	0.16	0.50	-0.06	-0.17
Low 0	0.83	**2.66**	0.64	**2.03**
Low 1	-0.39	-1.23	-0.45	-1.54
Low 2	0.59	1.79	0.54	1.62
Low 3	-0.31	-1.05	-0.54	-1.68
High -3	2.02	**4.69**	1.83	**4.25**
High -2	1.10	**2.80**	1.34	**3.11**
High -1	0.75	**2.57**	0.38	1.28
High 0	0.32	1.07	0.17	0.55
High 1	-1.08	**-3.42**	-0.76	**-2.33**
High 2	-0.18	-0.59	0.10	0.36
High 3	-0.82	**-2.35**	-0.57	-1.70
Controls	No		Yes	